Title	Gait-based Health Status Assessment by Large-scale Data Collection
Author(s)	Zhou, Chengju
Citation	大阪大学, 2019, 博士論文
Version Type	VoR
URL	https://doi.org/10.18910/72581
rights	
Note	

Gait-based Health Status Assessment by Large-scale Data Collection

Submitted to
Graduate School of Information Science and Technology
Osaka University

January 2019

Chengju ZHOU

Abstract

The advancements in medical science and technology have given rise to longer life expectancy and increasing rate of survival from severe disease globally in the past decades. As a result, there are more and more demands for healthcare service. Health Monitoring System (HMS), which is used to provide physical/mental health and activity status monitoring, emerged just for this purpose. Activity monitoring is an important component in this system. Wearable sensors and maker-based motion capture system are adopted in most of the researches to record motion data, which need to attach sensors and makers on human body and cause discomfort and cognitive burden to the users. Thus, the present thesis chose non-contact way, i.e. camera, to allow people live in a free environment. However, there existed only a few number of researches applied this way and they still counter some shortcomings, such as, no sufficient number of subjects in database to achieve reliable statistical conclusion, limited categories of disease/abnormality to be detected, limited aspects of health information to be assessed, and the proposed methods are vulnerable to noise. Those shortcomings constrain HMS to be a pervasive and convenient healthcare solution.

Therefore, in this thesis, to extend the camera-based HMS into a more practical and broader application, we proposed a convenient way to analyze human's health condition by observing the most commonly seen locomotion form - gait, through camera. In general, based on the different application purpose and situations, this HMS can be further divided into two sub-systems. One is a passive way to study physical aspect of health. It can be used to detect people with physical impairment in public place, i.e. shopping mall, to provide service when necessary. In addition to physical health, other aspects of information is also important for health. So we go further to provide active way to learn multi-aspect of health. This method can realize quick multi-aspect health assessment even at home. Considering two challenges related with dataset and performance representation, we introduce more details about the two proposed approaches as follows:

In the first sub-system, we proposed a novel method to detect people with physical impairment through walking style. To achieve this target, we first constructed a database with sufficient number of subjects, containing visual/leg impaired walking and normal walking. We then investigated which gait feature is effective to distinguish them among posture, temporal and stability information, which are correspondingly represented by gait energy image (GEI) that is a popular appearance-based feature showing high performance in human authentication, duration time, and phase fluctuation from silhouette sequence. After comparison experiments, we found that GEI was the most reliable feature. Further, considering that GEI is mainly about posture information, it must be

affected by the other parts of the human body except effective part. We thus proposed to use only the most discriminative body patches in GEI. Sufficient experiments were conducted to evaluate the contribution of various sizes and positions of body patches. At last, for the visual impairment discrimination case, we found that head and chest regions performed better than the whole body. As for the leg impairment detection case, the leg region performed better than the whole body. The results confirmed the effectiveness of patch-based GEI for impairment detection.

In the second sub-system, we designed a game-based system to screen children's three aspects of growth information, including anthropometric, kinematic and more important, cognitive aspects. This method is different from the conventional approaches to the assessment of growth status which involve manual evaluation and treat different aspects of growth status separately. This study presents an automated method for assessing growth status that considers various aspects of growth simultaneously. We first applied the dual-task paradigm (where two tasks are performed simultaneously, here we used combination of stepping while doing arithmetical calculation) to collect data on the three aspects of growth at the same time. With the collected data from a large number of typically developing individuals, we constructed a statistical model of growth features and ages and also estimated participants' ages using regression analysis. By comparing the value of discrepancy between estimated age and chronological age from a test child to that of average level from normally developing children, we were able to provide an initial judgment of the child's growth status. The experiment results demonstrated that, the growth features developed with age in childhood and that the estimation of growth status using this model was feasible.

Acknowledgements

There are many people to whom I would like to express my gratitude and thanks for their warmly support and encouragement during my Ph.D. studies.

First of all, I want to sincerely thank my supervisor Professor Yasushi Yagi for giving me the opportunity to undertake this research program, as well as his valuable guidance throughout my whole Ph.D. course.

I also would like to express my great appreciation to my second supervisor Associate Professor Ikuhisa Mitsugami for his patient guidance. It is him who tell me the manner and attitude to do science research.

I am also grateful to Assistant Professor Fumio Okura and Specially Appointed Associate Professor Kota Aoki for their guidance and assistance throughout the second topic research. And I will always remember the kindly help from other lovely Yagi lab members.

I would like to express my gratitude to Japanese Government (Monbukagakusho) Scholarship and Yagi lab for their financial support for a long research life.

Lastly, I would like to thank my dearest family and dearest friends for always supporting and encouraging me. Without their invaluable support, I would not have been able to face the challenges of this process and keep going to the final goal.

Publication List

Journal Publications

1. **Chengju Zhou**, Ikuhisa Mitsugami, Yasushi Yagi, Detection of Gait Impairment by Patch-GEI, IEEJ Transactions on Electrical and Electronic Engineering, Vol.10, No.S1, 2015. DOI:10.1002/tee.22166.
2. **Chengju Zhou**, Ikuhisa Mitsugami, Fumio Okura, Kota Aoki, Yasushi Yagi, Growth Assessment of School-Age Children from Dual-Task Observation, ITE Transactions on Media Technology and Applications (MTA), Vol.6, No.4, 2018.

Conferences (with peer review)

1. **Chengju Zhou**, Ikuhisa Mitsugami, Yasushi Yagi, Which Gait Feature Is Effective for Impairment Estimation, 20th Korea-Japan Joint Workshop on Frontiers of Computer Vision (FCV), 2014.

Conferences and Workshops (without review)

1. **Chengju Zhou**, Ikuhisa Mitsugami, Yasushi Yagi, an attempt to detect impairment by silhouette-based gait feature, 22th European Society of Movement Analysis for Adults and Children (ESMAC) 2013.
2. **Chengju Zhou**, Ikuhisa Mitsugami, Yasushi Yagi, Performance Evaluation of GEI for Impairment Detection, 16th Meeting on Image Recognition and Understanding (MIRU) 2013.
3. **Chengju Zhou**, Ikuhisa Mitsugami, Yasushi Yagi, Assessing Cognition Level of Elderly Using Dual-task Stepping, 18th Meeting on Image Recognition and Understanding (MIRU) 2015.
4. **Chengju Zhou**, Ikuhisa Mitsugami, Kota Aoki, Fumio Okura, Yasushi Yagi, Age Estimation from Dual-Task Behavior for Comprehensive Growth Assessment of Children, The International Workshop on Frontiers of Computer Vision (IW-FCV) 2018.

Contents

List of Figures

List of Tables

For my parents

Chapter 1

Introduction

1.1 An Intelligent Healthcare Solution: Health Monitor System

With medical science and technology advanced in the past several decades, the life expectancy increased dramatically all over the world. However, the longer life expectancy coupled with lower birthrate give rise to an aging population, and the speed even accelerates in near future [8, 9]. Take Japan who has the oldest population in the world as an example [10–12], according to statistics and prediction in work [11], young-age population (under 15 years) in terms of percentage of the total population, is expected to shrink from 12.5% in 2015 to 10.2% in 2065, while old age population (65 years of age and over) increases from the level of 26.6% in 2015 to no less than 38.4% in 2065. In addition to aging population, the rate of disability are increasing in part due to an improvement in chronic health condition. According to the statistics from World Health Organization [13], over a billion (about 15%) of the world's population have some form of disability, and among them, between 110 million (2.2%) - 190 million (3.8%) people have significant difficulties in functioning.

As a result, it is no doubt that the demands of healthcare services increase for elderly people and people with disability. They require regular monitoring and care to keep necessary activities and health in daily lives, which, conventionally, are mainly supported by their family and nursing staffs. These impose a significant financial and time burden on the patients and their family and also it is a big labor to clinical and nursing staffs. And also, with the improving general health consciousness, even healthy people look forward a solution which can inform the

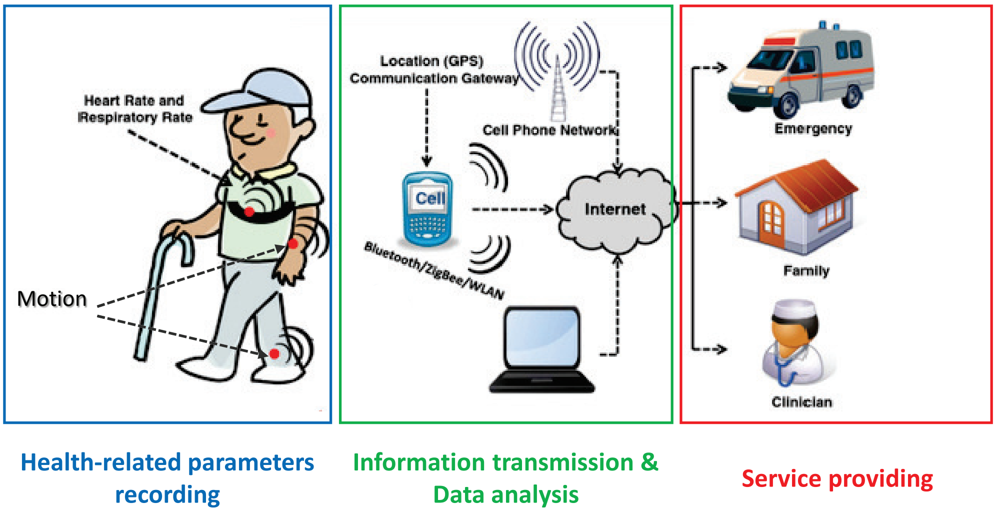


FIGURE 1.1: Illustration of a remote health monitoring system ©2012 Patel et al. [1]

appearance health disorder without going to clinical organization. Therefore, there has been a growing awareness to develop intelligent and convenient systems to provide affordable yet easy-to-use health monitoring services.

Fortunately, with the advanced development in computing and communication technologies along with modern sensing technologies, automated and intelligent techniques have been developed to replace manual manipulation during the implement of healthcare. Health monitoring system (HMS), which has evolved fast recent years, was just the technique emerging for this purpose [1, 14–25]. The general function of a HMS is to measure and monitor physical/mental health and activity status and then analyze the measured data to make decision of whether or not a person need healthcare service. Such kind of a system is able to monitor and support elderly people and people with impairment to live independently and detect abnormalities, i.e. diseases or urgent events (e.g. falls). Of course, it can also be used for normal people to measure their body parameters for diagnosis potential disease. To realize this purpose, a HMS needs record the parameters of subjects (e.g. physiological information [26], audio signals [14] and activities [21]) by various kinds of sensors and then transfer the measured data via communication networks to central computing system or the clinicians for decision making and at last providing the corresponding services [21]. A general image of the flow is shown in Fig. 1.1.

1.2 Brief Overview of Gait Analysis in Health Monitoring

1.2.1 An Indicator for Health: Gait

One of the major components of HMS is to monitor subject's activities in daily lives. One's health status can be deduced from various measurements of activities. By the observations, it is possible to qualitatively detect the disorder and quantitatively assess the progress/severity of abnormality, for providing support or medical intervention. For example, Hirayama et al. [27] monitored the sleep of a patient with Parkinson's disease and found that her head would sag on the onset of a sleep attach. The patient even wasn't aware of such thing happened. Then the sleep attack was resolved by control of her medication. Mihailidis et al. [28] helped people with dementia to complete hand washing by tracking the process of hand washing. However, those systems are too specific in that they specialized for a particular activity (e.g. hand washing) and limited at the indoor environment.

In contrast, gait is a more common and important form of human locomotion in our daily living, which can be quite easy to be observed either at home or at public place. Moreover, gait is an informative health indicator. It looks simple but actually involves lots of levels of the nervous system and many parts of the musculoskeletal apparatus as well as the cardiorespiratory systems [29]. A normal gait performing (i.e. stepping , walking and running) requires the coordination of the cerebellar, sensory, visual, vestibular, muscular, basal ganglia, and auditory systems. Any changes in these systems can result in gait alteration [30]. So gait is highly correlated with human's health status that it has already attracted great attention of researchers in healthcare field. Because of these attractive properties, gait is chose to be analyzed for the target of pervasive health monitoring in the present thesis.

1.2.2 Categories of Gait Analysis

Gait analysis is the systematic study of human gait. The essential purpose of gait analysis in healthcare is to learn the relationship between gait performance and various health conditions, for example, monitoring the physical activities to detect patients with Parkinson's disease [31, 32], detect knee osteoarthritis [33] during gait.

And in our daily lives, gait, based on its content, can be further divided into two categories: walking or walking while doing other tasks (e.g. making a telephone call, chatting with friends and holding a tray) simultaneously. Their corresponding terminologies are single-task walking and dual-task walking, respectively. In the medical field, both categories of gait are studied to reveal the health condition, but their emphasis are different. Researchers prefer to analyze the relationship between physical factors (e.g. visually impaired, osteoarthritis) based on the performance of single-task gait [34–39] while they tend to learn one's cognitive condition through observing the dual-task gait [40, 41]. Both single-task and dual-task gait are commonly-seen in daily life and important for analyzing people's health condition. Thus, in the present thesis, both types of gait are studied by computer vision and machine learning techniques to reveal one's health status.

From the perspective of procedures used to deal with gait data, in generally, there are three main steps in gait analysis: data collection, gait representation, and model construction (classification/regression). Based on the sensing approaches used to record gait data, the researches can be mainly divided into two categories: the contact-based way and non-contact-based way.

1.2.2.1 Contact-based Gait Monitoring

The most prevalent way to obtain gait measurements in healthcare field is based on the invasive way, marker-based motion capture system (e.g. VICON [42, 43] motion capture and GAITRite [44]) and wearable sensors (e.g. inertial measurement units, gyroscopes, accelerometers [1, 19]). A motion capture system, taking VICON as an example, detects the markers attached on the joints of human body as locations of body joint and then various spatial and temporal gait parameters are calculated from the trajectories of the detected markers. Similarly, the gait measurements can be recorded and calculated from the trajectories of output of wearable sensors which are attached to specified locations of human body parts. Such kind of sensors make the researchers be able to obtain the accurate measurements of gait performance without much efforts to do data processing, that researchers in healthcare field can dedicate their main efforts on learning the relationship between gait parameters and health status. So most of the researches about gait analysis for health, both about single-task [1, 42, 45] and dual-task gait [46, 47] are based on this type. However, even these invasive methods are efficient for researchers, they are not convenient for the users:

- The motion capture system requires several cameras and need to attach multiple markers on the human body. It is a set of large and expensive devices which need complicated setting and calibration processes. Hence, it is restricted to professional staff and specialized laboratory/clinical environments. And also it needs the cooperation from users. These constraints stop ordinary people to obtain their gait information conveniently.

- In contrast to the motion capture system, wearable sensor is small and portable that it can record gait parameters at anywhere without limitation. However, wearable sensors still cause some other problems to the users: 1) invasive and discomfort; 2) placing cognitive load on the user, especially to elderly people who suffer from dementia and children with cerebral palsy (It is a big burden for them to remember to wear the devices every day); 3) unable to capture the gait parameters of the whole body with one sensor, for one wearable sensor can just only measure the motion of one part of the human body it attaches to; 4) cannot be applied to public places for it is unpractical to ask everyone to wear a sensor.

1.2.2.2 Non-contact-based (Camera-based) Gait Monitoring

On the other hand, the non-invasive category, vision-based monitoring method which observes gait by a camera in a distance, is able to overcome the limitations mentioned above. It provides a continuous and unobtrusive system which allows the user to act and live in a comfortable and free environment.

However, different from invasive method that gait measurements and the corresponding human locations are already known, for vision-based monitoring method which records gait by RGB camera [6, 48–52], the output data of camera is a sequence of gait image. Researchers need to extract the gait features through complicated image processing. Usually, a silhouette is extracted from the original image and then gait features, either appearance-based (i.e. treat the silhouette as a holistic) or model-based (i.e. need to detect out each body parts on the silhouette) are obtained. The quality of the gait feature are heavily depended on quality of silhouette extraction, especially for the model-based gait feature. A recent alternative to plain camera is depth camera, e.g. Microsoft Kinect [53–55]. A Kinect can output depth image (the pixel value in the image indicates the distance of the object to Kinect) and also the 3D joint coordinates. People can extract the human silhouette from depth map easier or can directly use joint position information.

But it has a significant shortcoming that the capture distance should be within 4 meters, which constrains the Kinect being applied broadly.

There existed researches exploring vision-based method to do gait analysis for healthcare and they proved the feasibility of vision-based method for this purpose, but at the current stage, they still face some problems:

- The number of vision-based gait analysis for healthcare purpose is limited. The reason is that, to get the measurement of gait, it needs complicated processing on image sequences. To get rid of this step, most researchers in healthcare field would like to choose invasive method rather than using camera. And from the perspective of user, they don't like camera considering the privacy issue. Of course, with the increasing awareness about this problem and the sophisticated design, the privacy of users can be protected.

- Available databases for camera-based gait analysis in healthcare are limited. Some of them contain so limited number of subjects that cannot guarantee the statistical reliability, e.g. a publicly accessible database in work [56] contains only ten subjects and with very unbalance gender distribution (nine males and one female). On the other hand, there are multiple videos are captured by doctors for subjective observation. But the unstable capturing conditions (i.e. various illumination and view point, and also containing jitter during capture) make silhouette extraction difficult. So these are also not suitable for analysis.

- The gait representation are vulnerable to noise. Some works directly used the silhouette as feature to detect pathological gait [50] or extracted quantitative gait measurements (e.g. stride length, stance phase) and anthropometric information (e.g. height of head, foot location) from raw silhouette images [56, 57]. Those works are abased on silhouette of specified phase, so the quality of gait analysis highly depends on the quality of each single frame of silhouette. However, the quality of silhouette is always hard to guarantee, especially when the environmental factors e.g. illumination, are not well controlled. Even for Kinect, the quality of depth map at the head and foot is not stable. At this situation, the performance of gait analysis will deteriorate.

- The researches analyze only the single-task gait, which is mainly used for analyzing physical aspect of health information. But dual-task gait is also very common in daily life. It is always used for studying other aspects of health information that are also very important for assessing health. So analyzing dual-task gait is still necessary.

1.2.2.3 Summary

Comparing these two categories of gait monitoring, the contact-based way is widely used in gait analysis for health purpose. However, the gait performance can only be captured at laboratory or clinical environment under the manipulation by professional staffs for motion capture system and the wearable sensors cause a discomfort or cognitive burden to user. Both of these two methods in contact-based category have constraints in real application. Considering the convenience of users, in the present thesis, we choose to adopt camera to record the gait performance, which produces least disturbs to the lives of user.

There are some gait analysis for health adopted camera-based way. But the necessity of complicated image processing limited prosperity of this method. Only a few categories of abnormality/diseases are analyzed by single-task gait. Moreover the method highly depend on the quality of each single silhouette. Still there are no camera-based method to explore the performance of dual-task gait, which is also commonly-seen in daily lives and also extensively studied in medical field. In a word, there are still many works needed to make camera-captured gait analysis more useful in real application.

1.3 The Proposed Camera-based Gait Analysis for Healthcare

To extend the existed gait analysis of healthcare further for realizing a pervasive and convenient health monitoring system, we proposed two approaches which are based on camera and can be applied in different situations and purposes. These two approaches can observe both single-task and dual-task gait. And as primary stage of applying techniques of computer vision and machine learning in camera-capture gait, the focus of the studies in the present thesis is the qualitative detection of abnormality. Detecting the occurrence of abnormality is the primary step for medical intervention and it is much vital to early diagnose for early intervention. Though observing single-task gait, we can detect the people with physical impairments. And from the dual-task observation, we can deduce several aspects of health information, including cognitive aspect. When observing single-task gait, no cooperation is needed from subjects, so such kind of passive strategy can be applied in public place. It can inform service staffs/robot to provide service timely when necessary. As for the dual-task gait observation, to construct a database that can be used for analysis, subject need to performance the same motor and cognitive tasks. So this observation need the cooperation from subjects, that dual-task gait observation is called active way of gait monitoring. But it is an efficient way, it can provide a more convenient solution to assess several aspects of health information than conventional way.

1.3.1 An Example Scenario to Apply Proposed Techniques

We envision a scenario in which our techniques can be applied as the following: A subject walks into a supermarket and he is looking for a special kind of spice. However, he has some inconvenience on his eyes (e.g. cataract) that he need to walk near enough to the products on the shelf to check whether or not the product is the one he want. Without the help from other one, he might need to walk near to every product to check products for a long time. Fortunately, the surveillance cameras which are embed the function of physical impairment detection notice this customer and inform the service staff/robot in the supermarket. Then the staff/robot guides him to the spice he needs, saving him from a lot of trouble. When the subject goes back home, such kind of all time camera-based monitoring system is changed. Instead, we embed a function of efficiently and conveniently assessing health status to a motion sensing game system. The system can capture the data of subject by depth camera when the subject use it. The advantage of such engaging game form (the so-call dual-task paradigm) enables us to evaluate more aspects of health information (i.e. cognitive) of a subject. Two kinds of functions are provided based on the different age groups. For elderly people, we try to detect whether or not a subject has the suspicion of suffering from dementia. And for the children, we care about whether or not a child is growing normally. A user can select the corresponding function for him or his family based on the user's age.

The scenario above demonstrates how camera-based gait analysis approaches can provide pervasive and convenient health status assessment by naturally embedding the functions into the existed system like surveillance monitoring system and motion sensing game system. We sufficiently consider the different requirements at different application scenarios. Public places need passive non-cooperate way while in indoor environment, obtaining cooperation from subject is possible. With the combination of passive and active gait monitoring in both public and indoors environment, people's health condition can be pervasively accessed.

1.3.2 The Challenges

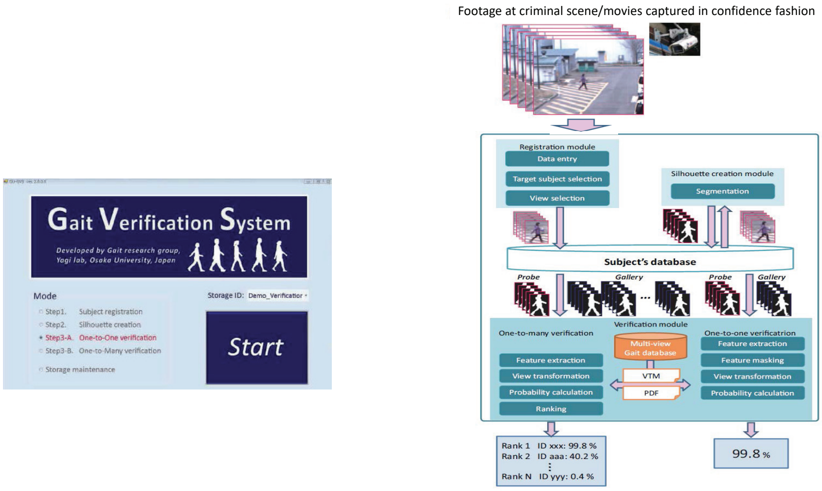
Camera-based method provides us the feasibility to realize the system mentioned above. However, we still face with some challenges:

(1) Database is the basis of gait analysis. As mentioned previously, that there are few public database which recording gait by camera for healthcare purpose. No suitable dataset captured by camera about different kinds of physical impairments existed. And also there is no database who try to collect the dual-task performance by camera. In order to realize the application in the scenario, we need to firstly construct the dataset by ourselves. The design of the experiment setting for gait data collection should be based on the knowledge of both clinicians and experts on computer vision.

(2) The purpose of gait analysis in healthcare is to distinguish the gait pattern between different health conditions, so it is vital to find out the appropriate gait features which can distinguish the gait styles under different health status. To address this challenge, we can learn some experiences from a more popular and successful application scenario for gait analysis, gait-based human recognition. An example of the system is shown in Fig. 1.2. Comparing with other biometrics like face [58, 59], iris [60, 61], fingerprint [62, 63] and hand vein [64, 65], gait has the advantage of capturing gait at a distance from camera (e.g. RGB/RGB-D cameras) without any cooperation with subjects. To make gait recognition more practical in wild environment, researchers in this field proposed gait representation which is robust to kinds of covariates (e.g. various illumination conditions, changing view angles (the angles of subjects to the camera) and even different package status) [3, 66, 67]. We can got some inspirations about gait representation from those works.

1.3.3 The Proposed Techniques

The challenges appear in both passive and active approaches. So in both approaches, we include ideas to cope with them. The brief introduction of the two



(a) The interface of gait verify system

(b) The data processing flow of the system

FIGURE 1.2: Gait verification system for criminal investigation ©2013 IEEE [2]

approaches are shown in the following. And to note that, the second active approach contains two works, one for elderly people and the other for children. As for the function of detecting dementia in elderly people, I collaborated with other researchers to collect the dual-task performance [7] and then tried to find out efficient features that might be useful for distinguishing healthy senior and senior with cognitive impairment, i.e. dementia [68]. And I mainly focused on analyzing the work for children group to assess their growth status. So for the active approach, I will introduce the work about children.

In the passive work, we proposed a non-invasive and economical method for estimating physical impairment of people through observing walking style by plain camera. To achieve this, we first self-constructed a dataset which contains two categories of impaired walking (leg/visual impaired walking) and also normal walking. Then we investigated which gait feature is effective for distinguishing different types of gait patterns. Based on the observations from the existed works in medical field exploring gait characteristics of people with physical impairments, we concluded that the posture, temporal, and also stability properties of gait might be affected by impairments. Correspondingly, we extracted gait energy image (GEI), which is a popular appearance-based feature showing high performance in human authentication, duration time, and phase fluctuation to represent these three categories of gait properties from image sequence. By comparison, we found that GEI is the most discriminative feature to distinguish impaired walking style from normally walking, among the three considered features. And we go further to consider that GEI is mainly about posture information, it must be influenced by the other parts of human body except the effective part. We thus proposed to use only the GEI features with the most discriminative body patches. From the experiments that evaluated the contribution of various sizes and positions of body patches, we found that head and chest regions perform better than the whole body for the visual impairment discrimination case. As for the leg impairment detection case, the leg region performs better than the whole body. The results confirm the effectiveness of patch-GEI for impairment detection.

For the active work, we provided an efficient and convenient method to assess the growth status about various aspects of growth (anthropometric, kinematic and cognitive) simultaneously. This method is different from the conventional approaches which involve manual evaluation: it can collect and estimate growth status efficiently and automatically. In our work, through dual-task paradigm, we can collect anthropometric, kinematic and cognitive aspects of growth-related information at the same time. The large-scale data collection was realized by an automatic data collection system. With the collected data from a large number of typically developing individuals, we constructed a statistical model of growth features and ages and also estimated the age of a test participant using regression analysis. By comparing the participant's value to the average levels of regression performance, we were able to provide an initial judgment of a child's growth status. The experiment results demonstrated that the growth features developed with age among children and the estimation of growth status using this model was feasible.

1.4 Outline of thesis

The remaining chapters of this thesis are structured as follows:

- **Chapter 2** provides a detailed survey of existing gait analysis methods, from the aspects of data collection and gait feature extraction. In this chapter, first, some typical and usually used database are listed out, and the differences between the dataset for human identification and healthcare purpose are clarified. As for the gait representation, I categorize the methods into two main classes: model-based and appearance-based. And in the model-based approaches, based on the data capturing equipment, they are further separated into time-series based and image-sequence based. At last, the advantages and disadvantage of each category are discussed.

- **Chapter 3** illustrates gait analysis to detect two types of physical impaired walking styles by exploring the suitable gait features. To find out the gait features which is effective for distinguishing impaired gait from normal gait, we compared the performance of different kinds of gait features from posture information (gait energy image (GEI)), temporal information (duration time) and stability information (phase fluctuation). Based on the comparison experiment results on an self-collected database, we found the best one is GEI. And based on the observation that GEI is highly affected by other parts of human body, further procedures to improve the performance by using only the most discriminative patch of the GEI are presented.

- **Chapter 4** describes the implementation of the dual-task paradigm used for children growth assessment. At first, an automatic system is applied to collect dual-task performance, then the description for three aspects growth information (including anthropometric, kinematic and cognitive aspects) from dual-task performance is present. And then a machine learning method is employed to construct the relationship between age and those three aspects of growth information. At last, the efficiency of this method is discussed.

- **Chapter 5** concludes this dissertation with a summary of the research as well as providing directions for future work to make the proposed methods more intelligent and practical in real application.

Chapter 2

Literature Review

2.1 The General Procedures for Gait Analysis

The general framework of gait analysis includes three modules. Data collection is the primary and important step in gait analysis. Various factors in dataset like the type of gait (e.g. walking, stepping, running or walking while doing other task), the sensor used for recording, the qualified participants who satisfy the experiment conditions (e.g. male or female, children or elderly people, healthy or pathological subjects) and the environment (e.g. indoors or outdoors, day or night) are determined based on the motivation of research. Then the following step of pre-processing is to filter out some outliers or noise data. For instance, the participants who don't satisfy the experiment condition or who do not execute the specified motion, should be eliminated. Next crucial step is to represent the collected data by various kinds of features. Of course, the categories of the features are also decided by the target of the research, i.e. which gait performance the researchers want to investigate and which gait features are efficient and effective to represent the different gait patterns. Usually, pre-processing and feature extraction are merged into one step for they are both related with feature manipulation. The last step is to study the relationship between gait features and the variables, such as the age, health level or even the cognitive level, by constructing suitable model for them. The modeling can be done by the traditional statistical method or by machine-learning techniques (say classification/regression). Based on the model, when comes a test sample, the judgment such as whether the test sample is the same as one in the gallery or whether the test subject has any abnormality/disease can be done. Finally, subsequent actions like unlocking the door (when the coming subject is one of the residents in the building) or providing medical intervention (when the test subject is diagnosed to a special disease) are carried out.

Gait analysis, from the perspective of application, can be categorized into two types: gait identification recognition and clinical gait pattern recognition. The former one emphasizes on analyzing the difference between different subjects to identify individual; while the latter one analyses the different gait patterns of particular type of subject group with different health status, disease, gender, age and even emotion, to reveal the factors that affect the particular gait pattern. The emphasis in these two application situations are different, thus the considerations in the procedures for gait analysis should be not the same.

Here has a seem contradictory phenomenon that gait authentication depends on individual difference, while impairment detection by gait is based on the common of individual, and gait can be used for these two adverse purposes. The reason is that: even input to authentication and impairment detection systems is the same, they are both the description of gait. But the targets are different, by applying machine learning algorithm, we can learn different final features that useful for different targets. E.g., the input of authentication and impairment detection are GEI, the machine learning techniques can learn different further information: the ratio of human body parts in GEI is used to identify different persons; while the posture of head bending in GEI is used to detect visual impairment. So the key point is the machine learning algorithm.

In the following, we give a brief review based on two important procedure steps of gait analysis: data collection and gait feature representation, considering their different application scenarios in healthcare and identification purpose.

2.2 Available Dataset

2.2.1 Dataset for Human Identification

In the scenario of gait-based human authentication, researchers aim to realize an automatic and robust long-distance human authentication. So they focus on making the discriminative ability of gait representation robust to kinds of variations such as view angle, clothing, carrying status, illumination, walking speed. That the data of each individual in the database might be captured in several different conditions. Some prominent gait databases are listed as followings:

(1) CMU MoBo (Motion of Body) Dataset [69]. This dataset recorded 25 subjects performing four different kinds of walking activities (including slow walking, fast walking, incline walking and walking with a ball) on a treadmill. They used six high-resolution color cameras to achieve 6 viewpoints capturing.

(2) SOTON (University of Southampton) HID (Human ID) Database [70]. It is the first dataset contains more than 100 subjects. The dataset captured walking sequences by digital cameras from two viewpoints and in both outdoor and indoor environments (walking on ground and on treadmill).

(3) CASIA Gait Database [71]. This is a relative newly developed challenge database. Four datasets are available in it. Dataset A contains 20 subjects with three capturing directions. Dataset B is a frequently used gait database for it has 124 subjects and large view and clothing variation (11 view angles and for each view angles with four sets of normal condition and two sets of subjects with bag and wearing coat). Dataset C recorded 153 subjects in outdoor night by infra-red camera and contains four types of walking conditions. Dataset D recorded 88 subjects walking on the foot pressure plate and captured by camera synchronously.

(4) OU-ISIR Biometric Database [3, 66, 67, 72, 73]. This is the largest database. It contains 8 datasets: treadmill dataset, large population dataset, speed transition datasets, OU-LP-Bag dataset, multi-view large population dataset and inertial sensor dataset and similar action inertial dataset. In general, these databases involve the covariates including surface, age, carrying conditions, viewpoints and speed. Besides 6 datasets are captured by color camera, there include two datasets data was recorded by inertial sensors. Take the OU-LP-Bag dataset [3] for an example, the dataset consists of 62,528 subjects (with age ranging from 2 to 95 years). Each subject was asked to walk straight three times at his/her preferred speed, one sequence with or without carrying objects (if he/she did not have carrying objects) and the other two without carrying objects. An overview of the capture system is illustrated in the Fig.2.1.

2.2.2 Dataset for Healthcare Purpose

Gait analysis in healthcare field aims to study the influence of specified factor on the gait pattern. So they need to compare between gait performance of subject

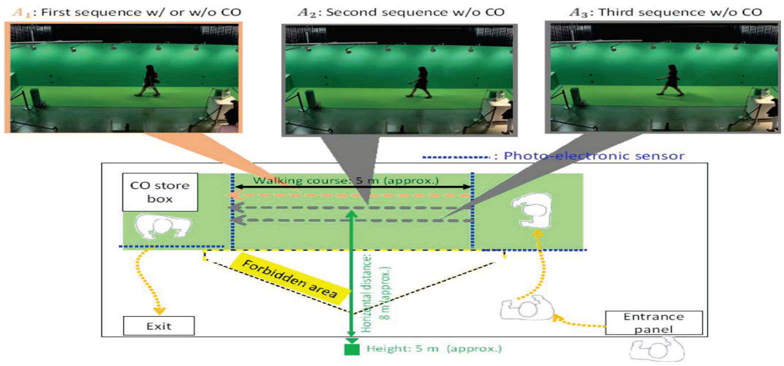


Figure 2.1: Examples of databases for human identification, OU-LP-Bag dataset in OU-ISIR biometric database with the largest number of subjects [3].

groups with different attributes like age, various diseases, to find out the gait characteristics under different health conditions. There are only a few access available databases for healthcare or healthcare purpose. We try to list out some of them as followings:

(1) Gait in aging and disease database [48]. This is a mini-collection of human gait data which was constructed as a teaching resource. It includes 5 healthy young adults (23 - 29 years old), 5 healthy old adults (71 - 77 years old) and 5 older adults (60 - 77 years old) with Parkinson's disease. The stride interval and the time between foot-strikes was provided based on the output of force sensitive resistors placed in shoe and microcomputer worn on ankles.

(2) Gait in Parkinson's disease Database [74]. This dataset contains measures of gait from 93 patients with idiopathic Parkinson's disease (mean age: 66.3), and 73 healthy controls (mean age: 66.3). The database recorded force as a function of time and location of subjects as they walked at their usual, self-selected pace for approximately 2 minutes on level ground. Especially, a subset of the database includes measures recorded as subjects performed a second task (serial 7 subtractions) while walking.

(3) Daphnet Freezing of Gait Dataset [4]. This dataset consists of the annotated readings of 3 accelerations sensors at the hip and legs of Parkinson's disease patients that experience freezing of gait (FoG) during walking, the example is shown in Fig.2.2. The dataset recorded ten Parkinson's disease patients doing several walking tasks (straight line walking, walking with numerous turns and

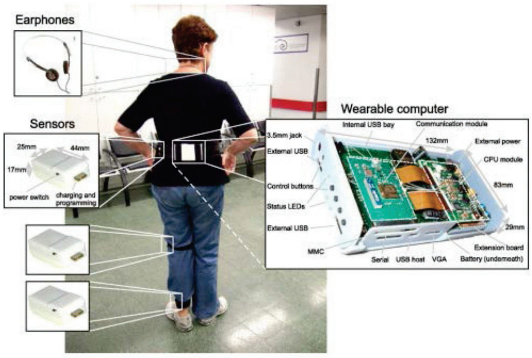


FIGURE 2.2: Examples of using wearable sensors for healthcare purpose ©2010, IEEE [4].

also a more realistic activity of daily living task, where the subjects went into different rooms while fetching coffee, opening door, etc.) in the laboratory for more than 8 hours. Finally, eight patients experienced FoG during the study, and 237 FOG events were identified. Apparently, this data set focus on recognizing the FoG of Parkinson's disease.

(4) CGA Normative Gait Dataset [75, 76]. This dataset provide the gait measurements of normal people, including children, adult and elderly people, which are captured by Vicon system. It contains many sub-dataset. For example, one sub-dataset includes 22 (around 8 years old) children's joint angular velocities and the other one contains 9 young adults' joint kinematics data. This dataset provides only normal gait measurement as a baseline for documenting impairments in patients.

(5) Gait datasets collected from university of Wisconsin-LaCrosse [77]. The dataset capture 25 young healthy adults gait as a normative gait trials by motion capture system (attaching passive optical markers, force platforms and EGM electrodes. Thus the data includes position, acceleration and velocity for bilateral hip, knee and ankle, ground reaction force of stance phase and EMG of right and left vastus intermedius, lateral hamstring, medial gastrocnemius and tibialis anterior muscles is provided.

2.2.3 Summary

By listing out some publicly available datasets for both human identification and clinical gait analysis, we found several different points lies in these two types of dataset:

- The number of recruited participants. The largest number of subjects in human identification reaches 62,528 (OU-ISIR Biometric Database) [3] while the number of subjects in healthcare purpose dataset is 166 (Gait in Parkinson s disease Database) [74]. The order of the number of subjects is much different from each other. And obviously, the small umber of subjects cannot provide reliable conclusion in statistical sense and cannot explore sufficient potential factors. Dataset with sufficient number of subjects is needed for healthcare field's research.

- Diversity in the dataset. Obviously, we can see that the datasets for identification collect gait data in different conditions, which enable researchers to cope with the covariate problems based on the collected data. However, the data for healthcare purpose is relative simple, the datasets contain only gait patterns of healthy people (as reference) and people with Parkinson's disease. And only one dataset [74] provides small number of subjects who suffer from Parkinson's disease performing dual-task on force platform. It is hard for us to learn other types of abnormal gait patterns and study the cognitive aspect information of subjects (which is usually learned on the dual-task gait performance) based on these existed datasets. So if we want to analysis different types of gait other than Parkinson's disease, we need to collect dataset by ourselves.

- The recording sensors. The former type of data used camera which has no obstruct on participants. While in the latter field of dataset, they tend to used wearable sensors or motion capture systems (like VICON) which need to attach multiple markers on body or even force plat form which restricts the movement region. With such kind of constraints by the sensors, it is hard to provide the subjects with a free living environment when monitoring their activities. And this way even impose burden or pressure to the users. So at the current stage, there are still urgent requirements to develop and improve non-invasive systems for monitoring activities of people.

2.3 Gait Feature Representation

There are various ways available to represent gait. In this subsection, we divide them into two main categories: the model-based and model-free-based (or say appearance-based) approaches. The model-based approaches explicitly model the structure of human body while the appearance methods use the silhouette directly without knowing the structure of human body.

2.3.1 Model-based Methods

Gait feature of this category need first determine the location of components of human body and then extract various gait features from the concerned components. The components of human body can be detected by several methods. The first way is to directly place wearable sensors (e.g. accelerometers, gyroscopes, inertial measurement units (IMUs)) or markers of motions capture systems to specified parts or joints of human body to record the motion of that components. And also Microsoft Kinect provides the function to track multiple joints of a whole body without any contact on subjects. The second way is to fit the prior human body's structure model to the camera capturing images to decide the location of the components. For the first way, we need to extract gait features from time-series signal while the second way needs to deal with image sequences. In the following, we introduce some mode-based gait representation based on the time-series signal based and image sequence-based input.

(1) Model-based method with time-series signal as input

Usually, the time-series signal is the output of wearable sensor and motion capture system. Since the gait signal is almost periodic, a large number of gait analysis first detect gait period and gait phase (e.g. heel strike, flat foot, heel off, toe off and swing) by threshold-based methods or machine-learning approaches [45, 73, 78–91]. Then researchers use the statistics of phase information to represent the characteristics of human gait. Ghoussayni S. et al. [78] employed three-dimensional co-ordinates of foot markers to detect the timings of four gait events (heel contact, heel rise, toe contact and toe off) using empirically thresholds. By comparing with the detection results from force platform and visual inspection, the validation of marker-based method was approved. Salarian A. et al. [82] used body attached gyroscopes to estimate spatio-temporal parameters of gait for comparing between normal people and Parkinson's disease patients. The authors first detect the initial and terminal contact of feet with the ground by observing the negative angular velocity peak. Then the temporal parameters such as gait cycle time, stance, initial double support and spatial parameters such as stride length are calculated by various equations. Abaid N. [45] analyzed gyroscope data to detect four gait phase (heel strike, flat foot, heel off and swing) for both healthy children and children with hemiplegia. It is realized by a hierarchical weighted decision on the output of two or more scalar Hidden Markov Models (HMMs). Then the authors used the gait phase percentage and the time spent in each gait phase to distinguish children with or without hemiplegia, and children with varying severity hemiplegia. Derawi et al. [84] applied accelerometry data for biometric gait recognition. The walking cycle was first determined from the extreme value point of signal then similarity of the cycle signal between two persons are measured by dynamic time warping (DTW).

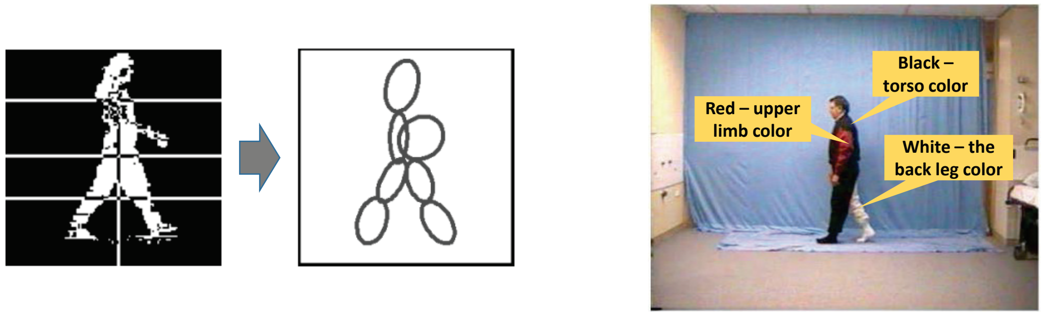
Recently, with prevalence of Kinect in commercial application (e.g. motion sensing game), there appear some works applying Kinect to do gait analysis in both clinical purpose [49, 54, 55, 92, 93] and human authentication [94–98]. Different from wearable sensor which can record the information of only one part for each sensor, Kinect is able to record the motion trajectory of the all the joints of whole body. Rocha A. P. et al. [49] used the skeleton data to discriminate between non-Parkinson's subjects and Parkinson's patient, as well as between two Parkinson's states. The features are the velocity, acceleration, the angle of multiple joints and also the distance between these joints. And also gait cycle duration, stride length and stride average velocity are calculated. From the results, the variance of the shoulder joint velocity presented the highest discriminative power to the task mentioned above. Aniruddha S. et al. [98] represent the gait for human identification through three types of features, length features which is the distance between the adjacent physical joints, area features which is the closed polygon area occupied by the upper hands and lower legs of the body during side walking, distance features which are the distances between centroid of different parts of the body with respect to the centroid of the upper body that can describe the change of each human body part and the last one is the angles between each other.

Beyond the spatio-temporal representation, time-serial signal can be described as frequency-domain features. The approaches used to convert the time domain signal into frequency domain signal are Fourier transformation, wavelet transformation [87, 99–107]. Mostayed et al. [102] distinguished normal and abnormal gait from the Fourier transform patterns from joint angles trajectories of ankle-knee, knee-hip and hip-ankle. While Pickrell et al. [104] chose to use continuous wavelet transform (CWT) to detect freezing of gait (one of the symptoms of Parkinson's disease). Comparing with Fourier transformation, CWT employs time domain information in a smaller sample window size that can detect the short-duration better.

(2) Model-based methods with image sequence as input

Unlike the time series outputted by wearable sensor and Kinect, whose location of body component are already known. Images captured by camera doesn't contain information of components. So model-based methods need to first detect the position of components by fitting or tracking body structures on the image. Then extract a series of static or dynamic gait parameters from the fitted model [108–110]. Jang-Hee et al. [110] extracted a 2D stick figure from gait silhouette by motion information with topological analysis guided from anatomical knowledge. Then the mean and variation of the gait angles are extracted as features, which are fed to neural network to recognize humans.

Some other model-based approaches, instead of modeling the human body as a holistic structure, would go further to explore human body parts information. The statistical structure features and kinematic features about the movement of human body parts with time can provide more information for gait analysis [5, 6, 111–115]. Lee et al. [5]fitted the ellipses to the human body part based on the statistics of the part region, as shown in Fig. 2.3 (a). Then two types of representation across time is extracted, the mean and standard deviation of region features across time, and magnitudes and phases to these moment-based region features. Nikolaos et al. [115] first separated the human body into separate parts and then combined the different body components into a common distance metric for evaluating the similarity between gait sequences for gait recognition. However, for clinical application, Lee H. et al. [6] directly required the subjects wear specified cloth, with different color meaning different part of human body, as shown in Fig.2.3 (b). This trick is used to avoid model fitting. After the body parts are segmented, they skeletonize the segmented image. At last, the distance feature and joint angle are calculated to identify patients with Parkinson's disease.



(a) The silhouette is firstly divided into 7 regions, then ellipses are fitted to each region.

(b) The human parts are detected by colored dress.

FIGURE 2.3: Model-fitting methods using camera-captured image sequences in (a) human identification ©2002, IEEE [5] and (b) Parkinson's disease detection [6].

2.3.2 Appearance-based Methods

Different from model-based gait representation, appearance-based method always directly use the extracted binary human silhouettes. The simplest way is to directly use the silhouettes frame. Kale et al. [116] extract the lower dimensional vector calculated from key frames to train a HMM model. This method can capture the structural and transitional feature which is useful for human recognition. Such kind of the method which directly used binary frame encounter with a challenge to detect the key frame. To reduce the difficulty, a more efficient and dominant way is to summarize the information from multiple frames [117, 118]. Bobick A.F. et al. [117] used accumulate the image differencing (binary image) to get Motion Energy Image (MEI) which represent the temporal information by gray intensity. And go further to represent how the motion is moving by record the temporal history of motion at each pixel to form Motion-History Image (MHI). In the MHI, the brighter pixel corresponding to the place with more recently moving pixels. Han J. et al. [118] present the gait by the average of the silhouettes in a walking cycle, naming gait energy image (GEI). GEI preserves the dynamic and static information of gait. After that, some researchers developed the representation of these gait features with the considerations to emphasize more on specific aspect of information or to deal with various conditions like clothing and carrying status [119–121]. Yang X. et al. [119] designed an Enhance Gait Energy Image (EGEI) to employ dynamic region analysis to improve dynamic information of GEI. The author identify the dynamic region in GEI into two type of motion, the regions with high intensity and low intensity are essentially the same among different individuals while the area of swing of limbs and the inclination of head and torso are different between individual. The dynamic region in GEI is enhanced by a pixel-wise multiplication with dynamic weight mask. Makihara Y. et al. [122] applied Fourier analysis to the silhouette sequence over the complete gait cycle. The low-order amplitude spectra of Fourier coefficients are used to present gait feature. The direct component is actually GEI and the one-time and two-times frequency preserve the asymmetric and asymmetric motion. Bshir K. [120] proposed Gait Entropy Image (GEnI) to divide the dynamic and static areas of GEI through Shannon entropy at each pixel of GEI. In the GEnI, the intensity of dynamic region is brighter than the static region. This property make the GEnI is not so sensitive to carrying status.

2.3.3 Summary

Features from model-based methods are easy to be interpreted, and generally view and scale invariant. The wearable sensors and maker-based motion capture systems can directly assess the motion information of specific parts of human body. What it needs for the researchers is to statistically analyze these features to examine the gait disorder or to do gait authentication. For the convenience, researchers in healthcare field always used this type of equipment. However, they require complex equipment setup in collection and the subjects need to wear kinds of sensors and markers which lead constricts on their daily life. And such kind of cooperation way is impractical for the purpose of human identification from a long distance or activity monitoring without obstruct. Those limitations can be overcome by using camera capturing, i.e. using skeleton information from Kinect or model-based silhouette sequence form images sequence from RGB camera. Comparing with Kinect, the model-based image method might suffer from shortcomings like sensitive to the quality of gait images, human body segmentation results, and also the large computation cost on model fitting. So Kinect sensor could be a good choice of non-invasive way of monitoring human gait considering under model-based method. But we need to well consider one significant limitation of Kinect, that its capturing range is limited within 4 meters.

At the same time, appearance-based methods release the shortcomings of model-fitting on a image sequence mentioned above. They can perform at a lower resolution images and has lower computer complexity. And since the images are captured from camera, the subjects need no cooperation which give the subjects maximum possible comfort during monitoring. Of course, appearance-based method has its disadvantage that it is sensitive to appearance variation such as clothing and carrying status. Thus the researchers in gait identification strive to propose methods of gait analysis which is robust to kinds of co-variants. And because the features from appearance-based method describe gait pattern as a holistic information, however researchers in clinical field prefers to use quantitative gait parameters to do quantitatively gait assessment, so appearance-based method is less used in clinical purpose. However, we think that this method is quiet valuable to do qualitative assessment in real application for early disorder diagnosis and for impairment detection in public places. So it can also be a good choice for non-intrusive manner for gait analysis.

Chapter 3

Detection of Gait Impairment Using Patch-based GEI

As mentioned in the chapter1, walking is one for the indicators of human health. It requires the coordination of various function systems of human body. When people get old or ill, those functions degenerate, which results in abnormal walking style. Indeed, people who have some impairments, such as poor binocular visual acuity, weak inter-joint coordination ability even loss of hearing, show different walking styles in postural and dynamic aspects comparing with people with no impairments [91, 123, 124]. We, human, can usually distinguish the differences quite easily just by observing their ways of walking. If we design a system that can automatically detect such impaired people from their walking styles, it could be very useful in public commercial environment to provide service to people with impairment, elderly care [125], gait related applications such as the diagnosis of diseases like Parkinson's Disease [50, 82, 126, 127], and the rehabilitation of injured people [128].

So in this chapter, we introduce the design of a system that can detect such impaired people from their walking styles in an automatic and non-intrusive manner. Under the monitoring system, people can maintain their daily-live activities freely and comfortably. The impaired gait patterns concerned in present method is the physical impairments. The mainly contributions of this method are that we collected a database with sufficient number of subjects, containing two kinds of impaired walking and normal walking, and we tried to find out the efficient gait representation to describe the gait patterns affected by physical impairments.

3.1 Feature Representation for Impaired Walking

3.1.1 Motivation to Utilize Appearance-based Methods

Again, as mentioned in the chapter 2, existing studies about gait representation for either gait identification or healthcare purpose, can be separated into two categories: model-based and appearance-based methods. The model-based methods usually apply a motion capture system or wearable sensors to capture accurate pose parameters. For example, Hallemans et al. [129] used a Vicon motion capture system to measure head orientation, stride length and trunk flexion to verify whether or not poor vision affects dynamic stability of walking. Other model-based studies [6, 110, 130] use movies captured by cameras. They estimate the pose parameters by fitting and tracking body components. Lee et al. [6] fit a skeleton model to binary human silhouettes to calculate their static properties like swing distances and joint angles for detecting Parkinsonian gait. To locate different components of human body, participants are instructed to wear color cloth, with different color corresponding to different body components.

From the promising results of these two model-based approaches, we confirm that the walking posture, the temporal cue and the stability properties are important for disorder gait detection. In fact, model-based approaches can measure precise trajectories of moving joint and body components. However, they require laboratory environment settings and cooperation of subjects; the subjects have to wear special clothes or devices. Further, they usually suffer from low quality of the pose estimation and high computation cost. Of course, kinect sensor is a good solution for non-contact manner which provide good precision of skeleton data. However, the capture range of kinect is so limited. So it is not suitable to recording walking which move in a relative long distance. In a word, these ways are not applicable for the target to provide a non-invasive and long-term monitoring environment that people can keep their daily-lives activities free and comfortable.

On the other hand, appearance-based methods use captured movies directly, thus subjects do not need to wear any special devices. Chen et al. [50, 126] use binary silhouettes extracted from color images to distinguish Parkinson's Disease people from normal ones. That study uses the binary silhouettes of specified phase directly for classification, hence, the results heavily depend on the extraction quality of each silhouette. Other works [119, 122, 131] summarize the shape and motion features from the gait observation and use them for gender recognition and human authentication. Among those features, Gait Energy Image (GEI) [131] was often used since it is well known to show high authentication performance for individuals from gait. Another advantage of GEI is that, it does not require high extraction quality for each single silhouette; it is quite robust against noise inevitably included in extracted silhouette images. Because GEI is defined as an average of sequential silhouettes in a walking period, that one or a few frames of unwell extracted silhouettes do not damage the information so much as those methods depend on only one specified phase of silhouette.

GEI can encode the shape of people very well, so that it is effective for personal authentication. It does not, however, preserve temporal information such as the duration time of a walking period. Therefore besides the GEI, we still investigate the effectiveness of the duration time which is relative to the walking speed. Considering that both GEI and duration time describe properties within a period, we furthermore study phase fluctuation [132] between the neighboring walking periods. This phase fluctuation is used for estimating the walking stability which is considered to be an important cue for assessing the ability to walk.

3.1.2 Extraction of Gait Features

In this section, we describe how to extract the shape, temporal and stability information features which might be effective to distinguish different types of walking from a subject. From the original input color image sequence, we first apply background subtraction to extract binary silhouettes. Then the extracted silhouette images are scaled. First, the top, the bottom and horizontal center which is the median of horizontal positions of the foreground region are detected. Next, after applying moving average filter to those positions, a normalization step is carried out. The output binary silhouette sequences are called Gait Silhouette Volumes (GSV) [122].

With GSV, assuming periodicity of walking, we estimate a walking period length by calculating the normalized autocorrelation of the silhouette images in temporal axis. The gait period N_{period} is determined as the number of frames which makes the normalized autocorrelation maximum. As the sequences usually contain more than a period, for duration time and GEI, we extract only the part $\{S_i\}(i = 1, 2, \cdots, N_{\text{period}})$ that corresponds with a period. Note that in our experimental setting, we pick up the period around the center of the image. N_{period} denotes the number of frames in a period, which we call "duration time" in this paper. Once we obtain GSV, the GEI feature $G(x, y)$ is calculated as follows:

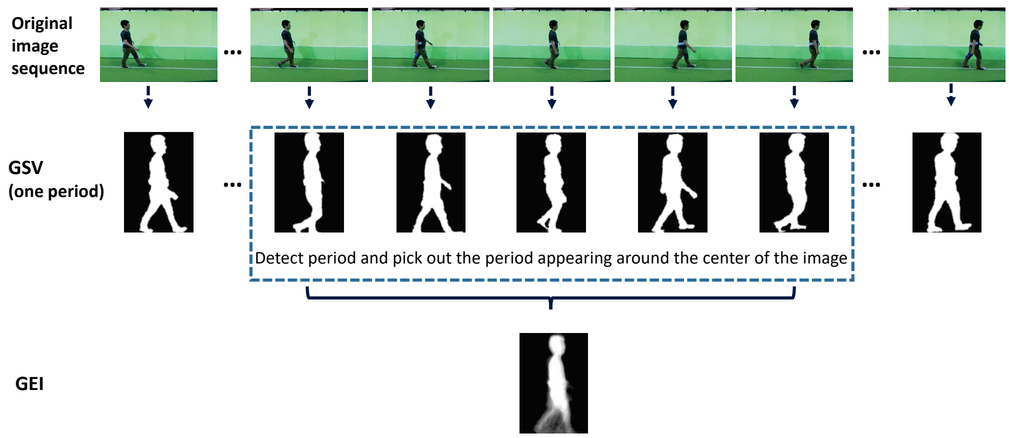


FIGURE 3.1: The procedures for generating GEI from original image sequence.

$$G(x, y) = \frac{1}{N_{\text{period}}} \sum_{i=1}^{N_{\text{period}}} S_i(x, y) \tag{3.1}$$

Where i is the number of frames in a period of walking silhouettes, x, y is the coordinate in the image and $S_i(x, y)$ is the intensity value of the GSV in the corresponding pixel. An example of the procedures of generating gait energy image is shown in Fig. 3.1. In the GEI image, the pixel intensity is related with the appearance frequency of the human body. A brighter intensity indicates a human body part which has less motion, such as the head and torso. On the other hand, gray parts correspond to regions with a lot of motion, like legs. Black means no body parts appear at the corresponding place, i.e. the background. In our experiments, the resolution of GSV is 120×80, so the dimension of GEI is also 120×80.

We then briefly introduce the main processing steps for calculating phase fluctuation using the method that was proposed by Makihara et al. [132]. The authors proposed an iterative optimization framework to estimate a phase evolution sequence from a given quasi-periodic signal by minimizing a certain objective function. The objective function composes of (1) a data term $D_d(S_Q)$ which construct the relationship between two phases with several periods shift; and (2) a smoothness term $D_s(S_Q)$ which makes the speed of local phase evolution coincide with an instantaneous frequency under the constraint of monotonic increasing trend for phase evolution. And because of the existence of the combination ambiguity in constructing the quasi-periodic signal: the combination of the phase evolution function and the normalized periodic signal is not fixed, (3) bias correction term $D_b(S_Q)$ is added to the objective function. Based on the assumption that phase fluctuations are unbiased, Makihara et al. consider phase deviation from a linear phase evolution average over all the periods (i.e. bias) should be zeros. To note here that, the time warping function (TWF) is just used to represents a mapping from a linear time evolution to the estimated relative phase for each period. Since the phase bias calculation and phase estimation depends on each other, an iterative optimization framework is adopted. In the objective functions, superscript r means the r-th iteration. The phase evolution sequence S_Q^{r+1} at the (i+1)-th iteration is estimated by also considering the unbiased phase $\hat{S}_{Q,i}^r$ at the r-th iteration for each sample. The objective function is described in the following [132],

$$S_Q^{r+1^*} = \arg\max_{S_Q^{r+1}} D(S_Q^{r+1}; \hat{S}_Q^r) \tag{3.2}$$

$$D(S_Q^{r+1}; \hat{S}_Q^r) = D_d(S_Q^{r+1}) + \lambda_s D_s(S_Q^{r+1}) + \lambda_b D_b(S_Q^{r+1}; \hat{S}_Q^r) \tag{3.3}$$

$$D_d(S_Q^{r+1}) = \sum_j \sum_{[i,u]\in X^j} (s_{Q,u}^{r+1} - s_{Q,i}^{r+1} - j)^2 \tag{3.4}$$

$$D_s(S_Q^{r+1}) = \sum_{i=0}^{N-2} (s_{Q,i+1}^{r+1} - s_{Q,i}^{r+1} - \frac{1}{\hat{P}_{Q,i}})^2 \tag{3.5}$$

$$D_b(S_Q^{r+1}; \hat{S}_Q^r) = \sum_{i=0}^{N} (s_{Q,i}^{r+1} - \hat{s}_{Q,i}^r)^2 \tag{3.6}$$

subject to $s_{Q,i+1}^{r+1} - s_{Q,i}^{r+1} \geq 0 \forall i = 0, ..., N-2$,

where X^j is a set of corresponding pairs of frames who have j periods shift. The optimal correspondence between a quasi-periodic signal and a period-shifted version of the same quasi-periodic signal are found by self dynamic time warping. $\hat{P}_{Q,i}$ is an estimated instantaneous period at the i-th frame, which is estimated by short-term period detection, λ_s is the smoothness coefficient and λ_b is a coefficient for the bias-correction term. At last, the phase sequence is estimated by the convex quadratic programming composed of the objective function. For more processing details, we refer the reader to [132, 133].

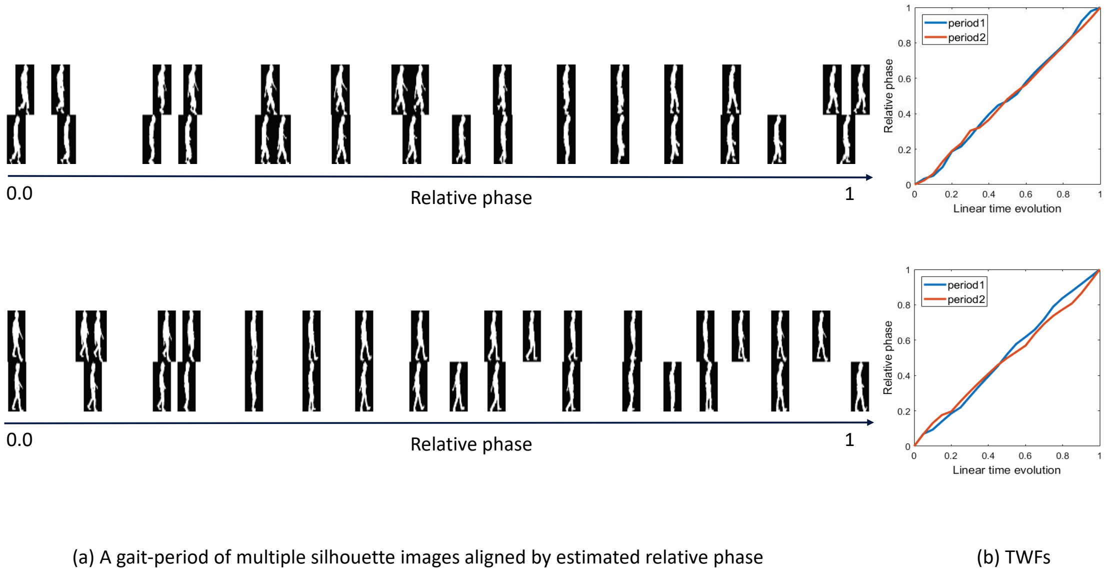


FIGURE 3.2: Variance in TWFs as the phase evolution instability measure. Time warping function (TWF)variance between periods for unstable gait. Top is from visual impaired gait and bottom is from leg impaired gait, the variance of bottom larger than that of top.

As Makihara et.al [132] pointed out that their proposed method reconstructs TWFs from a single quasi-periodic signal through a bias estimation process, so the variance in the reconstructed TWFs can be used as a kind of phase evolution instability measure. So we used this value in the present theis to decribe walking stability. An example of gait silhouettes of two subjects aligned by estimated relative phase and their TWFs are shown in Fig. 3.2 .

So, in summary, the three types of gait features represented in this section are:

(1) Duration Time: the temporal information, represented by the number of frames in a walking period;

(2) Gait Energy Image (GEI): mainly about the postural information, described by the average of silhouette frames in a period;

(3) Phase fluctuation: the stability property, revealed by the variance in the reconstructed TWFs among adjacent walking periods.

3.2 An Impaired Gait Dataset by Self-construction

In our study, we pick up two categories of commonly seen impairments: leg impairment and visual impairment. Stiff knee is a typical leg problem in the elderly. The reason for this problem is that joints become stiffer and less flexible with aging. In addition, old people are prone to have some lesions on the eye lens or retina which result in visual impairments with symptoms of blur and tunnel view. Of course, those types of the symptoms are popular among elderly people, but they might also occur among young adults with leg and eye injuries. So in this work, we are concerned with the symptoms showed out by the type of impairment other than age.

However, there is no suitable dataset which collect the impaired walking by camera. So we need to construct the dataset from scratch. And as you can image, it is hard to collect walking data of people who really have these impairments. One of the reasons is that it is difficult to find enough numbers of patients with real impairment. Moreover, even if we can find sufficient patients, it is still difficult to ensure their safety in experiments. Considering these limitations, we thus use age simulation kits to help healthy people "act as" these two kinds of commonly seen impaired people. For the simulation kit, we adopt a product of Sanwa Manufacturing Co., Ltd [134], see in Fig.3.3. Since it is a popular tool that has been used in many fields, it is reasonable for us to assume that it simulates well real impaired walking popular among elderly. We then prepare three types of walking, as follows:

(1) leg impaired walking by fastening leg supporters on both knees which restrict knee bending;

(2) visually impaired walking by wearing goggle glasses which blur the sight and narrow the view field;

(3) Normal walking without anything fixed.

Examples of these three kinds of walking styles are shown in Fig. 3.3 (a), (b) and (c), respectively. When collecting walking data, people walk on a straight path with a camera capturing sideways, so all of the silhouettes in our study are lateral. [1]

[1] As well-known, nowadays we have to obtain and manage such image data including personal information with extreme discretion. We consulted a lawyer about procedure to obtain and manage the data

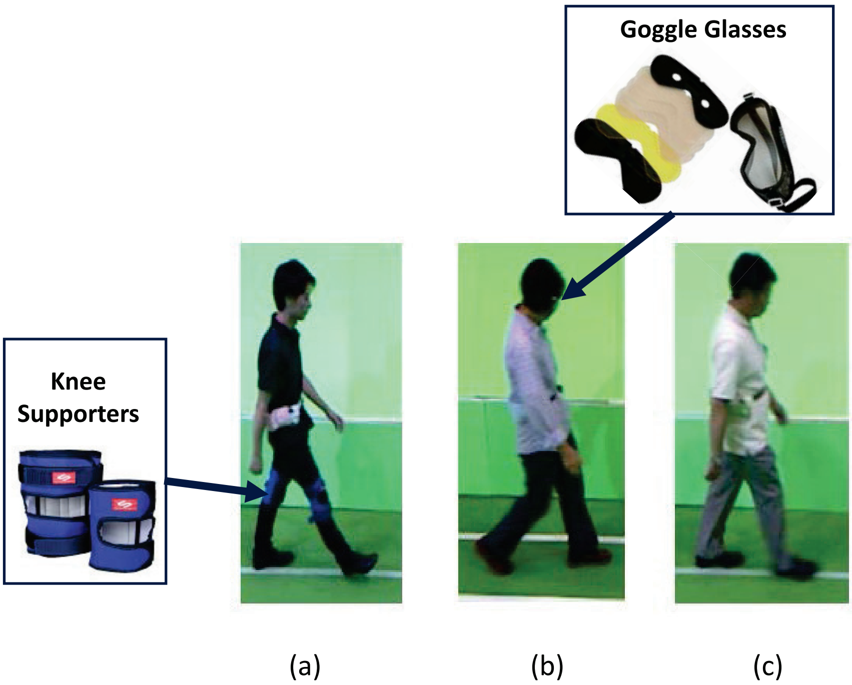


FIGURE 3.3: Three types of walking and the simulation kits. (a) leg impaired walking, (b) visually impaired walking, (c) normal walking

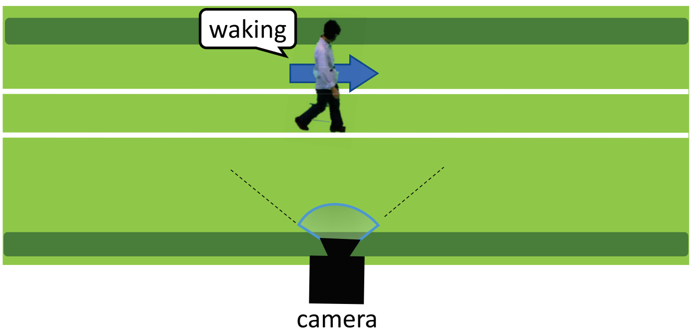


FIGURE 3.4: The top view of experiment environment.

In order to collect sufficient number of subjects, we placed our collection system in a public science museum. The top view of the experiment environment is shown in Fig.3.4. The participant walked from the left to right with RGB camera to capture walking sequence from side view. The numbers of subjects for leg impaired walking, visually impaired walking and normal walking are shown on Fig.3.5. Note that every participant in the data collection is instructed to finish two categories of walking: one type of impaired walking and normally walking. So the subject number of normal walking is much larger than that of impaired walking. The age range of participants is 4 to 78. By wearing the simulation kits, all the subjects are recognized as "old adults" who have the leg/eye symptoms mention above. At some situations, the number of subjects will decrease when the corresponding subjects cannot satisfy some conditions, such as some kinds of gait representation need specified length of frames, but the number of frames of some subjects is not enough.

For fair comparison, before applying computer vision and machine learning techniques on the database, we first manually observed the dataset to exclude subjects with apparent physical impairment. This step can guarantee the most of the subjects are in normal status. And also our analysis method is based on the statistical learning and the number of subjects is relative large, so the model is constructed based on character of major subjects, even there exist small number of subjects who are not very healthy (which cannot detected out by manual observation), they won't have much influence to the model.

3.3 Classification Method

To evaluate performance of discrimination, we apply Linear Discriminant Analysis (LDA) to the extracted gait features. Since our interest is in how much each impaired walking is changed compared to normal walking, we apply two-class LDA between normal walking and that with leg/visual impairment. And for two-class classification, we mapped the feature into a subspace with only one dimension, i.e. one direction of LDA. Note that, because subject number is not balanced for each class, we choose the same subject number for the two classes. In total we make 30 times selection, the results are the average of those 30 times and also

and about how to get agreement from subjects, and we carefully followed the procedure. Moreover, in the case that a subject was a child, who is not regarded to be responsible for the agreement, we ask his/her parent to give the agreement instead of him/her. Owing to this procedure, images in this dataset can be pasted on this paper, can be analyzed for our research purpose.

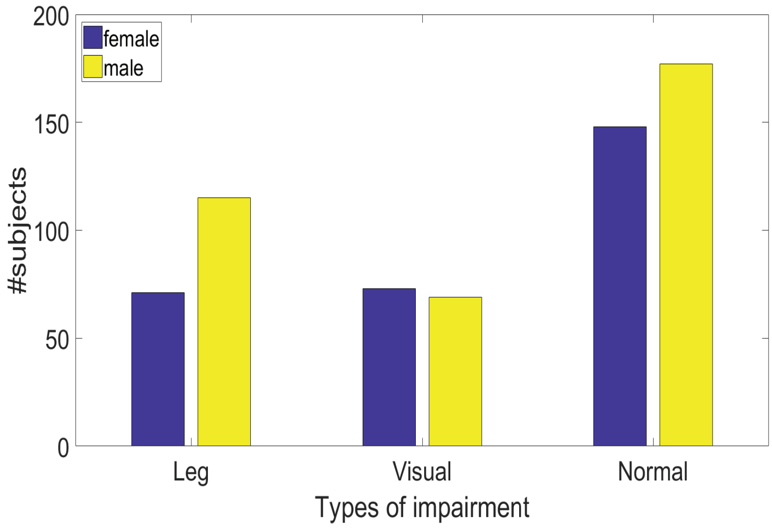


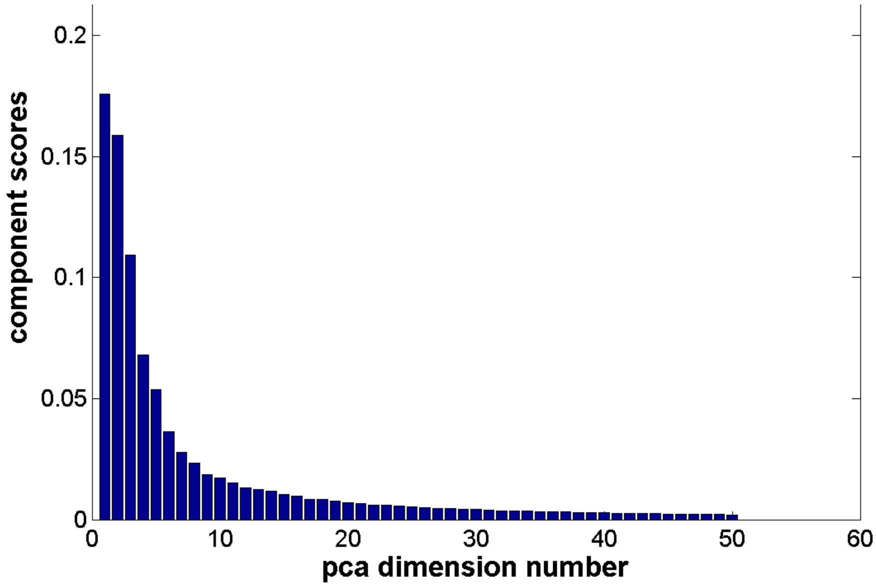
FIGURE 3.5: The number of subjects for each type of walking

their standard deviation. In the case of GEI, since the feature is high dimensional vectors, we preliminarily apply Principal Component Analysis (PCA) to compress them into the dimension number which preserves around 90% of the original energy. Each selection randomly choose GEI from different subjects to compose the input features for PCA. As a result, the number of components and distribution of principal component scores vary among each selection. So instead of a specific number of components, a range is given. Take the whole body GEI as input feature for example. Considering the situation of compressing features of subjects with normal and visual impairments, the range of component numbers corresponding to 90% of the original energy is 50–52. For case of normal between leg impairment, the range is 54–56. One example for the distribution of each principal component score is shown in Fig. 3.6.

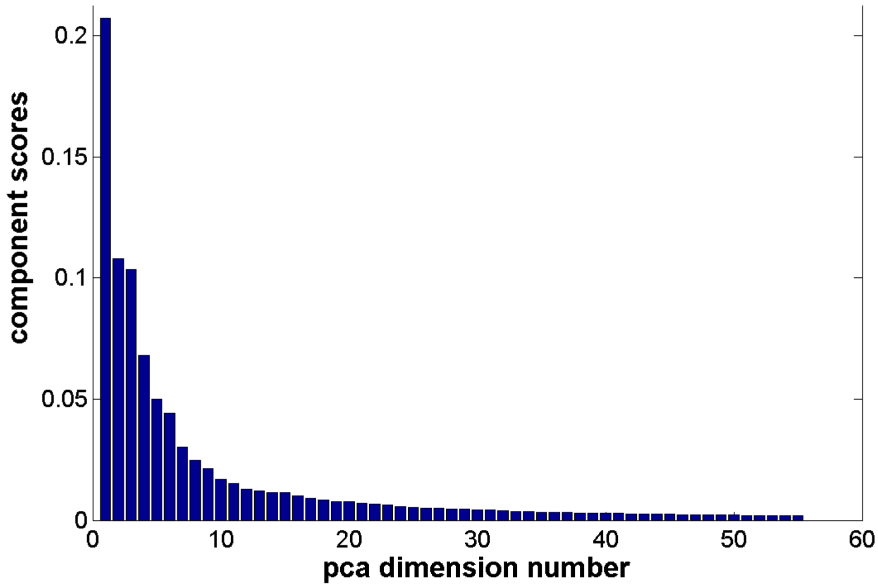
3.4 Discrimination Ability of Each Feature

3.4.1 GEI

We evaluate the performance of GEI in distinguishing impaired walking from normal walking. The table 3.1 shows the performance of normal walking and visual impaired walking. It says the accuracy is about 81%. The figure 3.7 are the reprojection of the most discriminative LDA direction. Comparing these two images, we can find that a person with visual impairment tends to bend his/her head more



(a)



(b)

FIGURE 3.6: Distribution of the principal component scores for GEI of subjects from (a) normal and visual impairment, and (b) normal and leg impairment

TABLE 3.1: The classification accuracy of GEI for detecting visually impaired walking.

normal	81.17% ± 2.84%
visual impairment	80.68% ± 1.99%
average accuracy	80.93% ± 1.90%

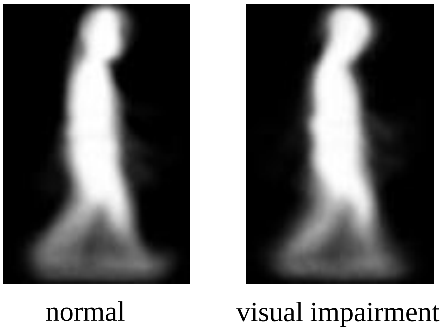


FIGURE 3.7: The re-projection of normal vs. visually impaired walking from the one LDA direction

TABLE 3.2: The classification accuracy of GEI for detecting leg impaired walking.

normal	70.27% ± 2.00%
leg impairment	68.33% ± 1.99%
average accuracy	69.30% ± 1.47%

to the front than a normal person. It sounds reasonable that people with lower visual ability need to be more careful about the road. As for the performance of the leg impaired walking and normal walking, results are shown in table 3.2 and Fig.3.8. As it shows, the classification accuracy is about 69%. The re-projection images on the right side show that leg impaired walking has a little smaller leg angle and lower head bending than that of normal walking. The performance of GEI shows that walking posture is affected by impairment.

3.4.2 Duration Time

Fig. 3.9 and Fig. 3.10, table 3.3 and table 3.4 show the distribution of the duration time of normal walking and visually/leg impaired walking and also their classification accuracy. The distributions of the normal and impaired walking are described by red and blue curves, respectively. The curves are generated from

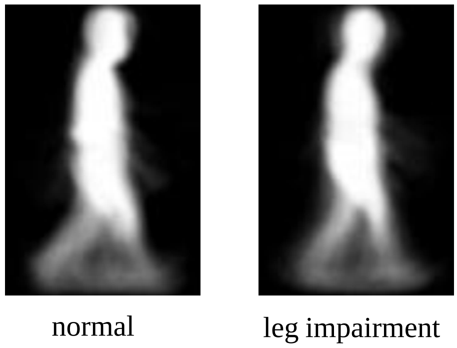


FIGURE 3.8: The re-projection of normal vs. leg impaired walking from the one LDA direction

interpolation fit on the discrete frequency values. In Fig. 3.9, the peaks of the two distribution are remarkably aligned. It means that the visual impairment does not affect the duration time. In Fig. 3.10, on the other hand, we found that the leg impairment affects the duration time; the duration time of the leg impairment is obviously longer than that of the normal walking. However, the large overlapped region of two distributions in each graph means that the duration time is not so effective for accurate impairment estimation and the classification results also prove that point.

3.4.3 Phase Fluctuation

Phase fluctuation of a neighboring phase estimated sequence is used to estimate the stability of a walking style. It is measured by the variance of the reconstruction of TWFs. The smaller the variance, the more stable the phase evolution between neighboring periods. That also means the walking style of the subject is more stable. To note here that to calculate the phase fluctuation, a walking sequence need to contain more than two periods. The numbers of subjects who fulfill this condition are: 198, 92 and 66 for normal walking, leg impaired walking and visual impaired walking respectively.

Fig. 3.11 and Fig. 3.12, and table 3.5 and table 3.6 show the distribution of variance of reconstruction DTW of normal walking and leg/visual impaired walking and also their classification accuracy. The distributions of the normal and impaired walking are described by red and blue curves, respectively. In both Fig. 3.11 and Fig. 3.12 the peaks of the two distribution are aligned. It means that the stability of the walking style is different between individual people, but not

TABLE 3.3: The classification accuracy of duration time for detecting visually impaired walking.

normal	50.77% ± 10.11%
visual impairment	47.68% ± 9.43%

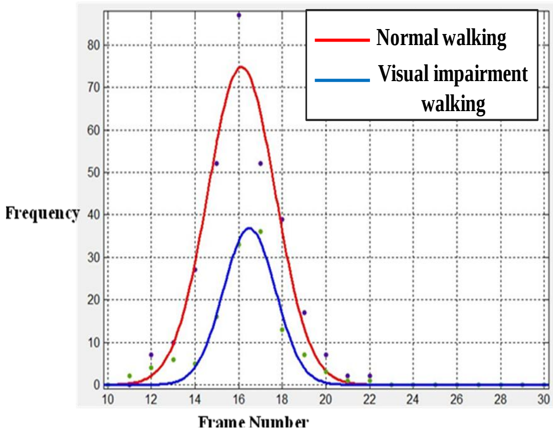


FIGURE 3.9: DT distribution between normal and visually impaired walking

TABLE 3.4: The classification accuracy of duration time for detecting leg impaired walking.

normal	55.87% ± 2.01%
leg impairment	73.97% ± 4.90%

TABLE 3.5: The classification accuracy of phase fluctuation for detecting visually impaired walking.

normal	37.02% ± 20.70%
visual impairment	65.20% ± 21.18%

affected by the physical impairment. The classification accuracy also proves this conclusion.

3.4.4 Influence of Gender on Gait Features

The paper of Cho et al. [135] tried to prove the assumption that healthy adults walk differently according to their gender, based on some aspects. In his experiments, after normalization which was used to avoid the body size effect, the authors reach the following conclusions, 1) no gender differences were found in walking speed and

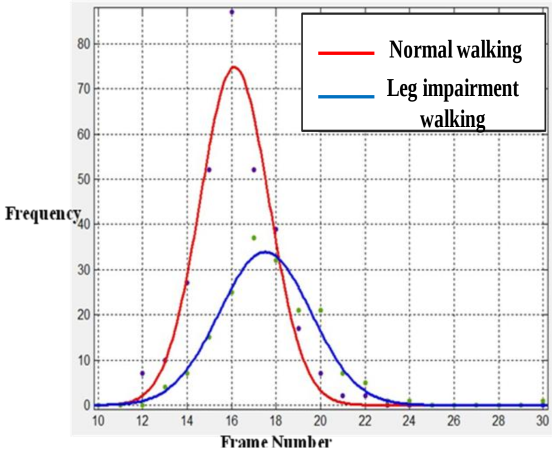


FIGURE 3.10: DT distribution between normal and leg impaired walking

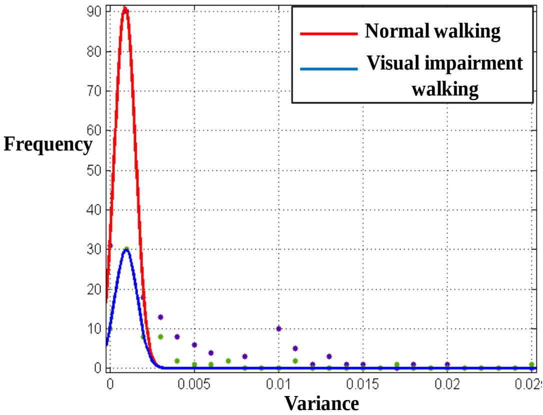


FIGURE 3.11: Distribution of variance of phase fluctuation between normal and visually impaired walking

also in the durations of the stance phase and the double support period; 2) some differences were discovered in postural aspects, females walked with their pelvis tilted more anteriorly, more up and down oblique motion, hip joints more flexed rotated, knee joint in more valgus angles, and narrower step widths.

Considering the property of the three gait features in this paper (namely GEI, duration time and phase fluctuation), GEI which describes the body shape of the walking subjects is probably affected by gender. We verify the assumption by comparing among the detection results using GEI from subjects of mixed gender, same gender and cross-gender, which are shown in table 3.1 and table 3.2, and table in Fig. 3.13 and Fig. 3.14, respectively. Note that mixed gender means subjects used without considering gender, mix together for training and testing. While cross-gender means using male (female) subjects for training but female (male) subjects for testing.

TABLE 3.6: The classification accuracy of phase fluctuation for detecting leg impaired walking.

normal	30.33% ± 8.80%
leg impairment	68.33% ± 9.04%

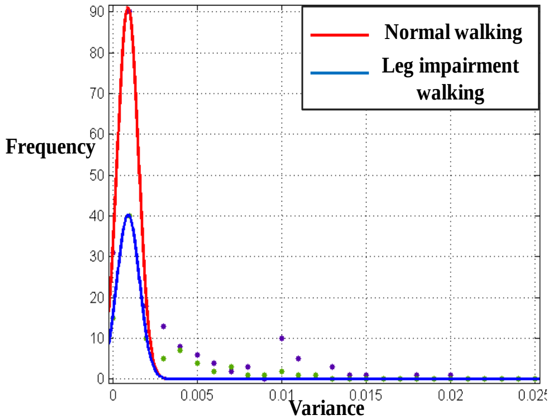


FIGURE 3.12: Distribution of variance of phase fluctuation between normal and leg impaired walking

From these figures, we find that the results change when applying different gender conditions, which means both categories of impairment detection are affected by gender factor. Leg impairment classification is further affected. This may be due to the fact that more obvious differences exist in gait-related anatomy in leg rather

normal vs. visual impairment **(female training, female testing)**	
normal	79.41%±3.27%
visual impairment	76.80%±3.41%
average accuracy	78.11%±2.81%

(a1)

normal vs. leg impairment **(female training, female testing)**	
normal	65.40%±4.66%
leg impairment	62.30%±3.42%
average accuracy	63.85%±3.42%

(b1)

normal vs. visual impairment **(male training, male testing)**	
normal	77.29%±2.67%
visual impairment	78.26%±2.50%
average accuracy	77.78%±1.93%

(a2)

normal vs. leg impairment **(male training, male testing)**	
normal	80.52%±2.36%
leg impairment	84.61%±2.25%
average accuracy	82.57%±1.8%

(b2)

FIGURE 3.13: Accuracy of same gender classification. (a1), (b1) female subjects training and testing; (a2), (b2) male subjects training and testing.

normal vs. visual impairment **(male training, female testing)**	
normal	63.09%±11.26%
visual impairment	72.42%±7.60%
average accuracy	67.75%±4.11%

(a1)

normal vs. leg impairment **(male training, female testing)**	
normal	68.17%±7.21%
leg impairment	42.77%±5.38%
average accuracy	55.47%±1.70%

(b1)

normal vs. visual impairment **(female training, male testing)**	
normal	77.74%±6.39%
visual impairment	78.16%±8.77%
average accuracy	77.95%±3.13%

(a2)

normal vs. leg impairment **(female training, male testing)**	
normal	48.40%±9.63%
leg impairment	70.64%±8.39%
average accuracy	59.52%±2.79%

(b2)

FIGURE 3.14: Accuracy of cross gender classification. (a1), (b1) male subjects training and female subjects testing; (a2), (b2) female subjects training and male subjects testing.

than neck between genders. Since the results decrease in most of the classification in same gender cases and in all cross-gender situations, and also gender information always lacks in the real scenarios, using the strategy of classification without considering gender factor is more robust.

3.4.5 Discussion

Among the features we list up, GEI gives fine performance, but duration time and phase fluctuation are not so effective. In the case of the duration time, although the statistical distribution is changed by impairment, it is not adequate for impairment estimation since the overlapped regions between the distributions are quite large. We also found the phase fluctuation information is not effective. Walking stability is not affected by the physical impairment, rather by the individual differences. So GEI is chosen to present the discriminative information of different walking styles. Even though gait is affected by gender, GEI evaluation results show that classification without considering gender is more feasible in real scenarios.

3.5 Performance and Real Application of Patch-based GEI

3.5.1 The Motivation to Use Patch-based GEI

As discussed in 3.4, it appears that GEI is the best feature to detect impaired walking, because posture difference between different walking styles can be described by this feature. In other word, walking posture contains the discriminative ability for impairment detection. On the other hand, however, the posture information from other body parts that are not useful for distinguishing might also has the negative effect on the classification performance. To reduce the intra-difference of the GEI, we thus propose to use only effective parts to decrease negative influence of the other part of body.

3.5.2 The Procedures to Extract Patch-based GEI and the Experiment Results

To decide which body patches contain the most discriminative information, we firstly need to determine the criterion for segment the whole GEI into patches. As mentioned previously, two works give detail analysis of contribution of body components for gender recognition [136, 137]. From their experiments, we found that results become different with the change of criterion for the segmentation of human component. Since our scenario is, of course, different from those studies, we have to find a new rule (the most discriminative patches) for our scenario. To do this, we apply various grid patch sizes of human region, and evaluate performance.

In this study, we evaluate the performance of 5 levels of patch sizes, they are 5×5, 10×10, 20×20, 30×30, 40×40. From the whole body GEI, we extract the region corresponding to the patch size with row scanning order and with the skipping step of 5 pixels. For each patch region, we also use the same processing flow with whole GEI, first PCA for compressing into the dimension which preserve about 90% energy of the original one and then LDA for classification. Their performances are shown in Fig. 3.15 and Fig. 3.16.

In Fig. 3.15 and Fig. 3.16, "classification accuracy" is the performance of patch shown in the third row, which is the best performance of the same patch size for a whole-GEI. And the gray human images in the these rows are the average of GEI from all the leg impaired subjects and all the visual impaired subjects for Fig. 3.15 and Fig. 3.16 respectively. The figures on the fourth row of each figure

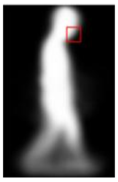
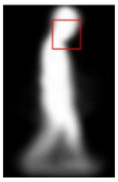
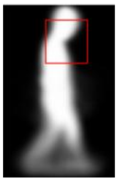
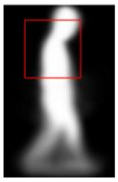
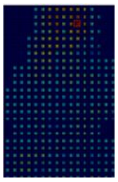
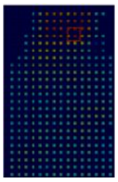
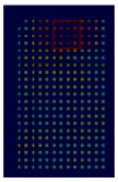
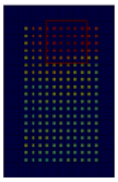
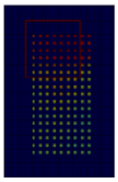
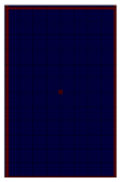
patch size	5*5	10*10	20*20	30*30	40*40	120*80
average accuracy	76.26%±1.40%	75.79%±1.18%	81.20%±1.61%	83.17%±1.36%	82.31%±1.75%	80.93%±1.90%
most effective patch						
patch accuracy of the whole image						

FIGURE 3.15: Classification accuracy of normal walking and visually impaired walking from different patch size (including whole body-size) and locations.

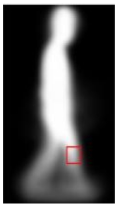
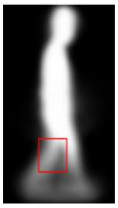
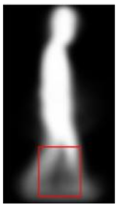
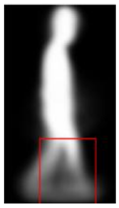
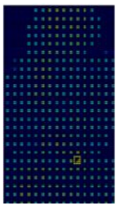
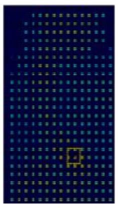
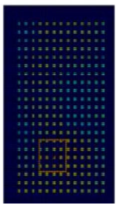
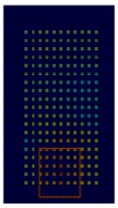
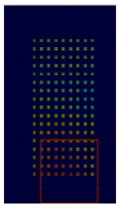
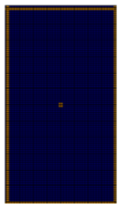
patch size	5*5	10*10	20*20	30*30	40*40	120*80
average accuracy	62.24%±1.59%	66.01%±1.49%	69.87%±2.05%	72.68%±1.38%	75.05%±1.60%	69.30%±1.47%
most effective patch						
patch accuracy of the whole image						

FIGURE 3.16: Classification accuracy of normal walking and leg impaired walking from different patch size (including whole body-size) and locations.

are the performance of all the patches of the same size. The points in the image are located on the center of the patches. And color of the points is relative to the classification accuracy using that corresponding patch GEI; color closer to the blue means lower accuracy and color closer to red means higher accuracy. Also note that the rightmost column is the performance of whole GEI.

From the results shown in Fig. 3.15, we found that patch with size of 30×30 positioning at the head and breast give the best performance with the classification accuracy of 83.17%. Comparing with the average accuracy of whole GEI of 80.93%, using only patch around the head and breast region can improve 2.24%. This result proves our assumption that other parts of the human body will influence the discriminative ability when using GEI is reasonable. Note that, though the other sizes of patches perform a little worse, all the red closer color appears at the upper region and all the highest accuracy appears at the head regions. This once again confirms the fact that people with visual impairments need to bend their heads to pay more attention to the condition of roads. And still, when we check the lower part of the color points image, we find that they are near to blue color, which means impairment on eyes have little influence on the lower body.

Fig.3.16 shows out the performance of patch-based GEI in detecting leg impaired walking. The patch size of 40×40 shows out the most discriminative ability at the accuracy of 75.05%, which improve 5.75% comparing with the performance of whole GEI. All the best performance at the leg region also confirm the fact that people with leg impairments walking with smaller stride length. And about the point color distribution, the red closer color appear besides around the leg region still some appears at the head region, but they are not so obvious. This fact says that, the leg impairment make the subject walk with smaller leg angle, and at the same time, to make the balance of the moving body, subject have a little front lean. But this "front lean" is less effective than the leg change, so using only the leg region only is enough. From the analysis mentioned above, patch-based GEI can decrease the influence of the other part of human body. It might also can solve the problem of sharp shape change due to carrying baggage. Using only the effective patch, like only head or leg regions can avoid the shape change around baggage regions.

3.5.3 A Solution to a Real Application of Patch-based GEI

Beside exploring the difference between impaired walking and normal walking, we go further to solve another issue which makes our research more practical, distinguishing multi-type impairments simultaneously. Considering that visual impairment and leg impairment are independent to each other, a subject might suffer from both visual and leg impairments at the same time. To label the subject as either visual impairment or leg impairment only is not so reasonable, therefore such kind of compound visual and leg impairment is considered as a new impairment type.

The direct multi-class classification would get confused in distinguishing pure impairment and compound impairment. We thus provide the classification strategy of using binary classifier to detect one type of impairment, that is one type of impairment vs. other types of walking (including impaired and normal). In detail, we employ the strategy of visual impairment vs. non visual impairment (including normal and leg impairment) to diagnose whether or not the subject suffers from visual impairment, and use the method of leg impairment vs. non leg impairment (including normal and visual impairment) to detect leg impairment. In our experiment, the accuracy of visual impairment detection is 77.82% and that of leg impairment detection is 72.65%.

Chapter 4

Growth Assessment of School-age Children from Dual-task Observation

In last chapter, we have introduced a passive method to detect the physical impairment by observing walking pattern. The passive way is able to monitor the multiple people at public places. However, it limited the study to physical aspect of health only. Thus, in this chapter, in addition to studying the physical health, we go further to investigate the other aspects of health status from subjects by an active way. This method is designed as a game for screening multiple aspects of health for children, including anthropometric, kinematic, and cognitive aspects. Of course, with some modifications, the system can also be used to measure the health status of elderly. And the research which can be used to estimated cognitive statues of elderly people is a collaborative work. In this thesis, we focus on my main work of assessing children's growth status.

In the following, we will introduce the method in detail for predicting various aspects of growth status. We first introduce the general ideas and feasibility of this work. Then introduce the method of data collection for dual-task performance. The following is to describe the feature representation and the regression method for age estimation. At last, we present experimental tests of age estimation with the extracted features, and discuss their implications.

4.1 The General Ideas and Feasibility of Our Approach

Healthy growth in childhood is a critical factor for determining whether an individual will have a healthy body and ability levels after grown up. Normally developing children tend to have growing patterns that corresponding to their true (chronological) age. And a child's growth status can be assessed by comparing various types of measurements related with growth with these growing patterns constructed by the corresponding measurements, which is summarized as statistical standard references. Among various types of growth characteristics, anthropometric, kinematic, and cognitive aspects are the most commonly examined. If a substantial discrepancy between measurement from a test child and the average level of that from his/her age is observed, then such a discrepancy often indicates some health issues. It should be noted that this assessment provides only an initial impression, and a more comprehensive diagnosis is typically required to confirm the evaluation. There are main two steps for such initial "screening": obtaining measurements from child and comparing with standard reference.

As for the data obtaining, in conventional approach, some measurements are obtained manually. For example, the Gross Motor Function Measure (GMFM) [138] which is used to measure change in gross motor function over time in children with cerebral palsy, needs physician to observe children's motor activities and then score each item. And the other problem is that and different aspects of information are measured at different time and occasions: they are measured separately. Such kind of manipulations is not convenient for the parents or physicians to get an initial judgment about the growth status of a child.

To address this problem, we thus proposed to used "dual-task" method, which involves the simultaneous performance of a motor task and a cognitive task, to collect several aspects of information at a time. And also automatic data collection is realized by an automatic data collection system. The adoption of "dual-task" paradigm is because this strategy can gather all the three commonly-seen aspects of information simultaneously. It saves considerable time, comparing with conventional approaches that collect different measurements at different times/places. The dual-task method is thus convenient for physicians and parents, easily providing an initial impression of children's growth.

In dual-task method, we used gait (stepping in place) as the motor task and arithmetic calculation as the cognitive task. This combination (stepping in place while performing arithmetic calculation) is popularly used for examining the cognitive

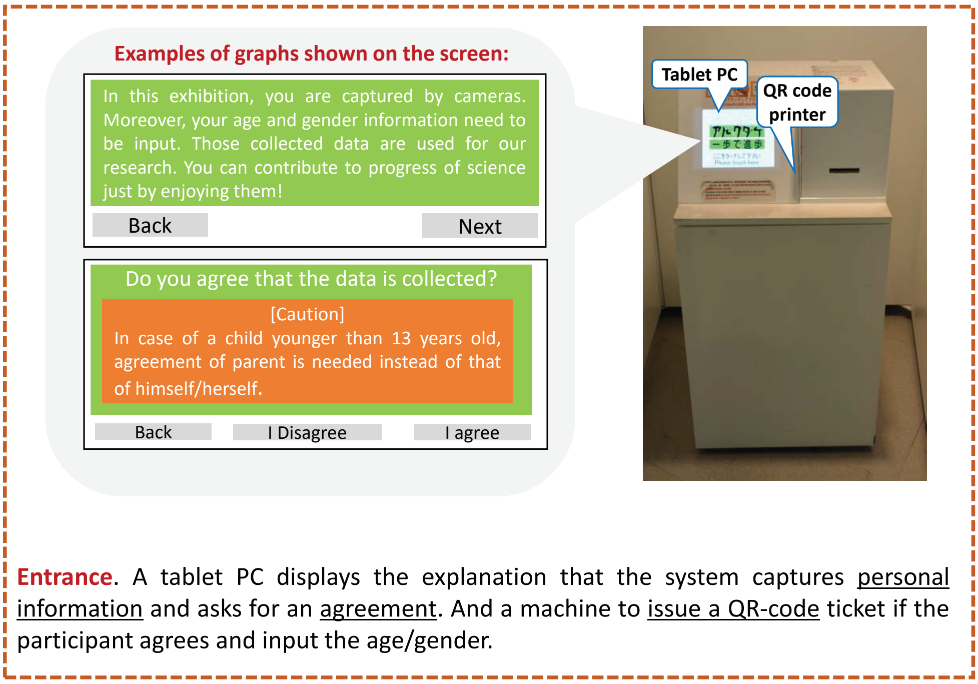


FIGURE 4.1: The entrance setting for automatic data-collection system [7].

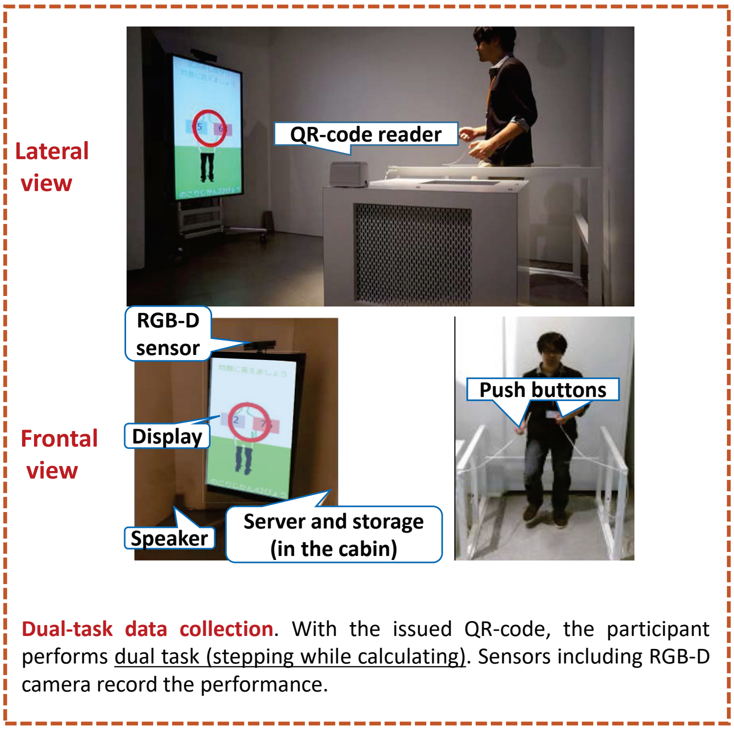


FIGURE 4.2: Dual-task experience system for automatic data-collection system [7].

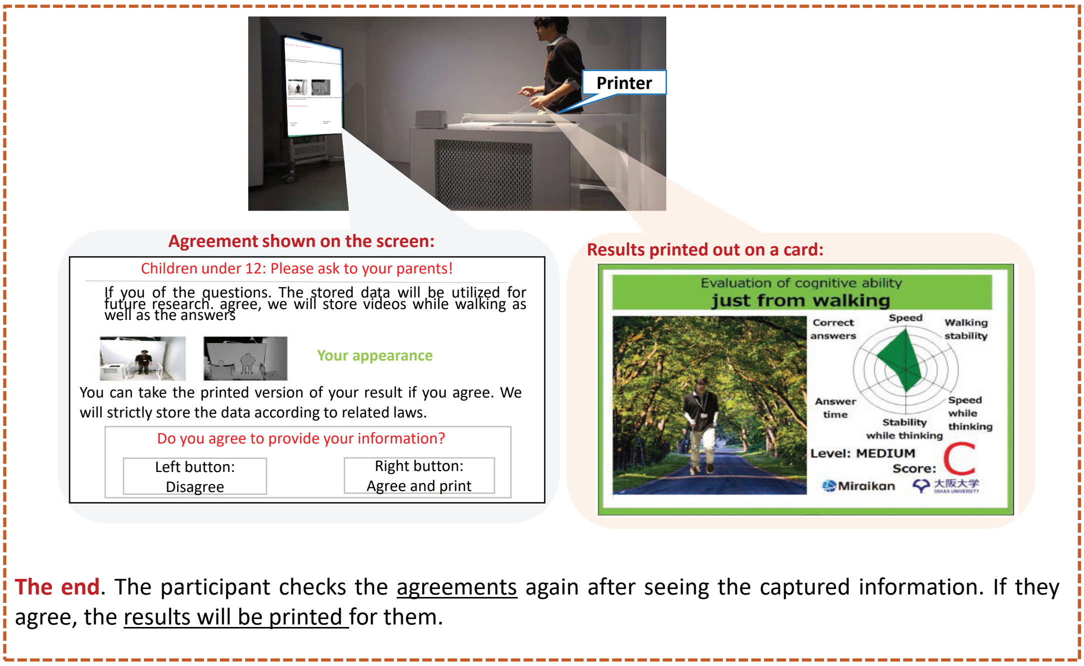
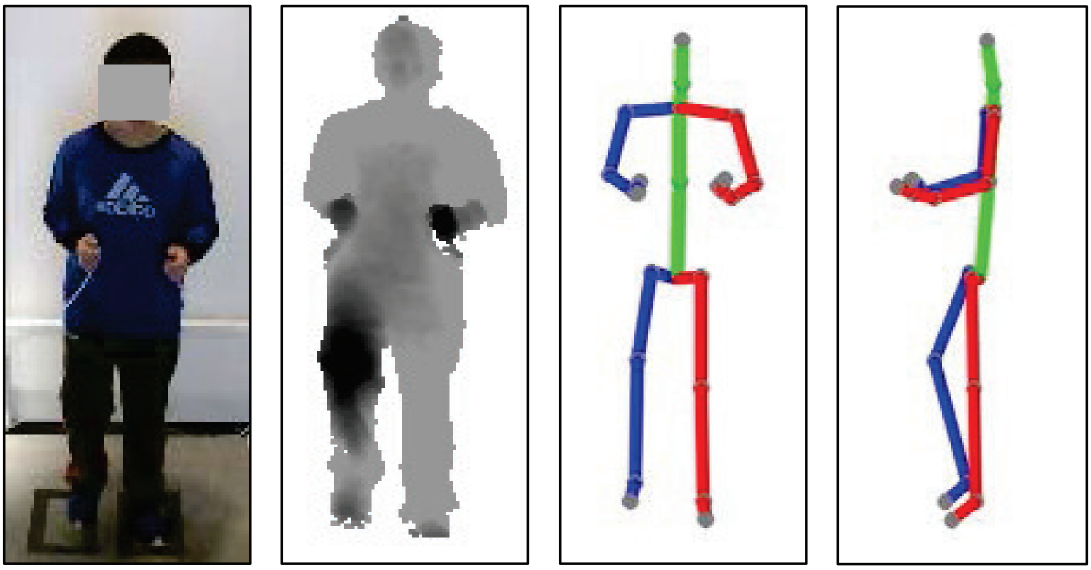


FIGURE 4.3: The exit session for automatic data-collection system [7].

status of children and elderly people [139–142]. Stepping in place is the simplest form of gait and is often used in place of walking [143]. Compared with other tasks such as running, walking, or jumping, stepping in place is the easiest for the participant to perform and also saves a great deal of space. These are good properties for the realistic application setting and for attracting participants. Arithmetic calculation is frequently used in the dual-task paradigm for early diagnosis of dementia, because this task requires the short-term memory function of the frontal cortex, the impairment of which is an early indicator for dementia [144, 145]. Following the convenience and popularity of task setting in the existed researches, in the present research, we also used gait and arithmetic calculation as the tasks in dual-task paradigm. Based on the task we used, the kinematic and cognitive abilities of children considered in our study correspond to gait-related kinematic (from gait performance) and mathematics-related cognitive (from calculation performance), respectively. We applied a data-collection system to record the gait and calculation performance of a participant automatically. Because the system captured the 3D shape of participants' bodies, anthropometric information was also measured at the same time.

As for comparing with standard reference to get initial judgment, for conventional approach, the obtained measurements are compared with the standard which is constructed from international or regional samples of healthy children, e.g. height and weight charts [146–148]. There are two problems existed for the conventional way, (1) the comparison are always manually; (2) such kind of comparison using obtained measurement directly is only available for one-direction measurement. But for most of the occasions, the number of dimensions for an aspect of growth information is much more than one dimension. For such cases, direct comparing the measurement with the statistical reference is unfeasible. Because to get reliable statics for high dimension measurement, it needs a huge number of samples and even the samples are sufficient to construct a statistical reference, from the direct comparison, we still cannot understand the growth status. The reason is that for high-dimension growth feature, it may happen that some dimensions are larger than the values of standard reference while some are smaller. To deal with this problem, represent the growth feature by a metric of "age". We first construct a statistical model between multiple-dimension growth feature and chronological ages. Then coming the growth feature from a test child, we can assign the age whose growth feature is the most similar to that of the test child to she/he. If the estimated age is near to her/his chronological age, it indicates the child growth normally, and vice versa. The modeling construction and age estimation are realized by regression.

The feasibility of regression comes from the discriminative ability of growth feature, i.e. the features develop with age increasing. Several previous studies [149–152] have examined the developmental tendencies of locomotor ability (e.g., running, walking) during childhood. According to Hagmann-von Arx et al. [151], gait fluctuation, which reflects the regularity of gait pattern, improves through childhood and adolescence. In one study of cognitive development, Moshman [153] reported that developmental changes in cognition continued through early adolescence. Furthermore, Nunes [154] reported that mathematical skill develops with education experience, and cognitive performance level is strongly related to age. In addition, anthropometric features such as height also increase with age. The developmental relationship between age and these three characteristics of growth suggest that it is reasonable to estimate a child's age based on these three aspects of growth information. Thus, we examined the performance of all participants, used the data to construct a statistical model and estimate age. And then calculated the average deviation between the estimated and chronological ages for all the participants to understand the average level of growth status among typically developing individuals. These averaged values can be seen as evidence for the feasibility of using the extracted features to measure growth assessment and also as a standard for screening.



(a) (b) (c) (d)

FIGURE 4.4: Data captured with a Kinect sensor. (a) color image; (b) depth map (extracted human body region); (c) and (d) are the skeleton images from the front view (X-Y plane) and lateral view (Z-Y plane), respectively.

The combination of efficient growth features collection and automatic growth status comparison enables a convient growth assessment system for user. After introducing the main ideas in our approaches, we summary the main contributions to this field:

- Database construction is the primary and vital step in a whole procedure of data analysis. In our work, the three aspects of growth information can be collected simultaneously by dual-task method and automatically by a data collection system. The efficiency and automation are important for real application. It is possible to collect sufficient number of subjects with least labor to construct reliable statistical model. And it is convenient to the users, for the automatic system can be embedded into a game system, so user can assess growth status even at home.

- Instead of directly comparing to the statistics of the growth feature, we used age estimation for growth assessment: the average level of age estimation among all the participants serve as threshold to evaluate growth status. The age estimation enables automatic growth assessment and also extends the assessment to multi-dimension of growth feature.

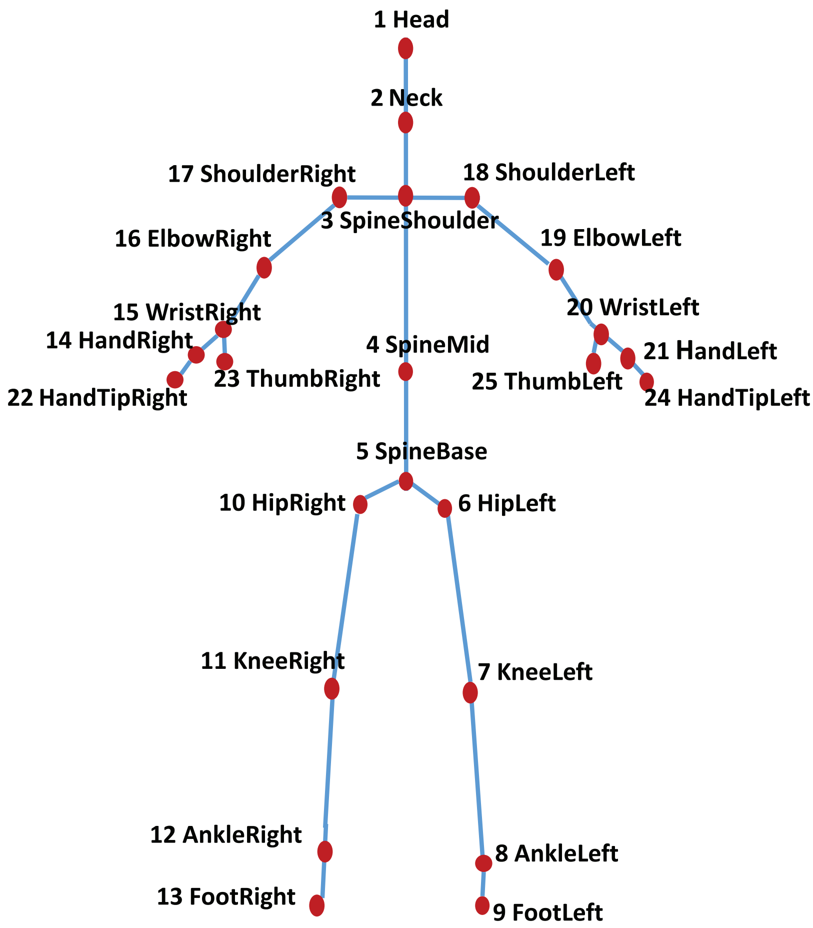


Figure 4.5: Kinect V2 joint hierarchy, the name and the number for each joint.

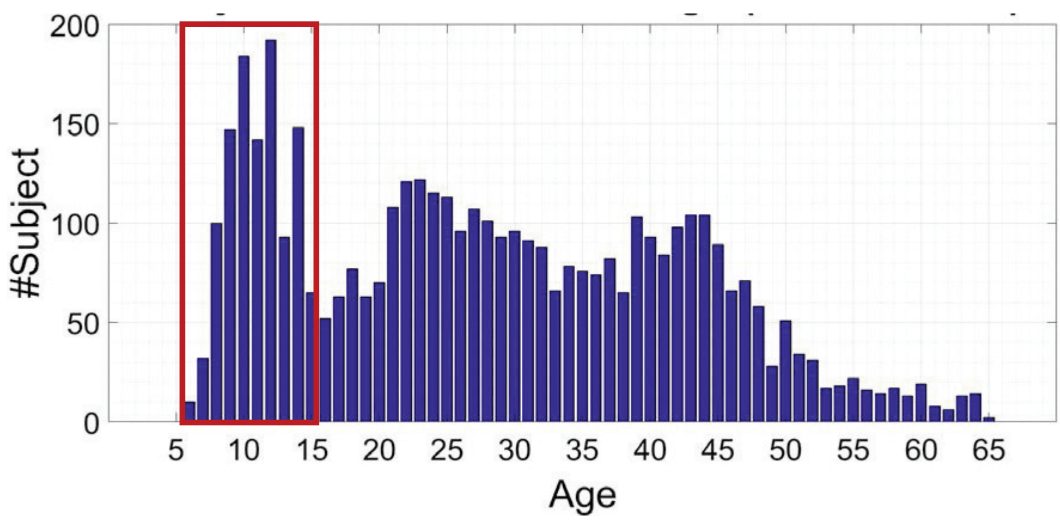


Figure 4.6: The number of participants at each age. The participants in the red rectangle are the child group, the focus of this study.

- By performing age estimation among different age groups and using various aspects of growth, we can elucidate growth trends in different age ranges, in addition to children, and for various aspects of growth.

4.2 Multi-aspect of Growth Data Collection

Manually obtaining various measurements is traditionally a labor-intensive task. For example, acquiring anthropometric information about height requires measurement with a scale, and manual recording of values. Thus, it is impractical to collect data on a large number of individual participants manually. In the current study we employed an automated system [7] to acquire various measurements while participants performed a dual-task. For the system, there are mainly three points the authors considering when constructed the system: 1) unmanned data collection; 2) privacy protection, and 3) attracting participants. Based on these considerations, I briefly introduce the procedures to experience the system. The basic procedures involved in the system are shown in Fig.4.1, Fig.4.2, and Fig.4.3.

At the entrance (the equipment and some graphic surfaces are shown on Fig.4.1.), a touchscreen tablet displayed the instruction to ask participants input their personal information including age, gender and choose the preferred language for the experimental instruction (Japanese or English). Then, the terminal presented the purpose and policies of the research to explain that this system will use camera to capture data of subject and the collected data will be only used for research purpose. This step is to protect the privacy of participants, by considering the suggestions from lawyers. If the participant accepted the agreement, then a QR code ticket which contained the subject ID was issued. Or else, the participant cannot go on to experience the system. To note that, if the age of participant is younger than 12 years, the agreement should be signed instead by their parents.

With the issued ticket, the participant moved to experiment dual-task collection system which was designed as an entertainment kiosk to attract the interest of participants. This system was originally designed to collect dual-task data for analyzing the relationship between dual-task performance and cognition. So it recorded single-task of physical activity and cognitive execution as well as dual-task performance. In the present study, we focus on efficient property of dual-task measurement to save time, because our main purpose was screening. So we used this system to collected dual-task performance only.

As shown in Fig.4.2, we used a stationary stepping task as our motor task, which required less space than walking, and used the calculation of addition or subtraction between a one-digit number and a two-digit number (e.g., $74 + 2 = ?$) as our cognitive task. Participant answered the question by selecting the answer from two candidates by a push button holding in each hand. Response times for calculation, and the accuracy rate of responses were recorded. A Microsoft Kinect 2 sensor, which consists of a RGB camera and a depth camera, was used to track the participant's whole body during stepping movements. The color image sequence, depth map sequence and time series of 3D coordinates of the body joints estimated from the depth data by Kinect SDK (Software Development Kit) were recorded. The direction of coordinate axes are defined as, the positive direction of X axis is from right to left when facing to Kinect, Y axis is from bottom to up and the positive direction of Z axis is facing to Kinect. Fig.4.4 shows examples of these data collected from one participant. And the name and number manually assigned for each joint is shown in Fig. 4.5.

After finishing the dual-task performance, participant has already known what kind of personal information had been actually recorded. They were offered a chance again to check if they want to provide the collected data for research usage, the content of the agreement is shown in Fig.4.3. If the participant agreed, a result score sheet would be printed for them. As also shown in Fig.4.3, the sheet shows out scores including stepping speed, stability, response accuracy and response time.

A relatively large number of participants was necessary for reliable statistical analysis. To collect data from a large number of participants, we installed our system at the National Museum of Emerging Science and Innovation (MIRAIKAN), which is the largest science museum in Japan, and is open to the public. The system was exhibited for almost 5 months, and we collected dual-task performance data from a total of 4,323 participants, with 1,113 children aged 6–15 years (indicated by the red rectangle in Fig.4.6) and 3,210 people aged 16–65 years. In the current study, we focused on the child group. The number of study samples at each age is shown in Fig.4.6.

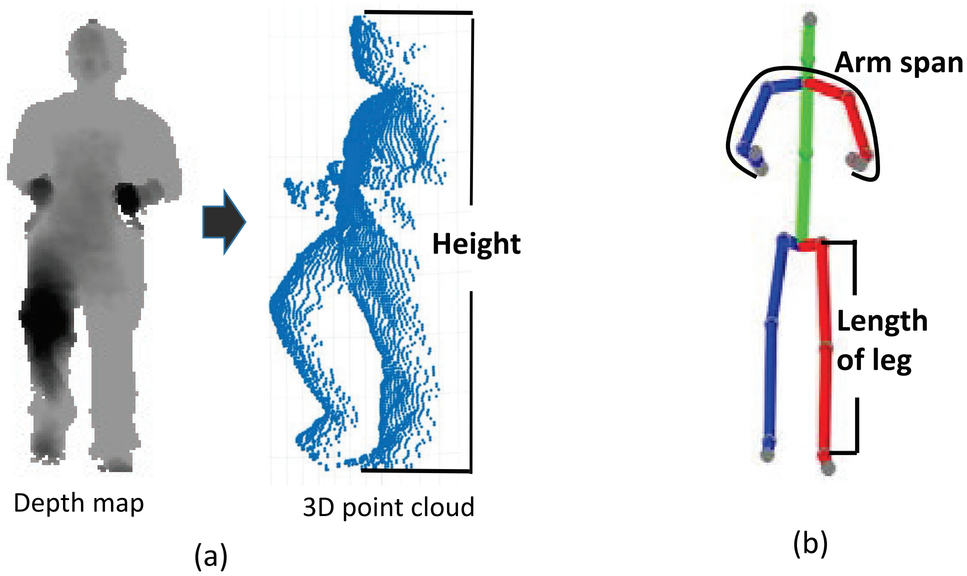


FIGURE 4.7: Extraction of three anthropometric features. (a) Height was extracted from 3D point cloud (converted from depth map). (b) Arm span and leg length were calculated from 3D joint coordinates.

4.3 Growth Feature Extraction and Regression Method for Age Estimation

In this section, to model the relationships between growth information and age for the chronological age estimation, we first present the methods for describing anthropometric, kinematic, and cognitive aspects of growth from the recorded data. Then, we briefly introduce the regression method we adopted to construct the age estimation model.

4.3.1 Growth Feature Extraction

Cognitive features based on arithmetic performance are relatively straightforward to obtain. We used the average response time and the ratio of correct responses across all problems. Thus, there were two dimensions of mathematics-related cognitive features.

Anthropometric refers to a set of non-invasive, quantitative body measurements used to assess growth and health parameters. Based on the Kinect sensor used in the current study, we expressed this aspect of growth as human body length, including height, body-part length, and body proportions [155, 156]. Many previous studies [94, 157–159] have attempted to determine these indicators by calculating the Euclidean distance from 3D joint coordinates for applications in human identification and re-identification. However, body height calculation using the head joint, which is represented by a point at the center of the head, has been found to differ from the true height. Thus, in the current study, we used depth images, which were originally used to estimate joint positions, to determine height more accurately.

We first transformed the depth map into a 3D point cloud and then rotated the ground plane to be horizontal for a Kinect sensor mounted on top of the screen. We then excluded the background surrounding the participant's body. From the point cloud of the participant's body (an example of which is shown in Fig.4.7 (a)),height could be captured as the distance between the highest and lowest points. Note that participants in our experiment performed a stepping motion, which caused height to change slightly across the different phases of stepping. We chose to use the phase where one leg was straight and the other was most bent (the upper body can be in any natural posture during stepping) to measure the participant's height (as shown in Fig.4.7 (a)), because this posture is closest to the height of the body while standing still. The timing of the specified phase is detected automatically based on the 3D coordinate signal of the knee, which is generated synchronously with the depth map. The valley points on the Z axis (the positive direction is facing to Kinect) of the signal correspond to the moment when the leg is straight and the other is the most bent. We then eliminated the noise data caused by unexpected poses such as bending the head down or the failure to capture the head region, by excluding the points with absolute z-scores (the proportion of a data point subtracted by mean to standard deviation) larger than 2 or smaller than -2 (which exclude the 5% of the extreme value) by experience.

In addition to body height, we measured the length of the arms and legs using joint coordinates. The arm span D_{arm} was calculated as the distance from the left hand, through the left elbow, left shoulder, right shoulder, and right elbow, to the right hand:

$$D_{arm} = \sum_{i=14}^{20} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2} \tag{4.1}$$

where x,y,z stands the 3D coordinate of joints. And the number assigned to each joint can be understand by checking Fig. 4.5.

The leg length D_{leg} is the average of the left D_{LLeg} and right leg D_{RLeg} (distances from hip, knee to ankle joints), as shown in Fig.4.7 (b), calculation is expressed by the following:

$$D_{LLeg} = \sum_{i=6}^{7} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2} \tag{4.2}$$

$$D_{RLeg} = \sum_{i=10}^{11} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2} \tag{4.3}$$

$$D_{leg} = \frac{D_{LLeg} + D_{RLeg}}{2} \tag{4.4}$$

The ratios between these lengths were also obtained, as shown in the following:

$$R_{LegHeight} = \frac{D_{leg}}{D_{height}} \tag{4.5}$$

$$R_{ArmHeight} = \frac{D_{arm}}{D_{height}} \tag{4.6}$$

$$R_{ArmLeg} = \frac{D_{arm}}{D_{leg}} \tag{4.7}$$

where the D_{height} means the human body height calculated from 3D point cloud.

Thus, in total, we obtained six dimensions for anthropometric features: body height D_{height}, leg length D_{leg}, arm spanD_{arm}, ratio of length of leg to height $R_{LegHeight}$, ratio of arm span to height $R_{ArmHeight}$ and ratio of length of leg to arm spanR_{ArmLeg}.

Kinematic characteristics which describe the stepping movement were extracted from time series of 3D joint position data. For each signal from one joint and one axis, we first smoothed the data using moving average subtraction (to eliminate the effects of moving in a distance) and Gaussian smoothing. We then detected the valley and peak points from the local minimum and maximum. Time intervals and amplitude were defined as the difference between neighboring peak and valley points in the time axis and feature axis, respectively. An example is shown in Fig. 4.8. In line with the way amplitude was extracted (the magnitude within a half-step cycle), time interval was also determined as a half cycle. This approach results

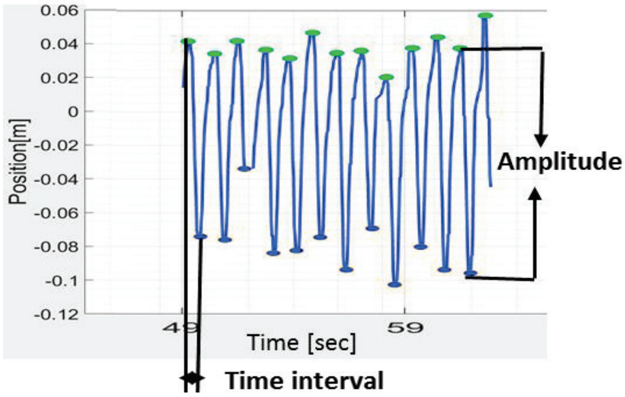
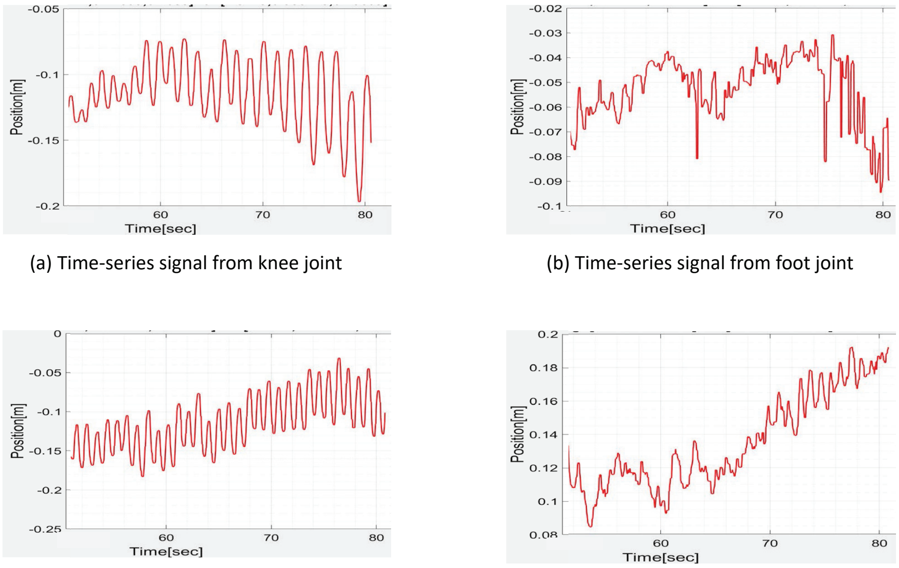


FIGURE 4.8: The method for extracting time interval and amplitude data from the signal of the right knee joint on the Z axis. The green dots are the peak points and the blue dots are the valley points.

in finer variability information, compared with using the whole cycle. We recorded 1200 consistent frames for each participant and used the average and standard deviation of time intervals and swinging amplitude to represent the speed and regularity (or variation) of the stepping movement in temporalspatial space. There were 204 feature dimensions, 17 joints (eight extremity joints, tip of right/left hand, thumb of right/left hand, right/left hands and right/left foot, were excluded because of the instability of Kinect capturing quality. The comparison between stable and noisy signals are shown in Fig. 4.9.), in 3 coordinate axes, and each has 4 kinds of statistical features.

4.3.2 Regression Method for Age Estimation

Previous studies of growth assessment have typically manually compared participants' measurements with a standard growth chart, which provides a statistical reference about the relationship between age and a single-dimension growth variable [148, 160]. Different from the previous studies, we can assess the growth automatically based on multi-dimension growth variable. We first modeled the statistical relationship between growth characteristics and age, and predicted age given various aspects of growth information automatically by machine learning method-regression. The estimated age reflect the growth level of the test child. Then the statics of deviation between estimated age and chronological age from large number of subjects is served as threshold to assess growth status. Comparing with assessing directly using raw high-dimension feature, calculating statics based on estimated age don't need huge scale number of subjects and also have a clear interpretation. Specified aspect of growth status is obtained by feeding



(a) Time-series signal from knee joint

(b) Time-series signal from foot joint

(c) Time-series signal from shoulder joint

(d) Time-series signal from hand tip joint

FIGURE 4.9: The example of time-serie signal of human body joints. The left side (a) and (c) the relative stable signals while the right side (b) and (d) are the ones from extremity joints which is noisy.

corresponding aspect of features into the regressor. For example, to investigate growth of cognitive aspect, the two-dimensions cognitive features (introduced in subsection 4.3.1) (and also the age information) are fed into the regressor. To note that our final target is not to estimate age of children, but by this age estimation, we can understand the growth level of a children by age scale instead of by multi-dimension of growth feature.

In the current study, we chose to use gradient boosting decision tree [161]. Xgboost[162] which is the implement of gradient boosting decision tree, is very popular in data competition (i.g. Kaggle) and always outperforms the other methods. This, to some extent, proves the effective regression ability of the algorithm. In the following, I will briefly introduce the algorithm. And obviously, from the name of this method, the gradient boosting decision tree can be divided into two parts for introduce: gradient-method based boosting and decision tree-based weak learner.

In machine learning, boosting and bagging is two types of algorithms in ensemble algorithm which aim to construct a linear combination of some models, instead of using a single fit of the method. Bagging emphasizes on reducing the variance in the error of learning method by generating weak learners independently and parallel using random sampling with replacement over equal weight samples while the boosting strives to reduce the bias in the errors of learning by build the weak learners in a sequential way using random sampling with replacement over weighted data[163]. The algorithm of gradient boosting decision tree belongs to the boosting family which dedicates to improve the accuracy of classification/regression. At the same time, by random selecting a fraction of samples and a fraction of variables for each tree and each split, this method also makes a good trade-off on the decrease of variance and bias. A main principle of boosting method is that it pay more attention to the wrong labeled samples judged from the previous weak learner, and then try to correct the wrongly labeling by learning a new hyperplane in the following weak learner. The typical Adboost [164] increase the weight to the wrong labeled samples to let subsequent weak learner generate hyperplane considering more on those larger weighted samples. Gradient boosting also follows this idea to improve bias. However, instead of changing the weight of the samples, it used the optimization framework to minimize the loss function when adding a new weak learner.

Give N samples $\{y_i, x_i\}_1^N$ as training samples and $\mathbf{X} = \{x_1, ..., x_n\}$. The model function $F(\mathbf{X})$ used to map x to y, is an additive expansions of the form $F(\mathbf{X}; \{\rho_m, \alpha_m\}_1^M) = \sum_{m=1}^{M} \rho_m h(\mathbf{X}; \alpha_m)$, M is the number of weak leaner $h(\mathbf{X}; \alpha_m)$. It is obtained by minimizing the expected value of some specified loss function $L(y, F(\mathbf{X}))$. General algorithm of gradient boosting [161] is:

1. $F_0(\mathbf{X})$, initial guess, e.g. $F_0(\mathbf{X}) = \frac{\sum_{i=1}^{N} y_i}{N}$
2. For m = 1 to M do:
3. $-g_i = -[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}]_{F(x)=F_{m-1}(x)}, i = 1, ..., N$
4. $a_m = \arg\min_{\alpha_m} \sum_{i=i}^{N} [-g_i - h(x_i; \alpha_m)]^2$
5. $\rho_m = \arg\min_{\rho_m} \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + \rho_m h(x_i; \alpha_m))$
6. $F_m(X) = F_{m-1}(X) + \rho_m h(X; \alpha_m)$
7. end For

The main idea of gradient boosting for constructing the subsequent weak learner is to make the loss function minimization, and the steepest-descent is one of the simple and frequent used method. So the current gradient is computed as shown in step 3. Then is to produce weak leaner $h(\mathbf{X}; \alpha_m)$ that most parallel to the gradient or say most highly correlated with the gradient over the data distribution by step 4. And then by minimize the loss function including the current weak learner, the weight ρ_m for this weak leaner is obtained by step 5. By adding the current weak learner to the previous model, the model for the current iteration is got. In our study, we choose square of errors as our loss function.

As mention above, the $h(\mathbf{X};\alpha)$ is the weak learner. It is usually a simple parameterized function of the input variable and can be any form of simple classifier/regression. The most common choice is classification and regression tree (CART) [165]. The regression tree partitions the space of input variables into rectangles. The partitions can be realized by a series of if-then statements. The visualization of the procedures looks like a tree. Each split on the tree represents an if-then condition based on the mean squared error that the samples are assigned to different side of branched, based the relation of their variables to the judgment condition [166]. For a CART, the parameters α_m are the terminal node, split locations and splitting variables. The big advantages of using CART in gradient boosting are that 1) With CART as the basis model, the method are invariant to scaling of the inputs; 2) This method enables an interpretation of the contribution of each feature dimension, so we can understand which dimension of features function best in the regression process.

4.4 Observing Growth Trends from Age Estimation Performance

In this section, the characteristics of growth tendency are examined using the regression results. Because the participants were recruited from the general public and the sample size was large in statistical terms, and also subjects who performed unnaturally were excluded by manual check, we thus consider that our conclusions represent the statistical characteristics of the normally developing state.

4.4.1 Experiment Protocol and Evaluation Methods

We first briefly introduce the evaluation methods. Age estimation using growth features was evaluated on the database collected at MIRAIKAN. We repeated five-fold cross-validation five times (i.e., a total of 25 evaluation times) to obtain a statistically reliable evaluation. Because the number of participants at different ages was not balanced, we used stratified sampling so that the same percentage participants at each age was approximately preserved in each trial. As for the regression method, I used the API (Application Program Interface) function (sklearn.ensemble.GradientBoostingRegressor) provided by scikit-learn [167] on Python environment. The parameters of gradient boosting regression were tuned with a grid-search strategy using cross-validation. For this experiment, some initial parameters are set as following: 1) the candidates of number of CART M (corresponding to $'n\_estimators'$ in scikit-learn): $\{30, 40, 50, 60, 70, 80\}$, the learning rate ρ (corresponding to $'learning\_rate'$): $\{0.01, 0.1, 0.2\}$. And as for the parameters for weak learner α, the max depth of CART (corresponding to $'max\_depth'$): $\{2, 3, 4, 5, 6\}$, the minimum number of samples in each leaf (corresponding to $'min\_samples\_leaf'$): $\{1, 3, 4\}$.

The output age from the regression reflects the age group to which a test child's measurements belong. The development speed of growth measurements and chronological age are always not matching, so there are gap between estimated age and chronological age (we call it age deviation). And different individuals have different growth condition with regard to ages, so there should exist variance of age deviation among individuals, even in a same age. We were interested in investigating the statics of age deviation among normally developing individuals. Such statistical characteristics from a large number of subjects were used to indicate how well the extracted features develop with age; smaller differences mean the features have more discriminability between different chronological ages and thus can be used as threshold to judge growth status.

We used the mean of absolute error (MAE) and the confusion matrix to demonstrate the deviation in whole age range and separate age for a age group (e.g. from 6 years old to 15 years old for children group), respectively. Given the estimated age $\hat{a}_i^t$ and ground truth age a_i^t for the i^{th} test sample, the definition of MAE (M) is

$$M = \frac{1}{N^t} \sum_{i=1}^{N^t} |\hat{a}_i^t - a_i^t|, \tag{4.8}$$

where N^t is the number of test samples.

MAE is an index that describes the average absolute difference between the estimated age and the chronological age for the whole age range within a specified age group. We can judge whether an extracted feature exhibits discriminability by comparing the MAE of the extracted feature to that of random chance. If the MAE of the extracted feature is much smaller than the level of random chance, we can say that the feature does change with age and can be used as a measure of children's growth assessment. The MAE can further be treated as a threshold to determine whether the difference between estimated age and chronological age for a tested child is within the average range of normal development. In a statistical sense, if the estimated age of a test participant deviates from their chronological age more than the range, it suggests that the participant exhibits potential abnormalities. The reported MAE value is the average of the 25 evaluation trials described above. When required, statistical significance tests were performed using one-way analysis of variance (ANOVA), with the null hypothesis that two sets of samples are drawn from populations with the same mean.

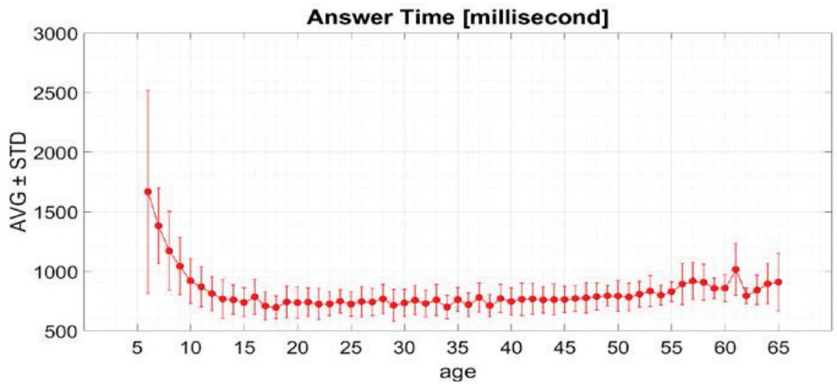
In addition, the confusion matrix, which presents the distribution between chronological age and estimated age, demonstrated the discrimination ability of the regression model for each age. For the ideal situation that estimated age is equal to chronological age, the intersection points between estimated ages and chronological ages locate on the diagonal line. In actual, the growth status between different individuals is different, so the intersection points distributing around the diagonal line in a distance. Less variance indicates better discrimination ability. From the visualized confusion matrix, we can see the developmental trend by examining the pattern of point distribution around the diagonal line for each age group.

4.4.2 Developmental Trend of Whole-generation on Single-dimension Variables

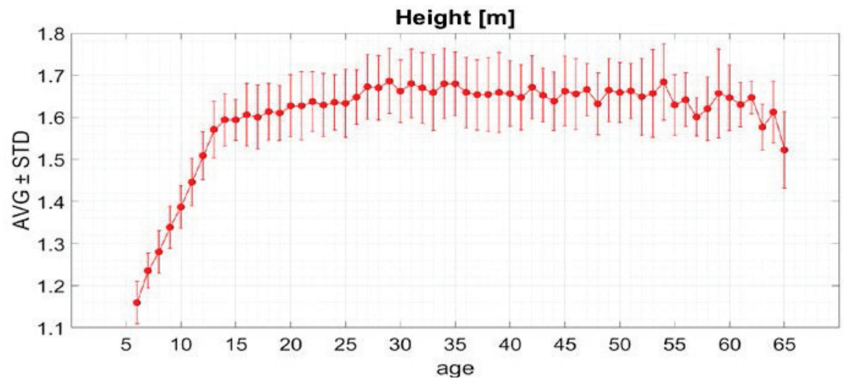
Before performing the age estimation, we examined the relationships between some single-dimension variables and age, to obtain an intuitive overall impression of growth trends. We examined the tendency on a whole-generation from 6 years old to 65 year old.

As illustrated in Fig. 4.10, we observed relationships between some features extracted from the three aspects of performance and age. From these example curves, we found that the near linear change tendency stopped at around age 15 years, after which the curves changed very slow with age increasing. Based on this observation, we set the age range of interest for children as 6–15 years, which corresponds to the age for compulsory education in Japan.

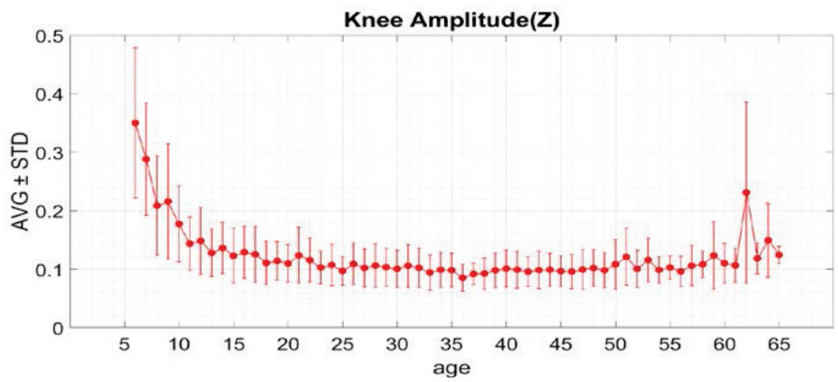
From the developmental trends during childhood, we can confirm the feasibility of using the examined tasks for growth assessment. Taking answer time from the cognitive task as an example, as shown in Fig .4.10(a), the average of the length of response time decreased as age increased. This graph shows that the degree of proficiency in arithmetic improved with age. Children in Japan begin learning



(a)



(b)



(c)

FIGURE 4.10: Distribution of single features and age. The solid dots show the averages and the error bars show the standard deviations of all participant' features at each corresponding age. (a) The relationship between response time for mathematical problems and age. (b) The relationship between body height and age. (c) The relationship between the variation of amplitude of knee motion and age.

Table 4.1: MAE of the three separate and comprehensive aspects of growth features

Aspects	Features	MAE[years]
Cognitive	Response time and correct ratio	1.57
Kinematic	Standard deviation/average of time intervals/amplitude	1.38
Anthropometric	Height, length of body parts and their ratios	0.89
Comprehensive	Concatenation of all aspects of features	0.84

Table 4.2: The contribution of features in the cognitive task

Feature name in each dimension	Importance
Answer time	0.71
Correct ratio	0.29

arithmetic operations in the first year of elementary school (i.e., at 6 years of age). The ratios of correct responses among younger children are 0.69, 0.72, and 0.83 at age 6, 7, and 8, respectively, demonstrating that children can understand arithmetic operations from the age of 6 years (because 0.69 is much better than the 0.5 that would be achieved through randomly guessing) and that level of mastery improves with age.

4.4.3 Growth Tendencies among Different Aspects of Growth for Children

In this section, we focus on analyzing the performance of age estimation among children. We used the multi-dimensional features described in Section 4.3.1 to represent the three aspects of growth information. We show the results using the separate aspects of growth information and comprehensive information as the input for the regression analysis. It should be noted that the comprehensive information was obtained by directly concatenating the anthropometric, kinematic, and cognitive features. This direct combination of features with different numbers of dimensions is acceptable when using gradient boosting regressors because the basis model of CART treats the variables separately and chooses the most discriminative variable according to information gain [165].

Table 4.3: The contribution of features in anthropometric measurements

Feature name in each dimension	Importance
Height	0.45
Arm span	0.18
Leg length	0.17
Ratio of leg length to height	0.08
Ratio of arm span to height	0.08
Ratio of leg length to arm span	0.05

Table 4.4: The first five most important variables in kinematic features. TimStd refers to standard deviation of time intervals. AmpStd and AmpAvg refers to standard deviation and average amplitude.

Feature name in each dimension	Importance
TimStd of left elbow in Z	0.020
AmpStd of middleSpine in X	0.020
AmpStd of left shoulder in Z	0.017
AmpStd of right knee in Z	0.017
AmpAvg of right of elbow in Y	0.016

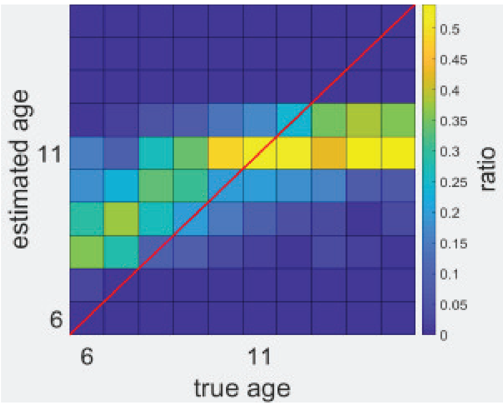
4.4.3.1 The Results of Age Estimation for Children

The MAE results of the age estimation are shown in Table 4.1. The average MAE values of the 25 times of evaluation in Table 4.1 were significantly different from each other (p-value $\ll 0.001$). The MAE values show that the average levels of deviation between the estimated and true ages of normally developing children for the cognitive, kinematic, and anthropometric aspects of growth were 1.57, 1.38, and 0.89 years, respectively. Also to note that the MAE of the chance level for age estimation at an age interval of 9 years is 2.5 years. The finding that the results from these individual aspects of growth information for age estimation are much lower than 2.5 years means that the extracted features are feasible for use in children's growth assessment and can be used as thresholds for screening. The MAE of the anthropometric aspect features was smallest, followed by the kinematic aspect, and the largest MAE was the mathematics-related cognitive aspect. Smaller MAE values indicate that the discrimination of growth features between ages was more apparent, meaning that development in the corresponding aspect is more correlated with age.

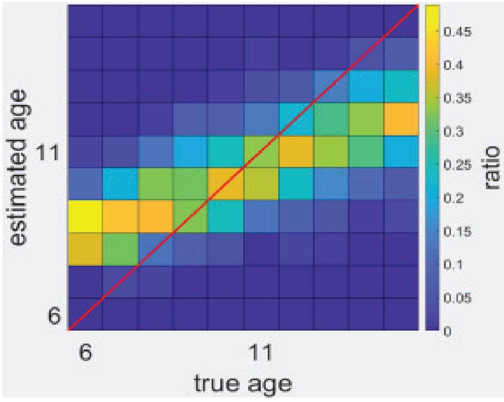
The visualized confusion matrices are shown in Fig. 4.11. The confusion matrix revealed that the distribution between true age and age estimated using anthropometric features appeared around a diagonal line with the least variance (in Fig. 4.11 (c)), followed by kinematic features from stepping performance (in Fig. 4.11 (b)). The distribution about cognitive features (in Fig. 4.11 (a)) became flat after 11 years of age. Thus, the distribution exhibited the same developmental tendencies as MAE values, but the confusion matrices enabled a more detailed analysis at each age, particularly in the distribution around the two ends of the ages in specified groups. The flat trend appeared in the confusion matrix of cognitive features after 11 years of age and in the confusion matrix of anthropometric features after 14 years of age, illustrating that the arithmetic ability of addition/subtraction of a one-digit number and a two-digit number reached almost maturity at 11 years of age, whereas body length became almost stable at 14 years of age.

In addition to examining the developmental trends of individual aspects of growth information, we examined comprehensive features by combining all three aspects together. The MAE value for comprehensive features was 0.84. This finding indicated that, if the absolute difference between the child's estimated age and their chronological age was within 0.84 years, they could be considered to exhibit averaged level of growth, considering all aspects. In addition, if parents or physicians wish to understand more about individual aspects of a child's development, they can refer to the performance on each aspect.

In our method, in addition to results for separate aspects of growth, a comprehensive result is also provided. This is based on consideration of the practical application situation. Taking the practical situation of health examination as an example, in addition to scores on each item, we simultaneously receive a general score that serves as a comprehensive judgment. Similarly, in real applications of our system, we plan to provide both individual assessment (i.e., anthropometric, kinematic, and cognitive) and comprehensive assessment. Participants can choose to check individual or comprehensive values, based on their needs. The performance on each aspect of features (i.e., MAE) is also provided. Participants can choose different aspects of features considering their performance. As mentioned above, the MAEs are significantly different from each other. Smaller MAEs indicate that the estimated age has less deviation compared with true age and that the participants can obtain a more precise assessment of their growth on that aspect.

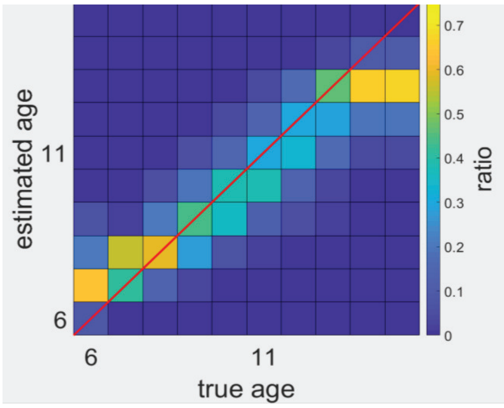


(a) Cognitive



(b) Kinematic

(c) Anthropometric



(d) Combination

FIGURE 4.11: Confusion matrix of age estimation for different aspects of growth information. The ratio of the number of participants of an estimated age to the total number of participants of an actual age is illustrated by different colors in the color bar; warmer colors indicate larger ratios, whereas colder colors indicate smaller ratios.

Observing the results, anthropometric performance (the best performance from the individual aspect) and comprehensive performance are in fact not the same. Comprehensive performance is better than the others, although the difference is slight. Participants can select assessment aspects based on this criterion.

4.4.3.2 The Fastest Developing Dimensions in Each Aspect

To determine which dimensions exhibit development that is the most closely related to age, we analyzed the contribution of each dimension to the age estimation. Usually, different dimensions of features don't contribute the same to predict target results. And the importance of each feature is measured by how they work for split in individual decision tree (i.e. CART). The basic idea is: the more often a feature is selected in the split points for a tree the more important that feature is. The importance of a feature in a gradient boosting decision tree is the average of the feature importance of each tree [167]. We repeated 5-CV five times, resulting in a total of 25 training sessions. In each training session, the contribution of each dimension to the feature could be expected to change because the fraction of features and samples being selected exhibit slight differences across sessions. We averaged the contributing factors from all training sessions for each dimension of the features. For high-dimension features, it was not possible to illustrate the contributions of all dimensions. We show the dimensions that appeared in most training sessions (those appearing in more than 20 training sessions) with the most important factors ranking in the top five.

Table 4.2 shows the contribution of features from mathematics-related cognitive features. The results revealed that response time changed with age more closely than did the ratio of correct responses in mathematical performance. This indicates that most children quickly master the skills of addition/subtraction of a one-digit number and a two-digit number from the year they enter elementary school, and the degree of proficiency improves gradually with the number of years of education. So the correct ratio doesn't improve with ages as apparently as that of answer time. Table 4.3 shows the feature contribution of each dimension of anthropometric features. The results revealed that height, arm span, and leg length were the dominant cues changing with age, compared with other components. The other dimensions were the ratios between those features and may thus be correlated with the first three features. There were 204 dimensions of features for kinematic performance. Table 4.4 shows the first five dimensions, which contributed most strongly to the age estimation. The results show that the variation in stepping movements improved more with age than did the speed of stepping. This finding indicates that children tended to achieve a more stable gait pattern with increasing age, whereas speed did not change substantially after 6 years of age. This pattern of results is consistent with the conclusions of a previous study [151].

4.4.3.3 Analyzing Examples with Age Deviation Larger than Average Level

In this subsection, we analyze some examples whose estimated ages far deviating from their chronological ages than average level. The samples can be detected by observing the confusion matrix; those examples appear in the regions where the deviation from the diagonal line was greater than the MAE value. We divided them into two types, based on their position. The first type tended to appear at both ends of the age range (e.g., at age 6 and age 15). As seen in Fig. 4.11, it was common for performance around these ages to have a larger age deviation between estimated ages and chronological ages for most aspects (including the comprehensive aspect). This result was likely caused by applying mean squared error as a loss function in gradient boosting regressor and as criterion to choose the best feature dimension and threshold to split in weak learner of CART. The age with greater sample size contribute more in the result of mean squared error that make algorithm focus more on those ages. However, the numbers of participants aged 6, 7, or 15 years were smaller, comparing with the other ages, so age estimation for children at these ages have larger deviation. This situation indicates that we should ensure a sufficiently large and balanced sample for constructing a more reliable model.

Table 4.5: MAEs of age estimation among different age groups

Age range	6-15	16-25	26-35	36-45	46-55	56-65
Anthropometric	0.89	2.31	2.44	2.41	2.32	2.40
Kinematic	1.38	2.31	2.42	2.43	2.33	2.31
Cognitive	1.57	2.31	2.41	2.44	2.31	2.33
Comprehensive	0.84	2.29	2.42	2.42	2.32	2.31

The second type of failure could appear at any age and occurred when the participants' features deviated widely from the typical features of their age group. Two factors likely account for errors of this type. First, inappropriate task design may have affected the results. For example, the design of the arithmetic calculation task for testing the cognitive aspect in the current study made it impossible to distinguish between a rapid random choice when the answer was unknown, and an immediate response when the answer was clear. Based on this design, younger children might be recognized as older children with higher calculation ability because age is estimated based mainly on response time. More detailed examination in future studies is required to resolve this limitation. The second possible explanation is that some participants do exhibit much faster or slower growth than the average at their age. For example, the height of a child aged 7 years might be 1.26 meters, whereas the average height of children of this age was 1.14 meters. Thus, the child may be judged as being 8 years old, because the average height of

8-year-olds was 1.24 meters. However, whether such kind of faster than average level is within normal development, should be further determined by physicians.

4.4.4 Growth Tendency among Different Age Groups

In this section, we present the age estimation results for different age ranges. The training and evaluation strategies were the same as those described in Section 4.4.3 above. The comparison results are shown in Table 4.5. The table shows that MAE values from the first column were consistently smaller, compared with those in the other columns. The MAE values of the other age range groups, except for the group of 6–15 year, were similar to the chance level of 2.5 years. These findings suggest that the proposed features have no discriminative ability after the age of 15 years. Thus, the growth characteristics observed in our study appear to become almost mature at around 15 years old.

Chapter 5

Conclusion and Future Work

5.1 Summary of Thesis Achievements

Gait is an informative indicator to one's health condition. In this thesis, in order to satisfy more and more healthcare demands from children/elderly people, people with impairment and even healthy people, we designed two computer-vision based techniques to assess people's health status through passive and active ways of gait observation. The former one can be used in public space to detect physical impairments and the latter one can provide efficient multi-aspect growth assessment at home. To note that the adoption of active way enables us to further explore the cognitive aspect of health in addition to physical aspect. Our studies extended the existed camera-based gait analysis for healthcare which were constrained in limited categories disorder and aspects of health and were vulnerable to noise into more pervasive and convenient solutions.

In detail, for the first purpose, we developed a scheme to detect people with physical impairment based on walking sequences captured by camera. As the basis step to realize this target, we first collected a dataset containing both impaired gait and normal gait with sufficient number of subjects. Then to find out the appropriate gait representation which is discriminative between different types of impaired walking (i.e. leg impairment and visual impairment). We first listed up three categories of gait features: posture, temporal and dynamic aspects of walking characteristics which are represented by GEI, duration time, phase fluctuation, respectively. Next, we used a 2-class LDA as classification. From the experimental results, we confirmed the discriminative ability of GEI over the three features. We also discussed the influence of gender in GEI. Further, considering that GEI is mainly about posture information, it must be affected by the other parts of the human body except the effective part for detecting impairments. We thus proposed using only the effective patch of GEI for classification. We can improve the performance by 2.24% and 5.75% to 83.17% and 75.05% respectively for detecting visual and leg impairment comparing with whole GEI. This proved the effectiveness of patch-GEI. Based on this fact, we consider the real application of distinguishing multiple types of impairments simultaneously using binary classification. The accuracy of detecting visual impairment is 77.82% and that of leg impairment detection is 72.65%.

Then we proposed an automated method to obtain growth information and estimate growth status among children, considering anthropometric, kinematic and cognitive aspects of growth information. We first demonstrated that three aspects of growth information could be simultaneously obtained using a dual-task paradigm with an automatic data-collection system. We collected large-scale of database of dual-task performance by the system. With the collected data, we constructed a statistical model of the relationship between growth features and age, and estimated age which reflected one's growth level using regression analysis. Based on this method, we were able to examine the developmental trends of typically developing children. The average level of absolute discrepancy between the estimated and true age was provided. The fact that this statistic is smaller than chance level proved it is feasible to used the extracted features as measurement of child's growth. And then by comparing a test child's performance with this average value, we were able to provide an initial assessment about the growth status.

Our two approaches show out the whole procedures to apply computer vision/machine learning techniques in gait analysis for healthcare. The main contributions in both works are: 1) constructing databases with sufficient number of subjects for each target; 2) investigating efficient techniques to study health status of subjects. Especially, construction database is the primary and vital step in the whole approach. Our works on the databases have prove the feasibility of assessing health status from camera-based gait-related observation. But the life of database doesn't end here. More advanced computer vision/machine learning techniques can also be applied to these databases to improve the performance or to explore more aspects of interesting facts.

5.2 Future Work

The researches in this thesis are served as a pilot study for pervasive monitoring health through observing gait performance by camera. The methods explore both physical and cognitive aspects of health and can be applied both at public and home environment. They extended the existed gait analysis for healthcare which are restricted at limited application situations and health aspects to a boarder range. However, even there already existed some researches applied camera to monitor people's activities (including gait) [50, 126, 168], it is still hard to find out the commercial solution for activity monitoring using camera. Most of them selected wearable sensors as the recording device and without intelligent decision unit [21]. So to make our camera-based gait monitor to become more intelligent and practical and speed up its usage in practical situation, some perspectives can be considered:

1. Verify the proposed methods using real impairment. The proposed methods analyzed gait from people who act impaired walking by simulation kits or from normally developing people. To confirm the feasibility of the methods in real application, we still need to test our methods on the real impaired people. This is an important step to push the approaches further to real application.

2. Extend the qualitative detection to quantitative assessment. Our current works are able to detect the abnormality of people in various aspects of health. It is important for that we can take action in time to cope with the problem at the primary step. However, to understand the progress of the abnormality also vital to provide medial intervention or evaluate the effect of treatment. Thus, extend to quantitative evaluation can make the system more useful in practice.

3. Integrate with human tracking to let the monitoring person specified. In the public places, surveillance camera has spread everywhere. We can directly embed the healthcare function to the surveillance system. We need to trace the specified person with impairment among multiple people appearing in public places, which can be realized by human tracking or human re-identification.

4. Consider about the privacy issue. The common concern with respect to camera based monitoring is the privacy problem. We can cope with this problem

by sophisticated consideration and design. For example, by blurring the face or restricting the recording information being transferred. By tackling this issue, camera-based monitoring can be applied in broader occasions.

Bibliography

[1] Shyamal Patel, Hyung Park, Paolo Bonato, Leighton Chan, and Mary Rodgers. A review of wearable sensors and systems with application in rehabilitation. *Journal of neuroengineering and rehabilitation*, 9(1):21, 2012.

[2] Daigo Muramatsu, Yasushi Makihara, Haruyuki Iwama, Takuya Tanoue, and Yasushi Yagi. Gait verification system for supporting criminal investigation. In *Pattern Recognition (ACPR), 2013 2nd IAPR Asian Conference on*, pages 747–748. IEEE, 2013.

[3] Md Zasim Uddin, Thanh Trung Ngo, Yasushi Makihara, Noriko Takemura, Xiang Li, Daigo Muramatsu, and Yasushi Yagi. The ou-isir large population gait database with real-life carried object and its performance evaluation. *IPSJ Transactions on Computer Vision and Applications*, 10(1):1–11, 2018.

[4] Marc Bachlin, Meir Plotnik, Daniel Roggen, Inbal Maidan, Jeffrey M. Hausdorff, Nir Giladi, and Gerhard Troster. Wearable assistant for parkinsons disease patients with the freezing of gait symptom. *IEEE Transactions on Information Technology in Biomedicine*, 14(2):436–446, 2010.

[5] Lily Lee and W. Eric L. Grimson. Gait analysis for recognition and classification. In *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*, pages 155–162. IEEE, 2002.

[6] Howard Lee, Ling Guan, and Ivan Lee. Video analysis of human gait and posture to determine neurological disorders. *EURASIP Journal on Image and Video Processing*, 2008(1):380867, 2008.

[7] Fumio Okura, Ikuhisa Mitsugami, Masataka Niwa, Kota Aoki, Chengju Zhou, and Yasushi Yagi. Automatic collection of dual-task human behavior for analysis of cognitive function. *ITE Transactions on Media Technology and Applications*, 6(2):138–150, 2018.

[8] World Health Organization et al. Global health and aging. *Geneva: World Health Organization*, pages 1–32, 2011. URL http://www.who.int/ageing/publications/global_health.pdf.

[9] United Nations et al. World population aging 2017: Highlights. *New York: United Nations*, pages 1–46, 2017. URL http://www.un.org/en/development/desa/population/publications/pdf/ageing/WPA2017_Highlights.pdf.

[10] Naoko Muramatsu and Hiroko Akiyama. Japan: super-aging society preparing for the future. *The Gerontologist*, 51(4):425–432, 2011.

[11] National institute of population, social security research, et al. Population projections for japan (2017): 2016 to 2065. *Japan: national institute of population and social security research*, pages 1–64, 2017. URL http://fpcj.jp/wp/wp-content/uploads/2017/04/1db9de3ea4ade06c3023d3ba54dd980f.pdf.

[12] ATOH Makoto. Very low fertility in japan and value change hypotheses. *Age*, 25:29, 2001.

[13] World Health Organization. Disability and health. 2018. URL http://www.who.int/en/news-room/fact-sheets/detail/disability-and-health.

[14] Abhishek Basak, Seetharam Narasimhan, and Swarup Bhunia. Kims: Kids' health monitoring system at day-care centers using wearable sensors and vocabulary-based acoustic signal processing. In *e-Health Networking Applications and Services (Healthcom), 2011 13th IEEE International Conference on*, pages 1–8. Citeseer, 2011.

[15] P.K. Binu, V. Akhil, and Vinay Mohan. Smart and secure iot based child behaviour and health monitoring system using hadoop. In *Advances in Computing, Communications and Informatics (ICACCI), 2017 International Conference on*, pages 418–423. IEEE, 2017.

[16] Alexandros Pantelopoulos and Nikolaos G. Bourbakis. Prognosisa wearable health-monitoring system for people at risk: Methodology and modeling. *IEEE Transactions on Information Technology in Biomedicine*, 14(3):613–621, 2010.

[17] Rifat Shahriyar, Md Faizul Bari, Gourab Kundu, Sheikh Iqbal Ahamed, and Md Mostofa Akbar. Intelligent mobile health monitoring system (imhms).

In *International Conference on Electronic Healthcare*, pages 5–12. Springer, 2009.

[18] Nadia Zouba, Francois Bremond, and Monique Thonnat. An activity monitoring system for real elderly at home: Validation study. In *Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on*, pages 278–285. IEEE, 2010.

[19] Mirza Mansoor Baig and Hamid Gholamhosseini. Smart health monitoring systems: an overview of design and modeling. *Journal of medical systems*, 37(2):9898, 2013.

[20] Srijani Mukherjee, Koustabh Dolui, and Soumya Kanti Datta. Patient health management system using e-health monitoring architecture. In *Advance Computing Conference (IACC), 2014 IEEE International*, pages 400–405. IEEE, 2014.

[21] Sumit Majumder, Emad Aghayi, Moein Noferesti, Hamidreza Memarzadeh-Tehran, Tapas Mondal, Zhibo Pang, and M. Jamal Deen. Smart homes for elderly healthcarerecent advances and research challenges. *Sensors*, 17(11): 2496, 2017.

[22] Sunaryo Sumitoro, Yoshimasa Matsui, Masaru Kono, Takuji Okamoto, and Katashi Fujii. Long span bridge health monitoring system in japan. In *Health monitoring and management of civil infrastructure systems*, volume 4337, pages 517–525. International Society for Optics and Photonics, 2001.

[23] Atika Arshad, Sheroz Khan, Ahm Zahirul Alam, Fadzil Ismail Ahmad, and Rumana Tasnim. A study on health monitoring system: Recent advancements. *IIUM Engineering Journal*, 15(2), 2014.

[24] Veysel Aslantas, Rifat Kurban, and Tuba Caglikantar. A low-cost wireless healthcare monitoring system and communication to a clinical alarm station. In *5th International Conference on Electrical and Electronics Engineering*, 2007.

[25] Filippo Sanfilippo and Kristin Y. Pettersen. A sensor fusion wearable health-monitoring system with haptic feedback. In *2015 11th International Conference on Innovations in Information Technology (IIT)*, pages 262–266. IEEE, 2015.

[26] Amaya Arcelus, Megan Howell Jones, Rafik Goubran, and Frank Knoefel. Integration of smart home technologies in a health monitoring system for the elderly. In *null*, pages 820–825. IEEE, 2007.

[27] Masaaki Hirayama, Tomohiko Nakamura, Norio Hori, Yasuo Koike, and Gen Sobue. The video images of sleep attacks in parkinson's disease. *Movement Disorders*, 23(2):288–290, 2008.

[28] Alex Mihailidis, Brent Carmichael, and Jennifer Boger. The use of computer vision in an intelligent environment to support aging-in-place, safety, and independence in the home. *IEEE Transactions on information technology in biomedicine*, 8(3):238–247, 2004.

[29] Walter Pirker and Regina Katzenschlager. Gait disorders in adults and the elderly. *Wiener Klinische Wochenschrift*, 129(3-4):81–95, 2017.

[30] Asraf Ali, Kenneth Sundaraj, Badlishah Ahmad, Nizam Ahamed, and Anamul Islam. Gait disorder rehabilitation using vision and non-vision based sensors: a systematic review. *Bosnian journal of basic medical sciences*, 12 (3):193, 2012.

[31] Steven T. Moore, Hamish G. MacDougall, and William G. Ondo. Ambulatory monitoring of freezing of gait in parkinson's disease. *Journal of neuroscience methods*, 167(2):340–348, 2008.

[32] Arash Salarian, Heike Russmann, François JG Vingerhoets, Pierre R Burkhard, and Kamiar Aminian. Ambulatory monitoring of physical activities in patients with parkinson's disease. *IEEE Transactions on Biomedical Engineering*, 54(12):2296–2299, 2007.

[33] Katia Turcot, Rachid Aissaoui, Karine Boivin, Michel Pelletier, Nicola Hagemeister, and Jacques A. de Guise. New accelerometric method to discriminate between asymptomatic subjects and patients with medial knee osteoarthritis during 3-d gait. *IEEE Transactions on Biomedical Engineering*, 55(4):1415–1422, 2008.

[34] Takashi Nakamura. Quantitative analysis of gait in the visually impaired. *Disability and Rehabilitation*, 19(5):194–197, 1997.

[35] Julien Favre and Brigitte M. Jolles. Gait analysis of patients with knee osteoarthritis highlights a pathological mechanical pathway and provides a basis for therapeutic interventions. *EFORT open reviews*, 1(10):368–374, 2016.

[36] Kenton R. Kaufman, Christine Hughes, Bernard F. Morrey, Michael Morrey, and Kai-Nan An. Gait characteristics of patients with knee osteoarthritis. *Journal of biomechanics*, 34(7):907–915, 2001.

[37] Seung-uk Ko, Jeffrey M. Hausdorff, and Luigi Ferrucci. Age-associated differences in the gait pattern changes of older adults during fast-speed and fatigue conditions: results from the baltimore longitudinal study of ageing. *Age and ageing*, 39(6):688–694, 2010.

[38] Tasuku Kimura, Hiromitsu Kobayashi, Eijun Nakayama, and Michiko Hanaoka. Effects of aging on gait patterns in the healthy elderly. *Anthropological Science*, 115(1):67–72, 2007.

[39] Wiltrud Berger, Eckart Altenmueller, and Vincent Dietz. Normal and impaired development of children's gait. *Human neurobiology*, 3(3):163–170, 1984.

[40] Manuel M. Montero-Odasso, Yanina Sarquis-Adamson, Mark Speechley, Michael J. Borrie, Vladimir C. Hachinski, Jennie Wells, Patricia M. Riccio, Marcelo Schapira, Ervin Sejdic, Richard M. Camicioli, et al. Association of dual-task gait with incident dementia in mild cognitive impairment: results from the gait and brain study. *JAMA neurology*, 74(7):857–865, 2017.

[41] Alberto Nascimbeni, Shiva Caruso, Adriana Salatino, Marinella Carenza, Marta Rigano, Andrea Raviolo, and Raffaella Ricci. Dual task-related gait changes in patients with mild cognitive impairment. *Functional neurology*, 30(1):59, 2015.

[42] Ebieta Mirek, M. Rudzińska, and Andrzej Szczudlik. The assessment of gait disorders in patients with parkinson's disease using the three-dimensional motion analysis system vicon. *Neurologia i neurochirurgia polska*, 41(2):128–133, 2007.

[43] Alvaro Muro-De-La-Herran, Begonya Garcia-Zapirain, and Amaia Mendez-Zorrilla. Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications. *Sensors*, 14(2):3362–3394, 2014.

[44] Shih-Lin Chien, Shinn-Zong Lin, Chung-Chao Liang, Yi-Sheng Soong, Sheng-Huang Lin, Yu-Loong Hsin, Chi-Wei Lee, and Shin-Yuan Chen. The efficacy of quantitative gait analysis by the gaitrite system in evaluation of parkinsonian bradykinesia. *Parkinsonism & related disorders*, 12(7):438–442, 2006.

[45] Nicole Abaid, Paolo Cappa, Eduardo Palermo, Maurizio Petrarca, and Maurizio Porfiri. Gait detection in children with and without hemiplegia using single-axis wearable gyroscopes. *PloS one*, 8(9):e73152, 2013.

[46] Jennifer Howcroft, Edward D. Lemaire, Jonathan Kofman, and William E. McIlroy. Dual-task elderly gait of prospective fallers and non-fallers: A wearable sensor-based analysis. *Sensors*, 18(4):1275, 2018.

[47] Jennifer D. Howcroft, Edward D. Lemaire, Jonathan Kofman, and William E. McIlroy. Analysis of dual-task elderly gait using wearable plantar-pressure insoles and accelerometer. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pages 5003–5006. IEEE, 2014.

[48] Jeffrey M. Hausdorff, Merit E. Cudkowicz, Renée Firtion, Jeanne Y. Wei, and Ary L. Goldberger. Gait variability and basal ganglia disorders: stride-to-stride variations of gait cycle timing in parkinson's disease and huntington's disease. *Movement disorders*, 13(3):428–437, 1998.

[49] Ana Patrícia Rocha, Hugo Choupina, Jose Maria Fernandes, Maria Jose Rosas, Rui Vaz, and João Paulo Silva Cunha. Parkinson's disease assessment based on gait analysis using an innovative rgb-d camera system. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pages 3126–3129. IEEE, 2014.

[50] Chien-Wen Cho, Wen-Hung Chao, Sheng-Huang Lin, and You-Yin Chen. A vision-based analysis system for gait recognition in patients with parkinsons disease. *Expert Systems with applications*, 36(3):7033–7039, 2009.

[51] Richard D. Green, Ling Guan, and John A. Burne. Video analysis of gait for diagnosing movement disorders. *Journal of Electronic Imaging*, 9(1):16–22, 2000.

[52] Fang Wang, Erik Stone, Wenqing Dai, Tanvi Banerjee, Jarod Giger, Jean Krampe, Marilyn Rantz, and Marjorie Skubic. Testing an in-home gait assessment tool for older adults. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, pages 6147–6150. IEEE, 2009.

[53] Jamie Shotton, Andrew Fitzgibbon, Mat Cook, Toby Sharp, Mark Finocchio, Richard Moore, Alex Kipman, and Andrew Blake. Real-time human pose recognition in parts from single depth images. In *Computer Vision and*

Pattern Recognition (CVPR), 2011 IEEE Conference on, pages 1297–1304. IEEE, 2011.

[54] Saeid Motiian, Paola Pergami, Keegan Guffey, Corrie A. Mancinelli, and Gianfranco Doretto. Automated extraction and validation of childrens gait parameters with the kinect. *Biomedical engineering online*, 14(1):112, 2015.

[55] Moshe Gabel, Ran Gilad-Bachrach, Erin Renshaw, and Assaf Schuster. Full body gait analysis with kinect. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pages 1964–1967. IEEE, 2012.

[56] Javier Ortells, María Trinidad Herrero-Ezquerro, and Ramón A. Mollineda. Vision-based gait impairment analysis for aided diagnosis. *Medical & Biological Engineering & Computing*, 56(9):1553–1564, 2018.

[57] Mario Nieto-Hidalgo, Francisco Javier Ferrández-Pastor, Rafael J. Valdivieso-Sarabia, Jerónimo Mora-Pascual, and Juan Manuel García-Chamizo. A vision based proposal for classification of normal and abnormal gait using rgb camera. *Journal of biomedical informatics*, 63:82–89, 2016.

[58] Matthew A. Turk and Alex P. Pentland. Face recognition using eigenfaces. In *Computer Vision and Pattern Recognition, 1991. Proceedings CVPR'91., IEEE Computer Society Conference on*, pages 586–591. IEEE, 1991.

[59] Erjin Zhou, Zhimin Cao, and Qi Yin. Naive-deep face recognition: Touching the limit of lfw benchmark or not? *arXiv preprint arXiv:1501.04690*, 2015.

[60] John G. Daugman. High confidence visual recognition of persons by a test of statistical independence. *IEEE transactions on pattern analysis and machine intelligence*, 15(11):1148–1161, 1993.

[61] Keith J Hanna. Efficient method and system for the acquisition of scene imagery and iris imagery using a single sensor, March 8 2016. US Patent 9,280,706.

[62] Raffaele Cappelli, Matteo Ferrara, and Davide Maltoni. Minutia cylinder-code: A new representation and matching technique for fingerprint recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32 (12):2128–2141, 2010.

[63] Chenhao Lin and Ajay Kumar. Tetrahedron based fast 3d fingerprint identification using colored leds illumination. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017.

[64] Zhi Liu, Yilong Yin, Hongjun Wang, Shangling Song, and Qingli Li. Finger vein recognition with manifold learning. *Journal of Network and Computer Applications*, 33(3):275–282, 2010.

[65] Wenxiong Kang, Yang Liu, Qiuxia Wu, and Xishun Yue. Contact-free palm-vein recognition based on local invariant features. *PloS one*, 9(5):e97548, 2014.

[66] Yasushi Makihara, Hidetoshi Mannami, Akira Tsuji, Md Altab Hossain, Kazushige Sugiura, Atsushi Mori, and Yasushi Yagi. The ou-isir gait database comprising the treadmill dataset. *IPSJ Transactions on Computer Vision and Applications*, 4:53–62, 2012.

[67] Haruyuki Iwama, Mayu Okumura, Yasushi Makihara, and Yasushi Yagi. The ou-isir gait database comprising the large population dataset and performance evaluation of gait recognition. *IEEE Transactions on Information Forensics and Security*, 7(5):1511–1521, 2012.

[68] Chengju Zhou, Ikuhisa Mitsugami, and Yasushi Yagi. Assessing cognition level of elderly using dual-task stepping. *18th Meeting on Image Recognition and Understanding (MIRU)*, 2015.

[69] Ralph Gross and Jianbo Shi. The cmu motion of body (mobo) database. Technical Report CMU-RI-TR-01-18, Carnegie Mellon University, Pittsburgh, PA, June 2001.

[70] Jamie D. Shutler, Michael G. Grant, Mark S. Nixon, and John N. Carter. On a large sequence-based human gait database. In *Applications and Science in Soft Computing*, pages 339–346. Springer, 2004.

[71] Shuai Zheng, Junge Zhang, Kaiqi Huang, Ran He, and Tieniu Tan. Robust view transformation model for gait recognition. In *Image Processing (ICIP), 2011 18th IEEE International Conference on*, pages 2073–2076. IEEE, 2011.

[72] Al Mansur, Yasushi Makihara, Rasyid Aqmar, and Yasushi Yagi. Gait recognition under speed transition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2521–2528, 2014.

[73] Thanh Trung Ngo, Yasushi Makihara, Hajime Nagahara, Yasuhiro Mukaigawa, and Yasushi Yagi. The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication. *Pattern Recognition*, 47(1):228–237, 2014.

[74] Galit Yogev, Nir Giladi, Chava Peretz, Shmuel Springer, Ely S Simon, and Jeffrey M Hausdorff. Dual tasking, gait rhythmicity, and parkinson's disease: which aspects of gait are attention demanding? *European journal of neuroscience*, 22(5):1248–1256, 2005.

[75] ME Wootten, MP Kadaba, and GVB Cochran. Dynamic electromyography. ii. normal patterns during gait. *Journal of Orthopaedic Research*, 8(2):259–265, 1990.

[76] AL Hof, H. Elzinga, W. Grimmius, and JPK Halbertsma. Speed dependence of averaged emg profiles in walking. *Gait & posture*, 16(1):78–86, 2002.

[77] John D. Willson and Thomas Kernozek. Gait data collection at univ of wisconsin-lacrosse. 2014. URL https://innsport.com/related-products/data-sets/uw-l-gait-data-set.aspx.

[78] Salim Ghoussayni, Christopher Stevens, Sally Durham, and David Ewins. Assessment and validation of a simple automated method for the detection of gait events and intervals. *Gait & Posture*, 20(3):266–272, 2004.

[79] Juri Taborri, Emilia Scalona, Eduardo Palermo, Stefano Rossi, and Paolo Cappa. Validation of inter-subject training for hidden markov models applied to gait phase detection in children with cerebral palsy. *Sensors*, 15(9):24514–24529, 2015.

[80] Robert L. Evans and D. K. Arvind. Detection of gait phases using orient specks for mobile clinical gait analysis. In *Wearable and Implantable Body Sensor Networks (BSN), 2014 11th International Conference on*, pages 149–154. IEEE, 2014.

[81] Ruud W. Selles, Margriet AG Formanoy, Johannes BJ Bussmann, Peter J. Janssens, and Henk J. Stam. Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls. *IEEE transactions on neural systems and rehabilitation engineering*, 13(1):81–88, 2005.

[82] Arash Salarian, Heike Russmann, François JG Vingerhoets, Catherine Dehollain, Yves Blanc, Pierre R. Burkhard, and Kamiar Aminian. Gait assessment in parkinson's disease: toward an ambulatory system for long-term monitoring. *IEEE transactions on biomedical engineering*, 51(8):1434–1443, 2004.

[83] Jae-Hwan Ryu and Deok-Hwan Kim. Multiple gait phase recognition using boosted classifiers based on semg signal and classification matrix. In *Proceedings of the 8th international conference on ubiquitous information management and communication*, page 90. ACM, 2014.

[84] Mohammad O. Derawi, Patrick Bours, and Kjetil Holien. Improved cycle detection for accelerometer based gait authentication. In *2010 Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, pages 312–317. IEEE, 2010.

[85] Michael Fitzgerald Nowlan. Human identification via gait recognition using accelerometer gyro forces. *Yale Computer Science*, 2009.

[86] Davrondzhon Gafurov, Einar Snekkenes, and Patrick Bours. Improved gait recognition performance using cycle matching. In *2010 IEEE 24th International Conference on Advanced Information Networking and Applications Workshops*, pages 836–841. IEEE, 2010.

[87] Hoang Minh Thang, Vo Quang Viet, Nguyen Dinh Thuc, and Deokjai Choi. Gait identification using accelerometer on mobile phone. In *Control, Automation and Information Sciences (ICCAIS), 2012 International Conference on*, pages 344–348. IEEE, 2012.

[88] Ciara M. OConnor, Susannah K. Thorpe, Mark J. OMalley, and Christopher L. Vaughan. Automatic detection of gait events using kinematic data. *Gait & posture*, 25(3):469–474, 2007.

[89] Dimitrios Kotiadis, Hermanus J. Hermens, and Petrus H. Veltink. Inertial gait phase detection for control of a drop foot stimulator: Inertial sensing for gait phase detection. *Medical engineering & physics*, 32(4):287–297, 2010.

[90] Fabio A. Storm, Christopher J. Buckley, and Claudia Mazzà. Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods. *Gait & posture*, 50:42–46, 2016.

[91] Shiu-Ling Chiu and Li-Shan Chou. Variability in inter-joint coordination during walking of elderly adults and its association with clinical balance measures. *Clinical biomechanics*, 28(4):454–458, 2013.

[92] Meng Meng, Hassen Drira, Mohamed Daoudi, and Jacques Boonaert. Detection of abnormal gait from skeleton data. In *VISIGRAPP*, 2016.

[93] Trong-Nguyen Nguyen, Huu-Hung Huynh, and Jean Meunier. Skeleton-based abnormal gait detection. *Sensors*, 16(11):1792, 2016.

[94] Virginia Ortiz Andersson and Ricardo Matsumura de Araújo. Person identification using anthropometric and gait data from kinect sensor. In *AAAI*, pages 425–431, 2015.

[95] Virginia Andersson, Rafael Dutra, and Ricardo Araújo. Anthropometric and human gait identification using skeleton data from kinect sensor. In *Proceedings of the 29th Annual ACM Symposium on Applied Computing*, pages 60–61. ACM, 2014.

[96] Bojan Dikovski, Gjorgji Madjarov, and Dejan Gjorgjevikj. Evaluation of different feature sets for gait recognition using skeletal data from kinect. In *Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2014 37th International Convention on*, pages 1304–1308. IEEE, 2014.

[97] Shuming Jiang, Yufei Wang, Yuanyuan Zhang, and Jiande Sun. Real time gait recognition system based on kinect skeleton feature. In *Asian Conference on Computer Vision*, pages 46–57. Springer, 2014.

[98] Aniruddha Sinha, Kingshuk Chakravarty, and Brojeshwar Bhowmick. Person identification using skeleton information from kinect. In *Proc. Intl. Conf. on Advances in Computer-Human Interactions*, pages 101–108, 2013.

[99] Imed Bouchrika. Parametric elliptic fourier descriptors for automated extraction of gait features for people identification. In *Programming and Systems (ISPS), 2015 12th International Symposium on*, pages 1–7. IEEE, 2015.

[100] R. Cabeza-Ruiz, X. García-Massó, RA Centeno-Prada, JD Beas-Jiménez, JC Colado, and L-M González. Time and frequency analysis of the static balance in young adults with down syndrome. *Gait & posture*, 33(1):23–28, 2011.

[101] Avishai Wagner, Naama Fixler, and Yehezkel S. Resheff. A wavelet-based approach to monitoring parkinson's disease symptoms. In *Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference on*, pages 5980–5984. IEEE, 2017.

[102] Ahmed Mostayed, Mohammad Mynuddin Gani Mazumder, Sikyung Kim, and Se Jin Park. Abnormal gait detection using discrete fourier transform.

In *Multimedia and Ubiquitous Engineering, 2008. MUE 2008. International Conference on*, pages 36–40. IEEE, 2008.

[103] Ahmed Mostayed, MMG Mazumder, S. Kim, and SJ Park. Abnormal gait detection using discrete wavelet transform in fourier domain. In *4th Kuala Lumpur International Conference on Biomedical Engineering 2008*, pages 383–386. Springer, 2008.

[104] Saba Rezvanian and Thurmon E. Lockhart. Towards real-time detection of freezing of gait using wavelet transform on wireless accelerometer data. *Sensors*, 16(4):475, 2016.

[105] Bing Sun, Yang Wang, and Jacob Banda. Gait characteristic analysis and identification based on the iphones accelerometer and gyrometer. *Sensors*, 14(9):17037–17054, 2014.

[106] Xijuan Wang. A human body gait recognition system based on fourier transform and quartile difference extraction. *International Journal of Online Engineering (iJOE)*, 13(07):129–139, 2017.

[107] Fei Wang, Shiguang Wen, Chengdong Wu, Yuzhong Zhang, and Hao Wang. Gait recognition based on the fast fourier transform and svm. In *Control and Decision Conference (CCDC), 2011 Chinese*, pages 1091–1094. IEEE, 2011.

[108] Chiraz BenAbdelkader, Ross Cutler, and Larry Davis. Stride and cadence as a biometric in automatic person identification and verification. In *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*, pages 372–377. IEEE, 2002.

[109] Aaron F. Bobick and Amos Y. Johnson. Gait recognition using static, activity-specific parameters. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, volume 1, pages I–I. IEEE, 2001.

[110] Jang-Hee Yoo, Doosung Hwang, Ki-Young Moon, and Mark S. Nixon. Automated human recognition by gait using neural network. In *Image Processing Theory, Tools and Applications, 2008. IPTA 2008. First Workshops on*, pages 1–6. IEEE, 2008.

[111] ChewYean Yam, Mark S. Nixon, and John N. Carter. Automated person recognition by walking and running via model-based approaches. *Pattern recognition*, 37(5):1057–1072, 2004.

[112] Liang Wang, Huazhong Ning, Tieniu Tan, and Weiming Hu. Fusion of static and dynamic body biometrics for gait recognition. *IEEE Transactions on circuits and systems for video technology*, 14(2):149–158, 2004.

[113] David Kenneth Wagg and Mark S. Nixon. On automated model-based extraction and analysis of gait. In *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*, pages 11–16. IEEE, 2004.

[114] David K. Wagg and Mark S. Nixon. Model-based gait enrolment in real-world imagery. 2003.

[115] Nikolaos V. Boulgouris and Zhiwei X. Chi. Human gait recognition based on matching of body components. *Pattern recognition*, 40(6):1763–1770, 2007.

[116] Amit Kale, AN Rajagopalan, Naresh Cuntoor, and Volker Kruger. Gait-based recognition of humans using continuous hmms. In *Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on*, pages 336–341. IEEE, 2002.

[117] Aaron F. Bobick and James W. Davis. The recognition of human movement using temporal templates. *IEEE Transactions on pattern analysis and machine intelligence*, 23(3):257–267, 2001.

[118] Ju Han and Bir Bhanu. Statistical feature fusion for gait-based human recognition. In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, volume 2, pages II–II. IEEE, 2004.

[119] Xiaochao Yang, Yue Zhou, Tianhao Zhang, Guang Shu, and Jie Yang. Gait recognition based on dynamic region analysis. *Signal Processing*, 88(9):2350–2356, 2008.

[120] Khalid Bashir, Tao Xiang, and Shaogang Gong. Gait recognition without subject cooperation. *Pattern Recognition Letters*, 31(13):2052–2060, 2010.

[121] Toby HW Lam, King Hong Cheung, and James NK Liu. Gait flow image: A silhouette-based gait representation for human identification. *Pattern recognition*, 44(4):973–987, 2011.

[122] Yasushi Makihara, Ryusuke Sagawa, Yasuhiro Mukaigawa, Tomio Echigo, and Yasushi Yagi. Gait recognition using a view transformation model in the frequency domain. In *European Conference on Computer Vision*, pages 151–163. Springer, 2006.

[123] S-S Shin, D-H An, and W-G Yoo. The effect of navigating obstacles when walking with deficient (inappropriate, deprived, limited) foot sensory input on spatiotemporal gait parameters of elderly individuals with different visual acuities. *European geriatric medicine*, 6(1):1–6, 2015.

[124] Lingsheng Li, Eleanor M. Simonsick, Luigi Ferrucci, and Frank R. Lin. Hearing loss and gait speed among older adults in the united states. *Gait & posture*, 38(1):25–29, 2013.

[125] Md Zia Uddin, Tae-Seong Kim, and Jeong Tai Kim. Video-based indoor human gait recognition using depth imaging and hidden markov model: a smart system for smart home. *Indoor and built environment*, 20(1):120–128, 2011.

[126] You-Yin Chen, Chien-Wen Cho, Sheng-Huang Lin, Hsin-Yi Lai, Yu-Chun Lo, Shin-Yuan Chen, Yuan-Jen Chang, Wen-Tzeng Huang, Chin-Hsing Chen, Fu-Shan Jaw, et al. A vision-based regression model to evaluate parkinsonian gait from monocular image sequences. *Expert Systems with Applications*, 39(1):520–526, 2012.

[127] Taha Khan, Peter Grenholm, and Dag Nyholm. Computer vision methods for parkinsonian gait analysis: a review on patents. *Recent Patents on Biomedical Engineering*, 6(2):97–108, 2013.

[128] Richard Baker. Gait analysis methods in rehabilitation. *Journal of neuroengineering and rehabilitation*, 3(1):4, 2006.

[129] Ann Hallemans, Els Ortibus, Francoise Meire, and Peter Aerts. Low vision affects dynamic stability of gait. *Gait & posture*, 32(4):547–551, 2010.

[130] Kosuke Okusa and Toshinari Kamakura. Normal/abnormal gait analysis based on the statistical registration and modeling of the frontal view gait data. In *Proceedings of World Congress on Engineering and Computer Science*, 2012.

[131] Jinguang Han and Bir Bhanu. Individual recognition using gait energy image. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (2): 316–322, 2006.

[132] Yasushi Makihara, Muhammad Rasyid Aqmar, Ngo Thanh Trung, Hajime Nagahara, Ryusuke Sagawa, Yasuhiro Mukaigawa, and Yasushi Yagi. Phase estimation of a single quasi-periodic signal. *IEEE Transactions on Signal Processing*, 62(8):2066–2079, 2014.

[133] Ngo Thanh Trung, Yasushi Makihara, Hajime Nagahara, Ryusuke Sagawa, Yasuhiro Mukaigawa, and Yasushi Yagi. Phase registration in a gallery improving gait authentication. In *Biometrics (IJCB), 2011 International Joint Conference on*, pages 1–7. IEEE, 2011.

[134] Home page of age simulation kit. 2008. URL https://www.sanwa303.co.jp/products/medicare/teaching-material/104-990.

[135] SH Cho, JM Park, and OY Kwon. Gender differences in three dimensional gait analysis data from 98 healthy korean adults. *Clinical biomechanics*, 19 (2):145–152, 2004.

[136] Xuelong Li, Stephen J. Maybank, Shuicheng Yan, Dacheng Tao, and Dong Xu. Gait components and their application to gender recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 38(2):145–155, 2008.

[137] Shiqi Yu, Tieniu Tan, Kaiqi Huang, Kui Jia, and Xinyu Wu. A study on gait-based gender classification. *IEEE Transactions on image processing*, 18 (8):1905–1910, 2009.

[138] Dianne J Russell, Peter L Rosenbaum, Marilyn Wright, and Lisa M Avery. *Gross motor function measure (GMFM-66 & GMFM-88) user's manual*, volume 159. Mac keith press London, 2002.

[139] Hsiang-Ju Huang and Vicki Stemmons Mercer. Dual-task methodology: applications in studies of cognitive and motor performance in adults and children. *Pediatric Physical Therapy*, 13(3):133–140, 2001.

[140] Ralf Th Krampe, Sabine Schaefer, Ulman Lindenberger, and Paul B. Baltes. Lifespan changes in multi-tasking: concurrent walking and memory search in children, young, and older adults. *Gait & posture*, 33(3):401–405, 2011.

[141] Emad Al-Yahya, Helen Dawes, Lesley Smith, Andrea Dennis, Ken Howells, and Janet Cockburn. Cognitive motor interference while walking: a systematic review and meta-analysis. *Neuroscience & Biobehavioral Reviews*, 35 (3):715–728, 2011.

[142] Takehiko Doi, Hiroyuki Shimada, Hyuma Makizako, Kota Tsutsumimoto, Kazuki Uemura, Yuya Anan, and Takao Suzuki. Cognitive function and gait speed under normal and dual-task walking among older adults with mild cognitive impairment. *BMC neurology*, 14(1):67, 2014.

[143] Christopher Dalton, Ria Sciadas, and Julie Nantel. Executive function is necessary for the regulation of the stepping activity when stepping in place in older adults. *Aging clinical and experimental research*, 28(5):909–915, 2016.

[144] Ryuta Kawashima, Katsuo Okita, Ritsumi Yamazaki, Nobumoto Tajima, Hajime Yoshida, Masato Taira, Kazuki Iwata, Takeo Sasaki, Katsujiro Maeyama, Nobuo Usui, et al. Reading aloud and arithmetic calculation improve frontal function of people with dementia. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 60(3):380–384, 2005.

[145] Ming-I B. Lin and Kuan-Hung Lin. Walking while performing working memory tasks changes the prefrontal cortex hemodynamic activations and gait kinematics. *Frontiers in Behavioral Neuroscience*, 10:92, 2016.

[146] World Health Organization and World Health Organization. Who multicentre growth reference study group: Who child growth standards: length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development. *Geneva: WHO*, 2007, 2006.

[147] Seizo Suwa and Katsuhiko Tachibana. Standard growth charts for height and weight of japanese children from birth to 17 years based on a cross-sectional survey of national data. *Clinical Pediatric Endocrinology*, 2(2):87–97, 1993.

[148] Mercedes De Onis, Adelheid Onyango, Elaine Borghi, Amani Siyam, Monika Blössner, and Chessa Lutter. Worldwide implementation of the who child growth standards. *Public health nutrition*, 15(9):1603–1610, 2012.

[149] Ilaria Masci, Giuseppe Vannozzi, Elena Bergamini, Caterina Pesce, Nancy Getchell, and Aurelio Cappozzo. Assessing locomotor skills development in childhood using wearable inertial sensor devices: the running paradigm. *Gait & posture*, 37(4):570–574, 2013.

[150] JM Hausdorff, L. Zemany, C-K Peng, and AL Goldberger. Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children. *Journal of applied physiology*, 86(3):1040–1047, 1999.

[151] Priska Hagmann-von Arx, Olivia Manicolo, Sakari Lemola, and Alexander Grob. Walking in school-aged children in a dual-task paradigm is related to

age but not to cognition, motor behavior, injuries, or psychosocial functioning. *Frontiers in psychology*, 7:352, 2016.

[152] EE Parrish, DE Giaschi, C. Boden, and R. Dougherty. The maturation of form and motion perception in school age children. *Vision research*, 45(7): 827–837, 2005.

[153] David Moshman. Cognitive development beyond childhood. *Handbook of child psychology (5th Ed.)*, 2:947–978, 1998.

[154] Lucy Cragg and Camilla Gilmore. Skills underlying mathematics: The role of executive function in the development of mathematics proficiency. *Trends in Neuroscience and Education*, 3(2):63–68, 2014.

[155] A Miranda Fredriks, Stef van Buuren, WJM Van Heel, RHM Dijkman-Neerincx, SP Verloove-Vanhorick, and Jan Maarten Wit. Nationwide age references for sitting height, leg length, and sitting height/height ratio, and their diagnostic value for disproportionate growth disorders. *Archives of disease in childhood*, 90(8):807–812, 2005.

[156] Barry Bogin and Maria Inês Varela-Silva. Leg length, body proportion, and health: a review with a note on beauty. *International journal of environmental research and public health*, 7(3):1047–1075, 2010.

[157] Ricardo M. Araujo, Gustavo Graña, and Virginia Andersson. Towards skeleton biometric identification using the microsoft kinect sensor. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pages 21–26. ACM, 2013.

[158] Hau-Wei Lee, Chien-Hung Liu, Kuan-Ta Chu, Yu-Chia Mai, Ping-Chit Hsieh, Kai-Chiang Hsu, and Hung-Chih Tseng. Kinect who's comingapplying kinect to human body height measurement to improve character recognition performance. *Smart Science*, 3(2):117–121, 2015.

[159] M. Robinson and M. Parkinson. Estimating anthropometry with microsoft kinect. In *Proceedings of the 2nd International Digital Human Modeling Symposium*, volume 1, page 2, 2013.

[160] Alan S. Kaufman, Susan Engi Raiford, and Diane L. Coalson. *Intelligent testing with the WISC-V*. John Wiley & Sons, 2015.

[161] Jerome H. Friedman. Greedy function approximation: a gradient boosting machine. *Annals of statistics*, pages 1189–1232, 2001.

[162] Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794. ACM, 2016.

[163] Peter Bühlmann. Bagging, boosting and ensemble methods. In *Handbook of Computational Statistics*, pages 985–1022. Springer, 2012.

[164] Yoav Freund, Robert E. Schapire, et al. Experiments with a new boosting algorithm. In *Icml*, volume 96, pages 148–156. Citeseer, 1996.

[165] Leo Breiman. *Classification and regression trees*. Routledge, 2017.

[166] Matthias Schonlau et al. Boosted regression (boosting): An introductory tutorial and a stata plugin. *Stata Journal*, 5(3):330, 2005.

[167] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12: 2825–2830, 2011.

[168] Alex Mihailidis, Joseph C. Barbenel, and Geoff Fernie. The efficacy of an intelligent cognitive orthosis to facilitate handwashing by persons with moderate to severe dementia. *Neuropsychological Rehabilitation*, 14(1-2):135–171, 2004.