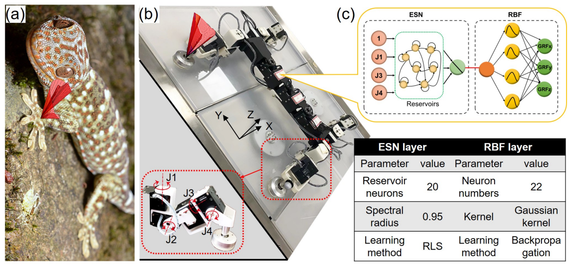
Virtual 3D ground reaction force sensors for a gecko-inspired climbing robot with dry adhesive foot pads

Donghao Shao[1], Zhendong Dai[1], Aihong Ji[1], Poramate Manoonpong[1,2*]
[1]Nanjing University of Aeronautics and Astronautics, Nanjing, China
[2]Vidyasirimedhi Institute of Science & Technology, Rayong, Thailand
*poma@nuaa.edu.cn

1 Introduction

Animals use their neural and musculoskeletal systems for cooperating with sensory information to exhibit adaptive locomotion when interacting with their environment. In the case of legged animals, the ground reaction force (GRF) is a crucial sensory feedback signal since it provides information about their moving state and environment. For example, horses are able to adjust their movement based on the frictional and normal force of the ground on which they are traveling [1]. Geckos, as the largest climbing creatures, can adapt to walls and slopes with varying tilting angles by utilizing 3D GRFs [2] (Fig. 1(a)).

Similarly, legged robots also exploit GRF information for their locomotion and adaptation to deal with rough and uneven terrain. Quadruped robots, such as ANYmal, utilize foot contact forces to adapt their gait to prevent slipping or falling when navigating challenging terrain, like gravel, grass, mud, and snow [3]. Climbing robots are capable of traversing other types of challenging terrain, such as walls and ceilings by utilizing adhesive forces to adhere to the surface and maintain continuous locomotion [4, 5]. However, these climbing robots might not be able to actively adapt or recover from disturbances, such as a slippery terrain. This is because, in order to maintain their lightweight design, such robots typically do not include GRF sensors. From this point of view, virtual GRF sensors are a good solution to obtain GRFs since they offer better weight, volume, and power saving than real physical GRF sensors. Echo state networks (ESNs) have been proposed to develop virtual GRF sensors. In other words, due to their neurodynamics and embedded temporal memory, they can predict GRFs indirectly from robot joint feedback, such as joint torque [6]. However, so far, they have only been applied to predict a vertical (normal or 1D) GRF on each leg of a quadruped robot. Additionally, when applied to complex 3D GRF profiles, their predicted GRFs (i.e., ESN outputs) are still inaccurate. Thus, this study introduces a method for enhancing the accuracy of complex 3D GRF prediction. Specifically, we combine an ESN with a radial basis function (RBF) network (called ESN-RBF net, Fig. 1(c)). This network architecture is applied to predict 3D GRFs of a gecko-inspired robot during slope climbing (Fig. 1(b)).



ESN layer		RBF layer	
Parameter	value	Parameter	value
Reservoir neurons	20	Neuron numbers	22
Spectral radius	0.95	Kernel	Gaussian kernel
Learning method	RLS	Learning method	Backpropa gation

Figure 1: The development of virtual GRF sensors based on an ESN-RBF net and joint torque feedback. (a) *Gekko gecko* climbs on the wall, while the red cone shows the 3D GRFs. (b) The gecko-inspired robot, Nyx with virtual GRFs. The red cone indicates the predicted 3D GRFs. (c) The network architecture of the ESN-RBF net. The table shows the parameter setting of the net.

2 Materials and methods

To develop the 3D virtual force sensors of a climbing robot, we needed well-processed and synchronized data for training the ESN-RBF network. Fig. 1(b) shows that we chose the climbing robot (Nyxbot) for data collection since it could interact with the 3D force platform and generate the adhesive force on this slope. We recorded the synchronized data, which included the network inputs (joint torques) and the network outputs (GRFs in x, y, and z directions).

2.1 Data recording system

Developing accurate virtual 3D GRF sensors requires well-synchronized data. Therefore, we used a synchronized joint torque-GRF system to record data from the robot motor joints and the 3D force platform. The force platform was equipped with a trigger that sent a falling edge signal to two computers responsible for recording the force signals and robot joint torque signals, respectively. Due to hardware limitations, we set the sampling rate for the robot at 20 Hz and the force platform at 200 Hz.

2.2 Preprocessing the recorded data

It is essential to obtain well-processed and correlated input (robot joint torques) and target (3D GRFs) data for training our ESN-RBF network for 3D GRF prediction. First, we standardized and normalized the input and target data to

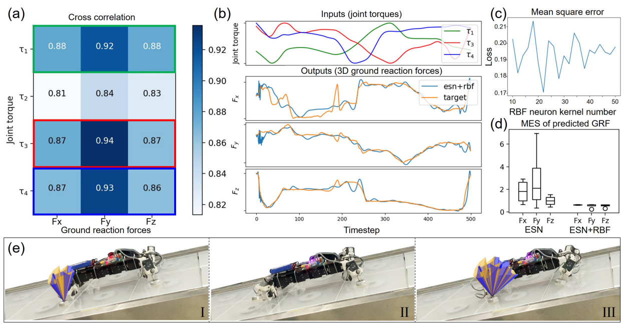


Figure 2: Training and testing the virtual 3D GRF sensors. (a) Cross-correlation of the joint torques and GRFs. (b) Testing result of a virtual GRF sensor. The upper figure shows the input signals (joint torques), while the lower figure shows the output signals (3D GRFs). (c) Training of the RBF network with different RBF neurons. (d) Performance comparison between the ESN-RBF network and pure ESN. (e) The gecko-inspired robot climbing up the slope with visualised dynamic force profiles.

a range of 0 to 1 and then smoothed the data. We used a spline function to fit the input and target data. Next, we resampled the input and target data to achieve the same data points. This ensured that the input and target data were aligned correctly, allowing us to create an optimal nonlinear transformation for the GRF prediction. A cross-correlation method was used to determine the joint torques that contributed the most to the GRF in each axis. The result is shown in Fig. 2(a). Higher values and darker blue shadows indicate a strong correlation between the input joint torque and target GRF data. Based on the cross-correlation result, the motor torques of joints 1, 3, and 4 (see Fig. 1(c)) were selected as the inputs for the ESN-RBF network.

2.3 ESN-RBF network for virtual GRF sensors

Since the ESN has an impressive feature for temporal data processing and prediction [6], it was employed here as the first signal processing layer that preprocesses proprioceptive joint torques (ESN inputs) and translates them into predicted GRFs in x, y, and z axes (ESN outputs). To enhance the GRF prediction accuracy, an RBF network was applied in a sequential manner after the ESN. It received the ESN outputs as its inputs to further reshape the predicted 3D GRFs to perfectly fit the real complex 3D GRF profiles obtained from the force platform. We empirically optimized the network parameters (e.g., hidden neurons, see Fig. 2(c)). The final ESN-RBF network structure and parameter setup are shown in Fig. 1(c).

3 Training and testing results

The virtual (software-based) GRF sensors based on the ESN-RBF network were trained using a two-step approach. The ESN output weights were first trained using the ridge regression method, followed by training the RBF output weights using backpropagation. Each ESN-RBF network was used to predict the 3D GRFs of each robot leg. In total, we used four ESN-RBF networks as four virtual GRF sensors for our robot. Fig. 2(b) shows an example of predicted 3D GRFs on the right hind leg according to the joint torques 1, 3, and 4. The proposed ESN-RBF network and a typical ESN are compared in Fig. 2(d). The result shows that the ESN-RBF network can achieve higher accuracy (lower mean square error) than the ESN network. Fig. 2(e) shows an example of the robot climbing on a slope with visualised dynamic force profiles. The significant overlap between the target force profile (orange color, Fig. 2(e)) and the predicted force profile indicates (blue color, Fig. 2(e)) that the ESN-RBF network's prediction is highly accurate.

4 Conclusion

The development of the virtual GRF sensors involved building the synchronized system, processing the recorded data, and developing and training the ESN-RBF-based neural model. The ability of the virtual sensors to predict 3D GRFs has been verified. Using the ESN-RBF can lead to accuracy improvement in 3D GRF prediction compared to a pure ESN. However, the use of only an RBF network makes temporal data (time series) prediction difficult. The virtual GRF sensors could offer an alternative for legged robots to detect their GRFs for robust locomotion and adaptation when navigating on unknown terrains. Due to ESN's temporal memory, the network can still generate the desired GRF signal even when the joint torque feedback is temporarily absent [6]. In the future, we will develop virtual 3D GRF-based neural control to allow our robot not only to climb a slope but also efficiently adapt its gait to maintain dynamic stability during climbing on different slope surfaces.

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