Multi-Sensor Fusion Based on BPNN in Quadruped Ground Classification

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***Abstract* – Appropriate perception of different ground substrates plays an essential role in realizing adaptive quadruped locomotion. In this paper, we propose a multi-sensor fusion method based on Back Propagation Neural Network (BPNN) using in real-time ground substrate classification for adaptive quadruped walking. In order to collect the body gyro information, foot-ground contact force, Direct Current (DC) motor information and joint angle to train the network, we present the enhanced walk strategy with Center of Gravity (COG) adjustment method with 6-axis motion sensor feedback and realize steady walk gait on different ground substrates. Using these method, the quadruped robot Biodog realizes multi-sensor information collection while walking on six different ground substrates. Then we train the BPNN using the collected data after calculation and normalization. In network training, about 99.83% samples have been classified correctly using BPNN. In real-time testing, about 98.33% has been classified successfully using trained BPNN.**

Index Terms – Trajectory planning; Quadruped robot; Terrain classification; BPNN; Multi-Sensor Fusion.

I. INTRODUCTION

Adaptive locomotion on various type of ground surface is significant for quadruped robots. When moving in unknown environment, appropriate perception of different ground substrates plays an essential role in realizing adaptive locomotion.

Terrain classification have been studied in many research. Kisung Kim et al.[1] use BPNN and SVM to classify different ground by values obtained from the 1-legged robot, and compare their performance. However, the proposed method is only verified in a 1-legged robot. Mark A Hoepflinger et al.[2, 3] propose a method to estimate terrain properties using multiclass AdaBoost to increase its locomotion capabilities. Matej Hoffmann et al. [4] assess different gaits' effect on performance of classification and illustrate that separate terrain classifiers for each motor program should be employed.

To form an expanded sense of the ground, multi-sensor fusion is useful. Sensor fusion can incorporate measurements of multiple sensors and reduce error[5]. Multi-sensor fusion technology is widely used in autonomous vehicle system, simultaneous localization and mapping (SLAM)[6-8], robot vision in industrial robot[9], and three-dimensional reconstruction[10]. Qingquan Li et al. [11] propose a real-time feature-level fusion method for the LIDAR and vision data. Nützi Gabriel et al.[8] make a fusion of inertial and visual data using extended Kalman filter. N. Ghosh et al. [12] develop a neural network-based sensor fusion model for tool condition monitoring. However, multi-sensor data fusion is rarely used in quadruped ground substrate classification.

As vision sensors can hardly play a role in recognition of ground substrates with different properties, we plan to use the body gyro information, foot-ground contact force, DC motor information and joint angle to train a BPNN for real-time classification. But the precondition is that the quadruped robot can walk stably on various ground substrates.

During walk gait, a quadruped robot has three leg standing on the ground with only one leg lifted off the ground. In order to collect sufficient sens • or information, walk gait is better than other gait, because a quadruped robot moves in low velocity and has the most supporting leg in walk gait. Realizing steady walk gait on different ground substrates will benefit the improvement of the classification accuracy.

There have been many research about quadruped locomotion. Kimura et al.[13]propose a bio-inspired controller based on pattern generators with sensory feedback including reflex and response. Duc Trong Tran et al.[14] present a novel Central Pattern Generator (CPG) model for controlling quadruped walking robots, and performs several dynamic trotting tasks on several unknown natural terrains with a real quadruped AiDIN-III with 16 Degree of Freedoms (DOFs). But this method requires high performance of the mechanical structure and at least 3 DOFs for each leg. In walk gait, however, movement of the COG based on static stability area must be highly considered, which is hard to realize under simple CPG controller due to low velocity in walk gait. So, in our previous work[15], we propose a walking strategy based on trajectory planning without any feedback, which can make the robot walk steadily and agilely only on simple flat ground.

On the basis of previous works, we firstly present the enhanced walk strategy with COG adjustment method with 6-axis motion sensor feedback. Then we detail the ground substrates classification method using multi-sensor fusion based on BPNN. Then, we introduce the quadruped robot built at our lab and used in experiment. Experiment results are demonstrated and conclusions are drawn after all.

II. COG ADJUSTMENT

During walk gait, a quadruped robot moves in low velocity with only one leg off the ground. Due to the low level of locomotion velocity, movement of the COG based on static stability area must be highly considered, which means the COG

need to be located rightly in the static stability area for every foot-step, and this is hard to realize under simple CPG controller. So we propose a walking strategy based on trajectory planning. In our previous work, we made two assumption. We assume that the center of mass is coincident with the geometrical center of robot's trunk, and the trunk is always close to parallel (neglected inertia). But when it comes to real robot walking on complex ground environment, it can hardly maintain stable. So we enhance the strategy by adding 6-axis motion sensor as feedback, to further adjust the COG location.

As illustrated in Fig.1, in each phase, three legs step on the ground and promote the COG forward when the last one leg swings forward. The COG are always placed within the triangular stability area between each period, which satisfy the principle of Stability Margin (SM).

We use two step to realize further adjustment of the COG. First, shrunken two forth leg when ready to raise hind leg, or shrunken two hind leg when ready to raise forth leg, in order to meet the pitch angle requirement. Second, extend the leg about to swing and shrunken two leg on the other side to meet the roll angle requirement. We give an example to illustrate the COG adjustment method in Fig.2. The green colored legs represent the shrinking ones, and the red colored leg represents the extending one. The red dots represent the projection of COG. In swing phase, foot trajectory is shown in Fig.3

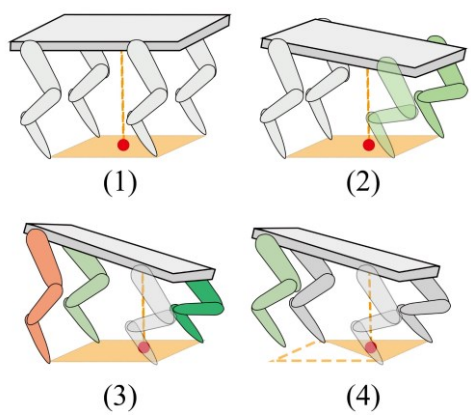


Fig. 2 COG adjustment according to torso orientation

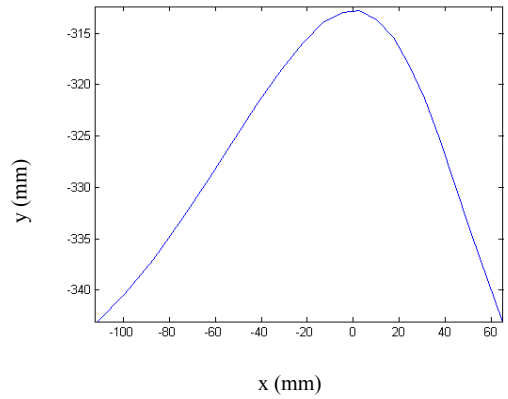


Fig. 3 Quadruped foot trajectory during one step

III. Ground Substrate Classification

Obtaining comprehensive information of the ground is conducive to optimize of the classification accuracy. To form an expanded sense of the ground, force and attitude information from various sensor source is needed. However, we cannot obtain the contact force between the robot toe and the ground directly, so value conversion is necessary.

First, we calculate the orientation of detected contact force. From the 6-axis motion sensor mounted on the torso, we can get the torso's pitch and roll angle θ_{pitch} and θ_{roll}. From the encoder attached on the hip joint, we can get the angle between torso and the hip limb θ_{hip}. As illustrated in Fig. 4(a), Coordinate.0 represents world coordinate, and we attach Coordinate.1 to the torso and Coordinate.2 to the hip limb. Because the ankle joint of the model is a passive joint, orientation of the detected force is the same as y_2 in the Coordinate.2. So the unit vector of the detected force in world coordinate can be solve using (1).

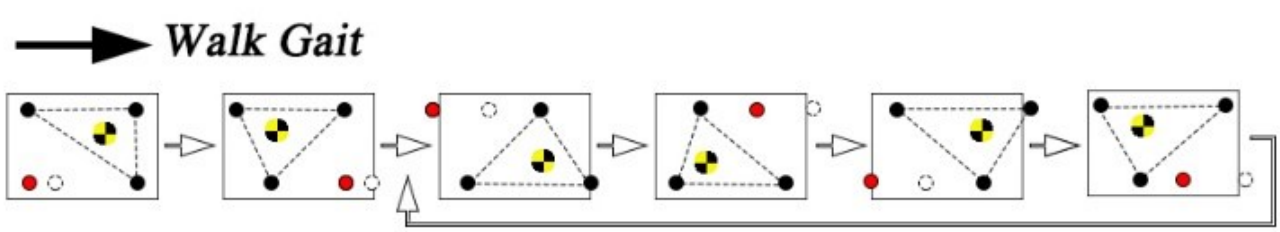


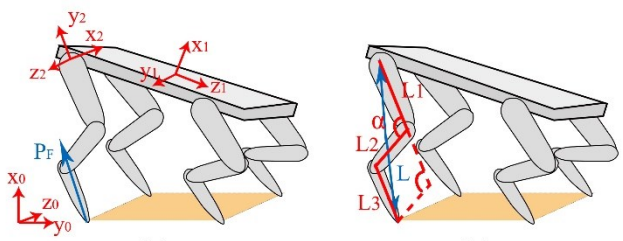
Fig. 1 COG and foot movement in walk gait (The black circles represent feet in stance phase, and red circles represent feet in the begin of swing phase; the black doted open circles represent the next supporting phase of the swinging feet; the black boxes represent trunk position of the quadruped robot)

$$
{}^{0}P_F = {}^{0}_{1}R\,{}^{1}_{2}R\,{}^{2}P_F = R_{pitch}R_{roll}\,{}^{1}_{2}R\,{}^{2}P_F
$$

$$
= \begin{bmatrix} \cos(\theta_{pitch}) & -\sin(\theta_{pitch}) & 0 \\ \sin(\theta_{pitch}) & \cos(\theta_{pitch}) & 0 \\ 0 & 0 & 1 \end{bmatrix}
$$

$$
\begin{bmatrix} \cos(\theta_{roll}) & -\sin(\theta_{roll}) & 0 \\ 0 & 0 & 1 \\ -\sin(\theta_{roll}) & -\cos(\theta_{roll}) & 0 \end{bmatrix}
$$

$$
\begin{bmatrix} \cos(\theta_{hip}) & -\sin(\theta_{hip}) & 0 \\ 0 & 0 & 1 \\ -\sin(\theta_{hip}) & -\cos(\theta_{hip}) & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \tag{1}
$$



(a) (b)

Fig. 4 Calculation of (a) orientation of detected contact force (b) detected force for the LH hip axes applied to the toe

Second, we calculate the detected force for the LH hip axes applied to the toe. The value we can obtain from the DC motor is current I. Converting motor current to torque τ, the torque constant C_t of the motor is needed. And converting motor torque to the force applied to the toe, the virtual leg length L is needed, equations as in

$$
L = \sqrt{L_2^2 + (L_1 + L_3)^2 - 2L_1(L_1 + L_3)\cos(\alpha)} \tag{2}
$$

$$
\mathrm{F} = \tau / L = \mathrm{C_t I} / L \tag{3}
$$

After conversion, we can get all the features for network training. Basic features including 8 motor current value, 8 joint angle, 4 contact force and its derivative and unit vector, roll and pitch angle, and the force for the 8 axes applied to the toe. And we compare the recent value within last 10s to obtain maximum and minimum value in the time domain. And each feather is scaled to the range from -1.0 to 1.0 using (4).

$$
z^* = \frac{(\eta_{max} - \eta_{min})(z - \min(z))}{\max(z) - \min(z)} + \eta_{min} \tag{4}
$$

where z represented each feature, $\eta_{max} = 1$ and $\eta_{min} = -1$.

After all, we can get 116 value in each input sample. Calculating the output values and then updating the weight factors by comparing outputs repeatedly, the optimal weight factor of the BPNN can be found. In this study, the neural network including one hidden layer that have 20 nets.

IV. Experiments And Results

We developed a quadruped robot called Biodog in our lab, as depicted in Fig. 5. The torso is 0.4m in length, 0.2m in width, and 0.33m in height. The total weight is 20kg. Each limb has two degrees of freedom including a hip joint and a knee joint, and each joint is actuated by a DC motor. The material of the quadruped toe is engineering plastics.

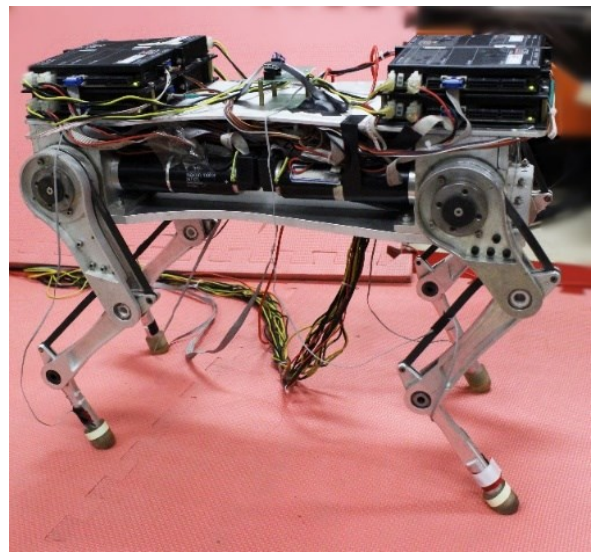


Fig. 5 The quadruped robot Biodog developed at our lab

In order to test the performance of the proposed methods, we conduct experiments about walking locomotion of the quadruped robot Biodog on six diverse ground substrates including vitrified tiles, plastic carpet, anti-static rubber slab, EVA and EPE, which are shown in Fig. 6, in the meanwhile, we collect the sensor data with sampling frequency of 8Hz. The six ground substrates' parameters are shown in Table I. The quadruped robot sinks deeper on GR5 than on GR4, and the deepest on GR6 as shown in Fig. 6.

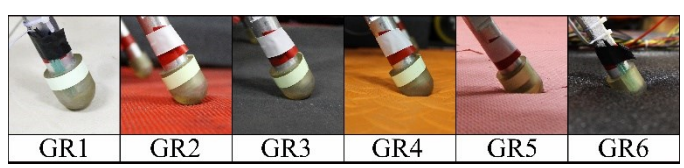


Fig. 6 Six different kinds of ground substrate GR1 (vitrified tiles), GR2 (plastic carpet), GR3 (anti-static rubber slab), GR4 (EVA), GR5 (EVA), and GR6 (EPE).

TABLE I
GROUND SUBSTRATES' PARAMETERS

Ground substrate	Elasticity modulus (MPa)	Thickness (mm)	Static friction coefficient
GR1	-	-	0.35
GR2	3500	3	0.45
GR3	7.84	4	0.6
GR4	91	10	0.5
GR5	91	30	0.5
GR6	60	50	0.33

A. Locomotion strategy Results

In the experiment, the quadruped robot Biodog walks for 15 times on each ground substrates, and each trial lasting for over 2 minutes. Twelve representative snapshots of one trial on GR5 are shown in Fig.7. In Fig. 7, the first row shows the stand-firm status, the second row shows the adjusting status, and the third row shows the lift-off status. The foot trajectory can be seen in Long-exposure photography shown in Fig. 8, which is a one-shot long time bulb exposure photography, performed additionally with movement of light from night glow sticker pasting on the RH toe. It can be seen that the order of the swing limb is RH-RF-LH-LF, and all swing limbs can lift off the ground after COG adjustment successfully.

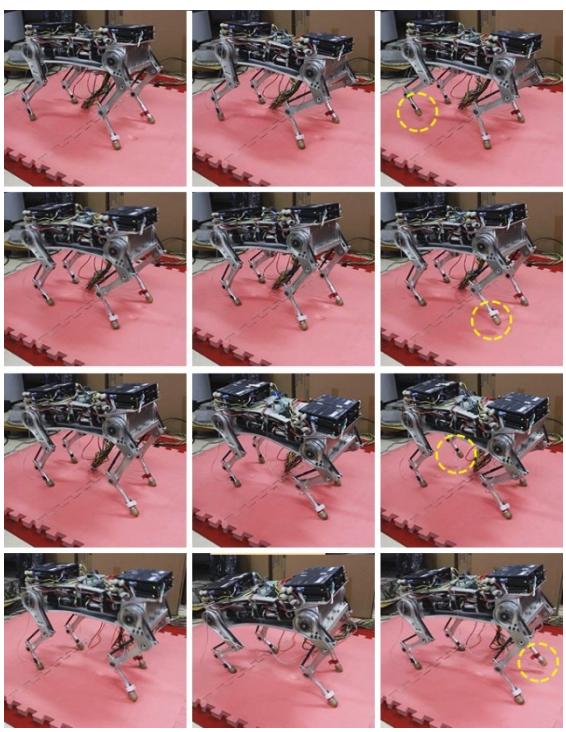


Fig. 7 The snapshots of the quadruped robot Biodog in walk gait

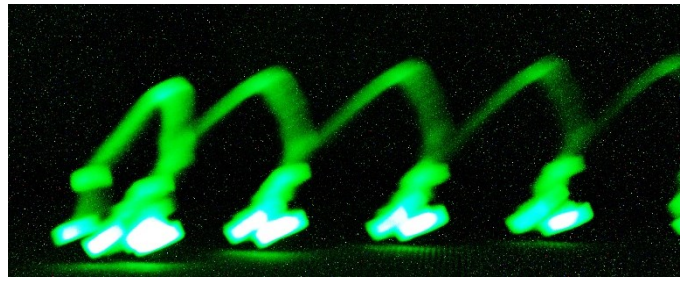


Fig. 8 Long-exposure photography of the foot trajectory

The foot-ground contact force signal and the force for the hip and knee axes applied to the toe of LH are collected and shown in Fig. 9 and Fig. 10, respectively. And the body angles during locomotion are shown in Fig.11. According to the characteristic of FSR sensor used in our experiment, we have converted the detected voltage value to force value.

The experiment shows that the COG adjustment method with 6-axis motion sensor feedback shows nice adaptability on different ground status. In Fig. 9, we can see that the LH foot can normally lifts off during the swing phase, and can supports its body during the stance phase. In Fig. 10, we can see that the force picks for hip axes appear just after landing, while the force picks for knee axes appear before swing phase, which means that hip and knee axes provide propulsion successively in stance phase. The roll angle is in range of [-4, 10] degree and the pitch angle is in range of [-12, 14] degree as shown in Fig. 11, which indicates that the quadruped robot walks firmly on GR5. And in the whole experiment, the roll angle is in range of [-16, 16] and the pitch angle is in range of [-11, 10], which indicates that the quadruped robot walks adaptively on all the six ground substrates.

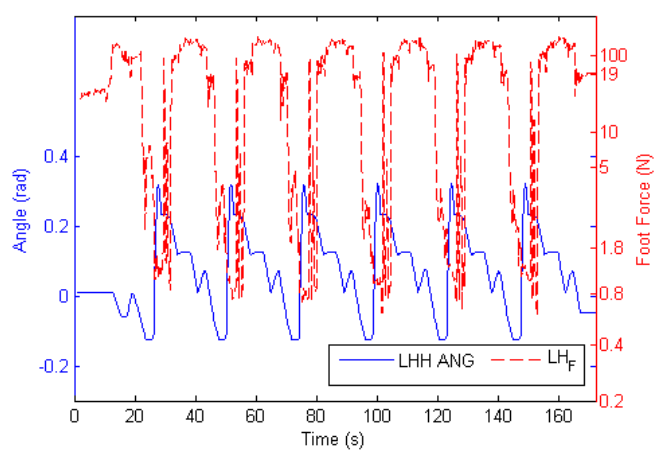


Fig. 9 The detected hip joint angle and foot-ground contact force of LH limbs

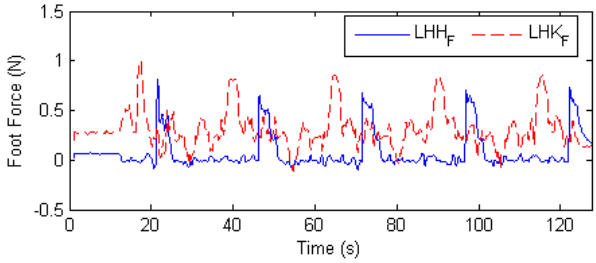


Fig. 10 The detected force for the hip axes and knee axes applied to the toe

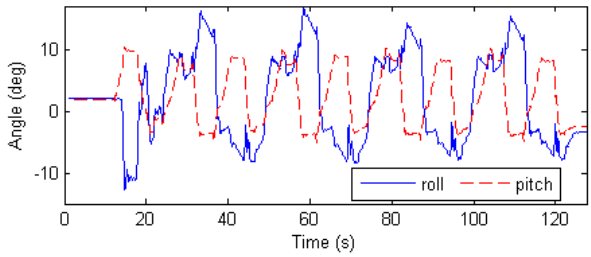


Fig. 11 The detected pitch and roll angles of the quadruped robot in walk gait

B. Learning and Classification

To conduct classification, we take 15 trials on each ground substrates (90 trials, 105869 samples total). We show an example of the detected foot-ground contact force and axes force of the quadruped robot locomoting on the six kind of ground substrates in Fig.12 and Fig. 13. Obvious distinction can be seen in Fig.12 that detected contact force on GR4, GR5 and GR6 are generally lower, which mostly due to the pulling-out action in swing phase after sinking in the ground in stance phase. In Fig. 13(a), we can see that it has only one force pulse in each period for GR6 while others has three, because of the superior impact mitigation effort by the ground material of GR6. The difference in sensor data benefits the classification for the six ground substrates.

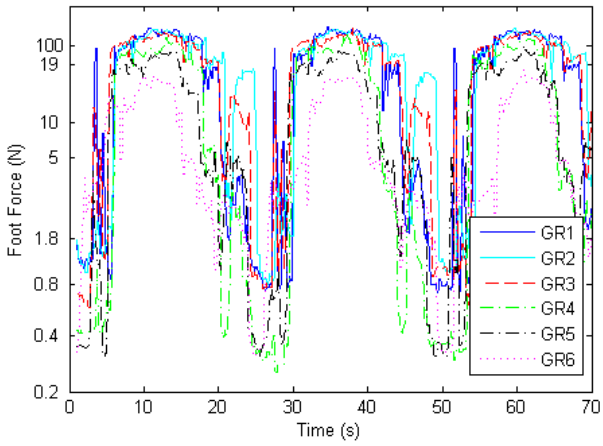
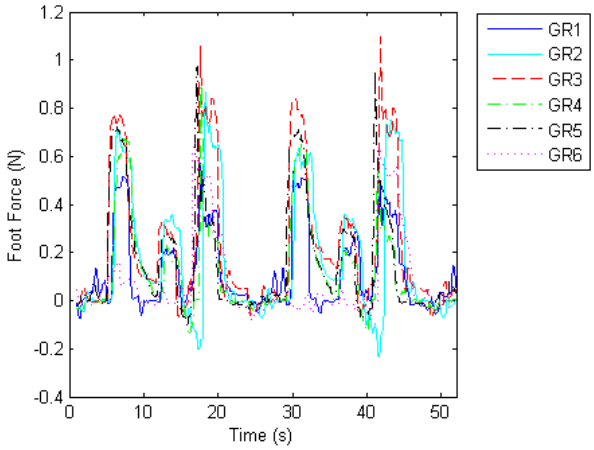
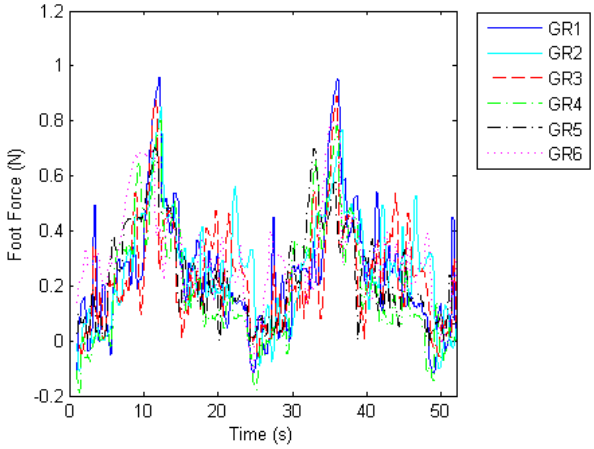


Fig. 12 The detected hip joint angle and foot-ground contact force of LH limbs



(a)



(b)

Fig. 13 The detected force for the LH hip axes and knee axes applied to the LH toe (a) hip (b) knee

Firstly, we randomly choose 63 trials using stratified random sampling method, and classify data into three data sets (learning (70%), verification (15%) and test (15%)) to train the BPNN for classification. As the BPNN results change for each learning, we take the best result within 10 learnings as shown in Table II. The average recognition rate is 99.83%, which reflects the availability.

TABLE II
RESULT OF CLASSIFICATION USING BPNN

		Classification Result (%)						
		GR1	GR2	GR3	GR4	GR5	GR6	Average
Terrain	GR1	**99.70**	0.20	0.09	0.00	0.00	0.00	-
	GR2	0.04	**99.84**	0.10	0.01	0.01	0.00	-
	GR3	0.09	0.20	**99.71**	0.00	0.00	0.00	-
	GR4	0.02	0.00	0.01	**99.90**	0.07	0.01	-
	GR5	0.01	0.00	0.00	0.12	**99.86**	0.02	-
	GR6	0.00	0.00	0.00	0.00	0.02	**99.98**	-
Success Rate		99.70	99.84	99.71	99.90	99.86	99.98	**99.83**

After BPNN-training, we use the rest 27 trails as extra test to verify the classification BPNN in real-time classification. As shown in Table III, the average recognition rate is 98.33%, which is slightly lower, but good enough for a real-time verification.

TABLE III
RESULT OF CLASSIFICATION USING BPNN (ADDITIONAL TEST)

		Classification Result (%)						
		GR1	GR2	GR3	GR4	GR5	GR6	Average
Terrain	GR1	**99.82**	0.18	0.00	0.00	0.00	0.00	-
	GR2	0.00	**99.84**	0.14	0.00	0.02	0.00	-
	GR3	0.00	0.07	**99.93**	0.00	0.00	0.00	-
	GR4	0.00	0.00	0.36	**98.45**	0.64	0.55	-
	GR5	0.00	0.00	0.14	0.05	**94.34**	5.48	-
	GR6	2.12	0.00	0.00	0.00	0.31	**97.57**	-
Success Rate		99.82	99.84	99.93	98.45	94.34	97.57	**98.33**

V. CONCLUSIONS AND FUTURE WORK

In this paper, we fuses data from foot-ground contact force senor, 6-axis motion sensor, DC motor current and joint encoder to achieve classification of the different ground substrates using BPNN. Moreover, in order to enhance the stability of the walk strategy proposed in our previous work to adapt different ground substrates, we present the COG adjustment method with 6-axis motion sensor feedback. As a result, the planned and the detected swing phase is consistent, and the foot can lift off successfully in swing phase. Using these method, the quadruped robot Biodog realized walking on six different ground material, and finished sensor data collection in the meanwhile. In network training, about 99.83% samples have been classified correctly using BPNN. In real-time testing, about 98.33% has been classified successfully using trained BPNN.

Future work will be aimed at testing the proposed methods in outdoor environment, such as gravel, grass, and paving land. Moreover, locomotion strategy needs to be further strengthened for outdoor environment.

ACKNOWLEDGMENT

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REFERENCES

[1] K. Kim, K. Ko, W. Kim, S. Yu, and C. Han, "Performance comparison between neural network and SVM for terrain classification of legged robot," in *SICE Annual Conference* 2010, pp. 1343-1348.

[2] M. Hoepflinger, C. Remy, M. Hutter, and R. Siegwart, "The quadruped ALoF and a step towards real world haptic terrain classification," in *12th Mechatronics Forum Biennial International Conference, Zurich*, 2010, pp. 173-180.

[3] M. A. Hoepflinger, C. D. Remy, M. Hutter, L. Spinello, and R. Siegwart, "Haptic terrain classification for legged robots," in *Robotics and Automation (ICRA), 2010 IEEE International Conference on*, 2010, pp. 2828-2833.

[4] M. Hoffmann, K. Štěpánová, and M. Reinstein, "The effect of motor action and different sensory modalities on terrain classification in a quadruped robot running with multiple gaits," *Robotics and Autonomous Systems,* vol. 62, pp. 1790-1798, 2014.

[5] D. L. Hall and R. J. Linn, "A taxonomy of algorithms for multisensor data fusion," in *Proc. 1990 Joint Service Data Fusion Symp*, 1990.

[6] B. Kuipers and Y.-T. Byun, "A robot exploration and mapping strategy based on a semantic hierarchy of spatial representations," *Robotics and autonomous systems,* vol. 8, pp. 47-63, 1991.

[7] F. Fang, X. Ma, and X. Dai, "A multi-sensor fusion SLAM approach for mobile robots," in *Mechatronics and Automation, 2005 IEEE International Conference*, 2005, pp. 1837-1841.

[8] G. Nützi, S. Weiss, D. Scaramuzza, and R. Siegwart, "Fusion of IMU and vision for absolute scale estimation in monocular SLAM," *Journal of intelligent & robotic systems,* vol. 61, pp. 287-299, 2011.

[9] R. C. Luo, M.-H. Lin, and R. S. Scherp, "Dynamic multi-sensor data fusion system for intelligent robots," *IEEE Journal on Robotics and Automation,* vol. 4, pp. 386-396, 1988.

[10] V. Dietrich, D. Chen, K. M. Wurm, G. v. Wichert, and P. Ennen, "Probabilistic multi-sensor fusion based on signed distance functions," in *Robotics and Automation (ICRA), 2016 IEEE International Conference on*, 2016, pp. 1873-1878.

[11] Q. Li, L. Chen, M. Li, S.-L. Shaw, and A. Nuchter, "A sensor-fusion drivable-region and lane-detection system for autonomous vehicle navigation in challenging road scenarios," *IEEE Transactions on Vehicular Technology,* vol. 63, pp. 540-555, 2014.

[12] N. Ghosh, Y. Ravi, A. Patra, S. Mukhopadhyay, S. Paul, A. Mohanty*, et al.*, "Estimation of tool wear during CNC milling using neural network-based sensor fusion," *Mechanical Systems and Signal Processing,* vol. 21, pp. 466-479, 2007.

[13] H. Kimura and Y. Fukuoka, "Biologically inspired adaptive dynamic walking in outdoor environment using a self-contained quadruped robot: 'Tekken2'," in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2004. (IROS 2004).* , 2004, pp. 986-991 vol.1.

[14] D. T. Tran, I. M. Koo, Y. H. Lee, H. Moon, S. Park, J. C. Koo*, et al.*, "Central pattern generator based reflexive control of quadruped walking robots using a recurrent neural network," *Robotics and Autonomous Systems,* vol. 62, pp. 1497-1516, 2014.

[15] Z. Huang and W. Wang, "Controller-switching based gait transition for a quadruped robot," in *2016 IEEE International Conference on Mechatronics and Automation (ICMA),* , 2016, pp. 653-658.