Research on Terrain Recognition for Gait Selection of Hexapod Robot

Xiang Zhou¹, Wu Wei¹, Yong Gao¹*, Kuilin Li¹ and Ruidong Chen¹

¹School of Automation Science and Engineering, South China University of Technology, Guangdong, China

*Corresponding author

Abstract. In order to improve the stability of the hexapod robot walking in different terrains, this paper adopts the strategy corresponding to the terrain environment and the motion gait, that is, the robot selects the gait that keeps the robot walk safer and more stable according to the identified terrain. In this paper, using the self-established data set, Terrain6, for terrain classification, the feature extraction of terrain images for hexapod robot is realized firstly based on the Convolutional Neural Networks and the transfer learning. Secondly, according to the stacking fusion method, a terrain recognition model with higher precision is obtained by integrating three terrain classification models include the support vector machine, the naive Bayes and the random forest algorithm. Finally, the experiments show that the hexapod robot selects suitable gait based on the result of terrain recognition to cross complex environment, and the stable and efficient motion of the robot verifies the validity of the research results.

1. Introduction

With its many degrees of freedom, multiple limbs and discrete landing points, the multi-footed robot can achieve stable walking and perform tasks under various complex terrains [1]. As a typical example of a multi-legged walking robot, the hexapod robot has a wide range of motion gait, flexible and variable control scheme, and extremely strong load capacity [2], so it has broad application prospects. In order to improve the stability and adaptability of the hexapod robot in the unknown complex terrain environment, it is necessary to perceive the terrain environment through the sensors carried by itself [3], and then adopt the corresponding gait control strategy to achieve the desired motion.

During the movement of the robot, the terrain environment picture can be obtained by the camera, and then the color, texture, shape and other characteristic information of the picture are obtained by the classifier model. This kind of terrain classification method based on visual information has been widely used in the field of robotics. In 2011, based on the local texture features of topographic images, Khan et al. selected a random forest classifier with the best overall performance to achieve terrain classification by comparing various classification models [4]. In 2012, Filichkin and Byl of the UCSB Robotics Institute extracted the image features of the terrain environment of the robot based on the Speed Up Robust Feature (SURF) algorithm, generated a relatively compact terrain feature vector through the visual word bag model, and implemented the terrain classification using Support Vector Machines (SVM) classification model. This method has been successfully implanted on the LittleDog robot of Boston Dynamic Robotics [5]. In 2013, for the hexapod robot AMOS II, Steffen Zenker et al. used Scale Invariant Feature Transform (SIFT) or SURF to realize terrain feature detection and implement terrain classification based on SVM [3]. In 2014, for the terrain recognition of outdoor mobile robots, Yuhua Zou et al. experimented with several classifiers of extreme learning machine.
(ELM), SVM and nearest neighbor (NN) to evaluate the performance of different image descriptors and classifier combinations [6].

Based on Convolutional Neural Networks, transfer learning and fusion algorithm, this paper classifies and identifies the terrain environment of the hexapod robot, and then selects the corresponding gait mode according to different terrain environments to achieve stable motion in complex environments. The terrain recognition algorithm framework for hexapod robot designed in this paper is shown in Figure 1. The terrain recognition method is divided into offline model training and online terrain recognition. The offline model training is based on the collected terrain dataset to train the recognition model. The online terrain recognition is based on the terrain information collected by the camera carried by the hexapod robot body for real-time terrain classification. Both parts need to use the terrain image of the environment in which the robot is located. Based on the MobileNet Convolutional Neural Networks model in the remote host of the robot control system (a PC with two 1080Ti GPUs), the features of the image are extracted and vectorized [7]. The offline part uses the collected terrain dataset to train three separate models of support vector machine, naive Bayes and random forest, and then use the stacking model fusion method to fuse the three models to obtain the final high-precision terrain recognition model. The online terrain recognition directly utilizes the offline training model, and the environmental terrain image acquired by the camera carried by the hexapod robot body is transmitted to the remote host system through the local area network for online classification and recognition. Finally, according to the results of terrain recognition, the hexapod robot selects the appropriate motion gait and control scheme to complete the specified motion control task.

![Figure 1. Terrain recognition flow chart.](image)

2. Data Set Establishment

This paper first establishes the data set Terrain6 which is suitable for the terrain classification of the hexapod robot. The data set includes six typical terrains that the subject robot may encounter: tile floor, concrete floor, grassland, sandy land, ground covered with roots, gravel floor, as shown in Figure 2. Each picture is cropped to a pixel value of 256*256, and each type of image contains 250 sheets. Most of the pictures are taken by the camera carried by the robot body under different lighting conditions and weather conditions, and a small part comes from the Internet.

![Figure 2. Terrain6 typical terrains.](image)
After collecting the required terrain images, the subject uses image augmentation technology to expand the acquired terrain image dataset by changing the brightness or contrast, random cropping, and rotation of the image to provide more training samples for model training. At the same time, because the augmentation technique randomly changes the sample, the model's dependence on certain attributes can be reduced, thereby improving the generalization ability of the model and preventing the model from overfitting.

3. Feature Extractor Design
Considering the hardware configuration of hexapod robot and the real-time requirements of terrain recognition, this paper uses MobileNet Convolutional Neural Networks to extract terrain image features based on transfer learning method, and then uses the extracted image feature training classifier to realize the recognition of terrain by robot. With classification.

![Figure 3. MobileNet neural network based on transfer learning.](image)

The MobileNet Convolutional Neural Networks model based on transfer learning built in this paper is improved by ImageNet large image dataset model. As shown in Figure 3, the model has 28 layers. The 1-26 layers extract features from the image, and the last two layers classify the images based on the extracted features. Since the self-built Terrain6 data set belongs to the image classification problem of small data sets, the transfer learning method is used to freeze the 1-22 layer parameters in the pre-training model [8], and only the 23-26 layer model parameters are retrained. A full connection layer of 500 nodes is added after the 26th layer for extracting picture features. The improved model is trained by using the hexapod robot terrain data set Terrain6, and the network structure parameters after 22 layers are updated to obtain and save the trained model. Finally, the fully connected layer of the original MobileNet neural network classifier part is removed, only retain the feature extraction part of the original model and the improved fully connected layer are added as a new picture feature extractor. The feature of each picture in the data set is represented as a feature vector of length 500, and the picture feature vector set and its corresponding terrain category tag are saved as a training data set of the terrain recognition classifier.

Based on the Keras deep learning framework, the cross entropy loss function commonly used in multi-classification problems is used as the loss function of MobileNet convolutional neural training, and the model is iteratively trained with Adam as the model optimizer. The number of iterations is 30 times. Figure 4 shows the training effect.

![Figure 4. Training effect of MobileNet neural network: (a) Accuracy, (b) Loss.](image)
It can be seen from Figure 4 that the MobileNet Convolutional Neural Networks based on transfer learning has a good training effect. The accuracy of the model on the training set and the cross-validation set is high (Figure 4 (a)), and the training error is small and tends to converge (Figure 4 (b)).

4. Design and Training of Terrain Classification Model

This section will use the 500-dimensional picture feature vector and picture category label obtained in Section 3 to train the machine learning model for terrain recognition. In this paper, using the accuracy of terrain recognition as an evaluation index, the support vector machine, the naive Bayes and the random forest models are independently trained, and the model parameters are adjusted by 5-folds cross-validation method.

The support vector machine classifier uses a linear kernel as a kernel function. During the training process, the penalty coefficient C of the model is adjusted by cross-validation. When C=8, the model is optimal. The learning curve of the training process is shown in Figure 5. The Naive Bayes classifier is a generation model that is trained using the scikit-learn machine learning library. There are no parameters to be adjusted during the training, and the model training is fast. Its learning curve is shown in Figure 6. The parameters of the random forest model mainly include the number of weak model CART decision trees and the maximum depth of the CART decision tree. Cross-validation shows that when the number of decision trees is 120 and the maximum depth of the decision tree is 15, the model recognition accuracy is the highest, and the learning curve is shown in Figure 7.

The support vector machine classifier uses a linear kernel as a kernel function. During the training process, the penalty coefficient C of the model is adjusted by cross-validation. When C=8, the model is optimal. The learning curve of the training process is shown in Figure 5. The Naive Bayes classifier is a generation model that is trained using the scikit-learn machine learning library. There are no parameters to be adjusted during the training, and the model training is fast. Its learning curve is shown in Figure 6. The parameters of the random forest model mainly include the number of weak model CART decision trees and the maximum depth of the CART decision tree. Cross-validation shows that when the number of decision trees is 120 and the maximum depth of the decision tree is 15, the model recognition accuracy is the highest, and the learning curve is shown in Figure 7.

For the above three independent classification models, the final high-precision model is obtained by using the stacking model fusion strategy [9]. The stacking model fusion algorithm framework is shown in Figure 8. The training process can be broken down into three steps:

1) The terrain data set is disassembled into a training set and a test set according to a 4:1 ratio. At the same time, the training data is randomly and evenly divided into m parts, where m is 4.

2) On the disassembled training set, use the same training set to train the three classifier models described above. In Figure 8, model one is a terrain classifier based on support vector machine, model two is a terrain classifier based on naive Bayesian method, and model three is a terrain classifier based on random forest. The specific training method is to use (m-1) data training models for each individual
model to predict the remaining one. Subsequently, the trained model is predicted using the test set disassembled in step 1.

3) Based on the results obtained in step 2, train a secondary classifier model to obtain the final fusion model. The three training set prediction results are combined into a new training set, and the three test set prediction results are taken as a new test set. Using the new training set and the new test set, a new terrain classification model is trained by logistic regression. This model is a terrain classification model with three independent models.

The accuracy of the identification of each terrain classifier on the test set is shown in Table 1. It can be seen that the terrain classifier model based on stacking fusion proposed in this paper has higher recognition accuracy for terrain.

**Table 1. Recognition accuracy of various shape classifiers on test sets.**

| Classifier type  | Recognition accuracy on the test set | Classifier type  | Recognition accuracy on the test set |
|------------------|--------------------------------------|------------------|--------------------------------------|
| SVM              | 88.2%                                | random forest    | 90.3%                                |
| naive Bayes      | 87.6%                                | stacking fusion  | 94.6%                                |

5. Gait Selection of Hexapod Robot and Experiments on Prototype

The experimental platform of the hexapod robot prototype designed in this paper is shown in Figure 9. The robot has a rectangular body structure, six legs are distributed on both sides of the body in an axisymmetric manner, and each leg has three active rotating joints, each of which is driven by a steering gear.

According to the static balance condition of the robotic body, the more legs of the hexapod robot are in contact with the ground, the more stable the robot movement [10], but the slower the walking speed. The optional walking gait of the hexapod robot designed by this subject mainly includes: tripod gait, tetrapod gait and wave gait [11]. The stability of the above three gaits increases sequentially, but the walking speed decreases sequentially.

Considering the terrain recognition results and the motion requirements of the robot: When the local terrain recognition result is flat terrain such as cement floor or tile floor, the robot adopts tripod gait to achieve fast walking; when the local terrain recognition result is grass or sand, the robot should adopt tetrapod gait to walk as fast as possible while keeping the body stable; when the local terrain recognition result is complex terrain such as the ground covered with roots or the gravel floor, in order to ensure the stability of the robot, a wave gait that can be slowly advanced should be adopted.

Figure 10 shows the use of tripod gait when the hexapod recognizes that its location as tile floor. When the hexapod recognizes that its location as the grass, it uses the tetrapod gait, as shown in Figure 11. Figure 12 shows the use of wave gait when the hexapod recognizes its location as the ground covered with roots.
6. Conclusion
This paper mainly studies the problem of the terrain recognition and the gait selection of the hexapod robot. Based on the Terrain6, a self-built topographic image dataset, and combined with MobileNet Convolutional Neural Networks and transfer learning, a method of feature extraction of terrain images for hexapod robot was designed. Then, using the stacking fusion method, the three terrain classification models including support vector machine, naive Bayes and random forest are combined to obtain a more accurate terrain recognition model. Finally, the experiment shows that the hexapod robot selects the appropriate motion gait based on the terrain recognition results in three different environments, and verifies the validity of the research results.

In this paper, for the different types of terrain environment identified by the hexapod robot, the fixed rhythm gaits are selected. In the future work, we can consider adding force sensors, integrating foot force analysis and visual information to guide the robot to achieve more stable, safe and efficient adaptive motion under different terrains.

Acknowledgments
This paper supported by the National Natural Science Foundation of China (61573148), the Science and Technology Planning Project of Guangdong Province (2015B010919007, 2016A040403012, 2017B090901043), and the Science and Technology Planning Project of Guangzhou (201604046015, 201604046014, 2017171201).

References
[1] Manhong Li, Minglu Zhang, Jianhua Zhang, et al. 2015 Review on Key Technology of the Hexapod Robot (Tianjin: Journal of Machine Design) pp 1-8.
[2] He Zhang 2014 Research on Force Sensing Based Hexapod Robot and Control for Walking on Uneven Terrain (Harbin: Harbin Institute of Technology).
[3] Zenker S, Aksoy E E, Goldschmidt D, et al. 2013 Visual Terrain Classification for Selecting Energy Efficient Gaits of a Hexapod Robot 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) (New York: IEEE) pp 577-584.
[4] Khan Y N, Komma P, Bohlmann K, et al. 2011 Grid-based Visual Terrain Classification for Outdoor Robots using Local Features IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems (CIVTS 2011) Proceedings (New York: IEEE) pp 16-22.
[5] Filitchkin P and Byl K 2012 Feature-based Terrain Classification for Littledog 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (New York: IEEE) pp 1387-1392.
[6] Zou Y, Chen W, Xie L, et al. 2014 Comparison of Different Approaches to Visual Terrain Classification for Outdoor Mobile Robots vol 38 (Amsterdam: Elsevier) pp 54-62.
[7] Krizhevsky A, Sutskever I and Hinton G 2012 ImageNet Classification with Deep Convolutional Neural Networks NIPS (New York: Curran Associates Inc) pp 1097-1105.
[8] Gogul I and Kumar V S 2017 Flower Species Recognition System using Convolution Neural Networks and Transfer Learning 2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN) (New York: IEEE) pp 1-6.
[9] Zicheng Zhou 2018 The Research and Design of Telecom Customer Credit Model Based on Stacking Model Fusion (Guangzhou: South China University of Technology).
[10] Ding Kai 2016 Research on Biomimetic Gait Planning and Locomotion Control System for Hexapod Robots (Nanjing: Southeast University).
[11] Xiaolin Yin 2013 Research on Gait Planning and Control Strategy for Biomimetic Hexapod Robot (Harbin: Harbin Institute of Technology).