Self-Adaptive Correction of Heading Direction in Stair Climbing for Tracked Mobile Robots Using Visual Servoing Approach

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Abstract. In this paper, we describe a heading direction correction algorithm for a tracked mobile robot. To save hardware resources as far as possible, the mobile robot's wrist camera is used as the only sensor, which is rotated to face stairs. An ensemble heading deviation detector is proposed to help the mobile robot correct its heading direction. To improve the generalization ability, a multi-scale Gabor filter is used to process the input image previously. Final deviation result is acquired by applying the majority vote strategy on all the classifiers' results. The experimental results show that our detector is able to enable the mobile robot to correct its heading direction adaptively while it is climbing the stairs.

1. Introduction

In the field of indoor mobile robots, climbing stairs is a basic skill for mobile robots. Climbing stairs commonly include alignment stage, climbing stage and landing stage. In this paper, we focus on the posture correction of mobile robots in the climbing stage. At present, there are not many literatures about the heading correction in climbing stairs for mobile robots. For example, fusing rotational velocity measurements from 3-axial gyroscope and measurements of the stair edges acquired with an onboard camera, authors in reference[1] estimated the quaternion-based attitude by an extended Kalman filter and proposed a centering- and a heading-control control model to guide a tracked mobile robot upstairs by the estimates. The authors in reference [2] proposed a stair climbing algorithm based a Kinect sensor for a tracked mobile robot. This algorithm is able to make the robot have the ability to
align to the stairs, keep balance while climbing and land on the stair platform. In the climbing stage, the mobile robot correct its heading direction by the difference of two blocks from the depth image of stairs. A Kinect depth sensor is the only equipment needed for all the stages. The authors in reference [3] also used a Kinect sensor to correct the attitude of a mobile robot in climbing ramp. The reference [4] describes a tracked mobile robot, which takes a horizontal and a vertical LASER range finder to detect the staircase autonomously, correct the initial posture, climb the stairs and land on the stair platform.

To minimize the number of sensors on the mobile robot, in this paper, we intend to use monocular vision to achieve adaptive correction of the heading direction for the mobile robot in climbing stairs. To this end, we take the heading direction deviation detection problem as a classification problem, and therefore an ensemble heading deviation detector is proposed in this paper to predict whether the mobile robot’s heading direction has deviated. According to the predicting results, the mobile robot takes corresponding actions to correct its heading direction.

2. Overview of the System
The images used in this paper are captured by the wrist camera of a self-designed mobile robot. This mobile robot is a kind of tracked mobile robot, which is used for reconnaissance detection [5]. Before self-adaptive correcting the heading direction, the mobile robot rotates the wrist camera to face the stairs, as shown in Figure 1.

![Figure 1. Mobile robot for experiments](image1)

![Figure 2. Gabor filter bank](image2)

![Figure 3. Structure of ensemble heading deviation detector](image3)
Our proposed ensemble heading deviation detector consists of three phases, image texture information extraction, training and predicting of ensemble heading deviation detector. Figure 3 shows the overall block diagram of our proposed ensemble heading deviation detector in this paper.

3. Proposed Method

3.1 Multi-scale texture feature extraction

To eliminate the interference of vertical segments in the image, a multi-scale Gabor filter (five scales at seven directions, not including 90 degree) is used to extract the image texture features, as shown in Figure 2. The impulse response of the Gabor filter is defined as a sine wave (2D Gabor filter is a sinusoidal plane wave) multiplied by the Gauss function [6]. The complex form expression of the 2D Gabor filter is shown below:

\[
G(x, y) = \frac{1}{2\pi \sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \exp(i(2\pi \frac{x}{\lambda} + \psi))
\]

\[
x = x \cos \theta + y \sin \theta
\]

\[
y = -x \sin \theta + y \cos \theta
\]

where \(\lambda\) is the wavelength of sine wave, \(\theta\) represents the direction of parallel wavelet of Gabor wavelet, \(\psi\) is phase offset, \(\gamma\) is the aspect ratio of Gabor wavelet, which determines the shape of the Gabor wavelet, \(\sigma\) is standard deviation of the Gaussian function.

3.2 Ensemble heading deviation detector

In this paper, our ensemble heading deviation detector adopts the homogeneous ensemble method, and a variant of Convolutional Neural Network, INF-net, is taken as the basal classifier. The structure of INF-net is shown in Figure 4. The activation function of each layer is ReLU function, and the pooling layer takes max-pooling strategy. The output layer contains three neurons, which represent left deviation, right deviation and no deviating respectively. The INF-net can also be seen as a special case of SPP-net [7] where its pyramid layer number is one.

In this paper, to get the sample set of our ensemble heading deviation detector, the mobile robot is controlled to climb stairs. After having captured the samples of left deviation, right deviation and no deviating, corresponding labels are given to them. Considering the samples balance, a total of 4850 frames (60 \times 60) is collected. Partial frames are shown in Figure 5. We extract 1/5 frames from those frames randomly as the test sample set, and the remaining frames as the training sample set.
3.3 Predicting and correcting

Heading deviation angle $\theta$ is defined as the angle between the robot’s heading direction and the centerline of staircase. To improve the generalization ability of the ensemble heading deviation detector, a multi-scale Gabor filter banks is used to process input image previously. Before this preprocessing, the images is converted to grayscale image firstly. At each scale a frame of texture feature image is calculated by summing and normalizing all directions of the texture image. The formula is as follows:

$$ F_i = \frac{\sum_{m=1}^{M} f_i^m}{M} $$

(2)

where $M$ represents the number of filter directions, $f_i^m$ represents the $m$-th texture feature image at i-th scale, $F_i$ is the texture feature image at $i$-th scale. Final deviation result is acquired by applying the majority vote strategy on all the deviation results predicted by each classifier.

$$ \text{Final Output} = \text{majorityvote}(\text{Output}_1, \ldots, \text{Output}_N) $$

(3)

After the ensemble heading deviation detector outputs the final result, the robot correct the heading direction according to this final result. Specifically, the robot correct its heading direction according to the formula (4). Where, action represents the executable action of the mobile robot.

$$ action = \begin{cases} 
\text{right forward}, & \theta = 1 \\
\text{forward}, & \theta = 0, \text{ where } \theta = \begin{cases} 
-1, & \text{left deflection} \\
0, & \text{no deflecting} \\
1, & \text{right deflection}
\end{cases} \\
\text{left forward}, & \theta = -1
\end{cases} $$

(4)

4. Experiments

4.1 k-fold cross validation and comparison experiment

To eliminate the interference of vertical segments in the image, we used a Gabor filter (five scales at seven directions, not including 90 degree) to preprocess the input image. To validate the performance of the detector, we used the 10-fold cross validation method in the testing experiment. The learning rate of each INF-net at five scales was set to 1, the iterations was set to 10, the dropout rate was set to 5% and the kernel size of Gabor filter was all set to 10. The Figure 6(a) shows the training error curve of INF-net at five scales. From the Figure 6(a), we find that the training error decreases rapidly with the increase of the iterations. At the end of each iteration, our proposed algorithm was tested on the test set. The blue line in Figure 6(b) shows the accuracy of our proposed algorithm. In order to verify the performance of our proposed algorithm, we compare our proposed algorithm with the traditional
algorithm (single scale gray feature and single classifier). The red line in Figure 6(b) shows the accuracy of the traditional algorithm.

As can be seen from the above figures, the recognition rate of our detector can reach up to 99.67%. From the sixth iteration, the recognition rate has a slight decrease, which may be due to the over-fitting. Overall, our proposed algorithm (multi-scale texture feature extraction + ensemble classifier) has a better performance than the traditional algorithm (single scale gray feature + single classifier). In order to achieve the best results, the five INF-nets was used as the basis classifier of the ensemble heading deviation detector when the sixth iteration was finished.

![Figure 6. Training errors and accuracy rates](image)

4.2 Artificial disturbance

![Figure 7. Heading direction correction with artificial disturbance](image)

To verify the correction ability, artificial disturbances were added while the mobile robot was climbing the stairs (ascending-stair and descending-stair). By recording the heading directions, we got the process of our detector correcting the heading direction. Figure 7(a) shows the changes of the heading direction while the mobile robot climbing an ascending-stair, where section A and C are the changes of heading direction while the robot got an artificial disturbance and section B and D are the changes of heading direction while the mobile robot correcting the heading direction. Figure 7(b) shows the case of climbing a descending-stair, section E and G are the artificial disturbance phase and section F
and H are the correcting phase. As can be seen from the Figure 7, our proposed algorithm is able to enable the mobile robot correct its heading direction even if it is disturbed by an artificial disturbance, so as to ensure the mobile robot’s course has no deviating.

5. Conclusion
In this paper, an ensemble heading deviation detector is proposed, and this detector is applied to adaptively correct the heading direction for the mobile robot in climbing stairs. To improve the generalization ability, we combine the multi-scale Gabor filter with a majority vote strategy. The comparison experimental result shows that our proposed algorithm has a better performance than the traditional algorithm. In addition, an artificial disturbance experimental results show that our algorithm has a good ability to enable the mobile robot to correct its heading direction even if it is disturbed by an artificial disturbance while it is climbing stairs (ascending-stair and descending-stair).

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