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Implementation of the Status Control System by Using Environment Recognition and Motion Control

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Abstract: This paper presents the efficient status control system for a biped walking robot. A biped walking robot should have the ability to autonomously recognize its surrounding environment and make right decisions in corresponding to its situation. To solve the problem, we suggest the status control system which has two sub-parts, environment recognition system and motion control system. The environment recognition system transmits the information regarding obstacle conditions to a biped walking robot. We describe an adaboost algorithm as the obstacle region extracting module from input images. Besides, PCA is applied as a feature extracting module from the obstacle region and a hierarchical support vector machine is applied as an obstacle recognizing module. The data from vision system is combined with information from other sensors and the walking assist commands transmit to the biped walking robot. In the motion control system, a robot dynamically generates its walking trajectories of each joint by using neural networks when facing new obstacle such as stairs, and it maintains its walking stability by using closed loop fuzzy method. From the results of experiments, the proposed method can be applied to biped walking robot effectively.

Keywords: Environment recognition, Motion control, Biped walking robot.

1. INTRODUCTION

Biped walking robot has the similar structure to human being and has better mobility than wheeled robot. In other words, biped robot can walk on the non-continuous and uneven ground such as stairs, doorsill, while wheeled robots cannot move only on a continuous and even ground. However, biped robot is very difficult to control its posture.

Over the years, a number of researches are ongoing in environment recognition area. In the obstacle recognition area, the most common method for recognizing obstacles is line-based method in the literatures of vision system[1]. Besides, model-based obstacle recognition methods have been used in wheeled or biped walking robot[2]. Recently, SIFT(Scale Invariant Feature Transform)[3] is widely used in wheeled robot. Especially, it has been used mainly for vehicle recognition or obstacle/object recognition of wheeled robot[4][5]. However, those are not appropriate methods for a biped walking robot since the whole background moves with the target object when a robot walks unlike the cases of vehicle or wheeled robot. So, we propose the status control system involving the environment recognition system and walking control system which is appropriate and efficient. Environment recognition system provides the proper information to climb up and down or avoid obstacles. Then walking control system realizes intelligent walking of the biped robot. In detail, environment recognition system have four parts - motion compensation as the preprocessing, extraction of obstacle candidate region using adaboost[6], obstacle feature extraction using PCA[7], and obstacle classification using hierarchical SVM. Besides, walking control system have two part, walking trajectory generation using neural networks[8] and walking control for real-time feedback using fuzzy method[9].

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This paper is organized as follows. In Chapter 2, the proposed environment recognition system and motion control system are introduced specifically. In Chapter 3, the results of experiments focusing on verifying the performances of the proposed system is given. They are distance measuring to a moving object and adaptive walking trajectory planning for walking in unknown environments. Chapter 4 concludes the paper by presenting the contributions.

2. STATUS CONTROL SYSTEM

2.1 Environment recognition system

In the environment recognition system, environment conditions for a biped walking robot are classified into three categories: slope, stairs and wall in a broad sense. Fig.1 shows the environment recognition system for the biped walking robot. This system is composed of four parts: motion compensation, obstacle region extraction, obstacle feature extraction, and obstacle classification. Image sequences are acquired form the vision camera installed on the biped walking robot. The robot and hostPC are connected with a BlueTooth wireless communication module using RS-232C.. The detailed methods are given as follows.

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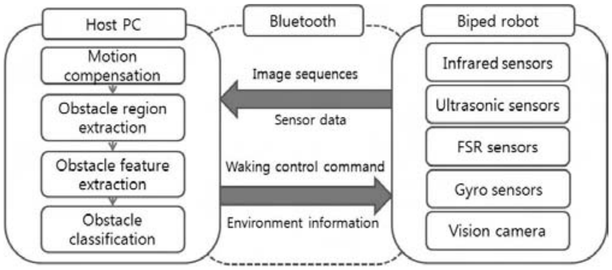

Fig. 1 The structure of environment recognition system.

2.1.1 Motion compensation

In the motion compensation, the motion model which reduces the effect of walking motion is generated in the biped walking robot platform. To generate a motion model, we need to analyze the walking motion of the biped walking robot.Fig. 2 shows the walking patterns of the biped walking robot by using fast cross correlation.

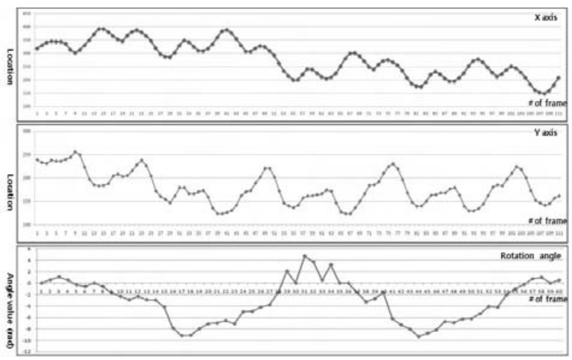

Fig. 2 Walking patterns of the biped walking robot.

As shown in Fig. 2, walking motions of the biped walking robot are periodic. In detail, the motion cycle of the biped robot is approximately 0.8sec. From the walking pattern, motion model is generated by the average periodic trajectory. Average periodic trajectory can be computed by the two stages. In the first stage, every motion trajectories which have many periodic cycles are divided into the motion cycles. Then all of the motion cycles are aligned for the peak point. In the second stage, the walking motion model which is used as the compensation model are generated by computing the average cycle for the all of cycles what we gets in the first stage. Fig. 3 shows the results of motion compensation by using the compensation model to the optical flow vectors in the biped walking robot platform. As shown in Fig. 3, motion compensation module efficiently reduces the motion effects which are translation and rotation motion of the biped walking robot.

2.1.2 Obstacle region extraction

In the obstacle recognition system, boosted classifier with a set of Haar filters as features is used as obstacle region extractor[10]. The basic scheme of a cascade of boosted classifier, as known as adaboost or general boosting algorithm, is to combine multiple weak classifiers into a more powerful decision rule for classification[6].

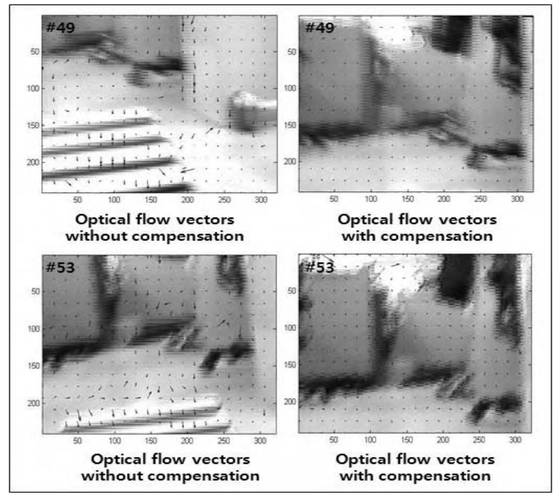

Fig. 3 The results of the compensation.

The algorithm performs a sequence of training rounds, and at each round a new classifier is trained. Initially, each training vector has an associated weight that encodes its importance in the learning algorithm. The training set is classified according to the decision rule of the current step, and then the weights are modified according to the classification results. The result is a set of classifiers which combined achieve higher classification ratios. A weak classifier is not capable of detecting a rotated or translated input image. However, once a boosted classifier is generated, it is able to adaptively detect the obstacles even when they are rotated or translated.

Given example images $(x_1, y_1), \ldots, (x_n, y_n)$
where $y_i = 0,\ 1$ for negative and positive examples repectively.
Initialize weights $w_{1,i} = \frac{1}{2m},\ \frac{1}{2l}$ for $y_i = 0,\ 1$ respectively,
where m and l are the number of negatives and positives respectively.

For $t = 1, \ldots, T$:

1. Normalize the weights,
$$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
so that w_t is a probability distribution.
2. For each feature, j, train a classfier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\varepsilon_j = \sum_i w_i \left| h_j(x_i) - y_i \right|$.
3. Choose the classfier, h_t, with the lowest error ε_t.
4. Update the weights :
$$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, $\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$.

The final strong classifier is :
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
where $\alpha_t = \log \frac{1}{\beta_t}$

Fig. 4 Procedure of adaboost classifier.

The brief algorithm of adaboost is introduced in Fig. 4. Consequently, the region of obstacle from input image is obtained as a result of using the generated cascade of boosted classifier.

2.1.3 Obstacle feature extraction

PCA is known as a useful technique to extract dominant features or reduce the dimensionality of large data sets in image processing and data mining and can also be used to find signals in noisy data in signal processing. In some cases, the dimension of the input is too large, but the components in the input are highly correlated, PCA is useful to reduce the dimension of the input. PCA has three representative effects: First, it orthogonalizes the components of the input vectors. Then, they are uncorrelated with each other. Second, it orders the resulting orthogonal components (principal components). Then, those with the largest variation come first. Third, it eliminates those components that contribute the least to the variation in the data set[7]. Since the results derived from PCA are orthogonal to each other, there is much less redundancies in the resulting data.

In this paper, input dataset which have different dimension, 50 and 25 are generated to be modeled by SVM. The whole input data (320 x 240) from input images are transformed by PCA first. Then the generated arrays having the trends of the original data (number of samples x 50 or number of samples x 25) are extracted. Hence, the finally resulting arrays contain 50 or 25 dimensional data containing the principal information of the original input image. These arrays are split into training and test dataset for training and testing SVM, respectively. Moreover Mahalanobis distance[11] which is based on correlations between variables by which different patterns can be identified is used to represent the features precisely.

2.1.4 Obstacle classification

To recognize and classify the obstacles which a biped walking robot faces while walking, a hierarchical SVM is implemented to construct an efficient classifier.

Because SVM can be analyzed theoretically using concepts from the statistical learning theory, it has particular advantages when applied to problems with limited training samples in the high-dimensional space[12]. Consequently, SVM can achieve a good performance when applied to real problem.

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The structure of the proposed hierarchical SVM is depicted in Fig. 5. When an obstacle is detected by the vision and ultrasonic sensors installed in the robot, the input image is processed by the procedures represented in Fig. 5. In the classification process, SVM classifier trained to classify even surfaces and walls is applied to the extracted features of the input image at the first stage. It determines whether the robot can climb up the obstacle or not, and returns the possibility of climbing up to the robot by using the bluetooth communication. Then the robot modifies its motion trajectory to avoid the obstacle in case of wall or other unclimbable obstacle. If the obstacle is classified as climbable by the first SVM classifier, the features are applied to the SVM second classifier and it classifies the object into the categories of stairs or a slope. Then the recognition system determines the more detailed information such as the height and width of a stair and the inclining degree of a slope, according to the information obtained from infrared sensors. Also, the determined result is transmitted to the robot and the robot generates a corresponding trajectory to the obstacle.

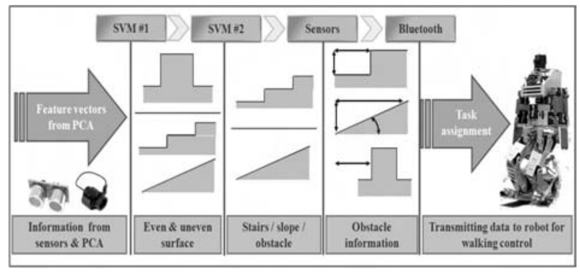

Fig. 5 Proposed hierarchical SVM structure.

2.2 Walking control system

This chapter briefly describes the procedure of autonomously generating walking motion trajectory from the result of the environment recognition system.

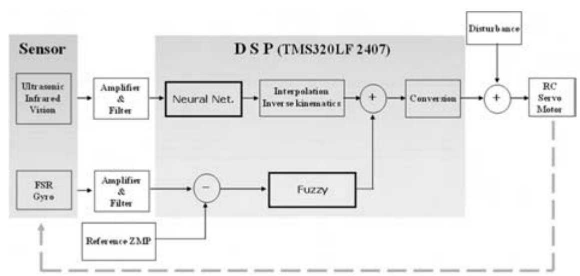

Fig. 6 Motion control system for a biped walking robot.

Fig. 6 shows the structure of motion control system in a biped walking robot. When an obstacle is recognized by the environment recognition system using the vision camera, the robot tries to model the obstacle by using ultrasonic and infrared sensors. For instance, in case of moving from a plain surface to an inclining surface, the approximated starting point of the inclining surface is detected by the distance value obtained from ultrasonic sensors and the inclining degree is calculated by the time series of data from the sensors. For the real-time autonomous trajectory generation process, a neural network generates the starting points, the highest points and the end points in hip and ankle trajectories. Fig. 7 shows the procedure of trajectory generation.

By using those outputs of neural networks, the whole trajectories in hip and ankle are calculated in the forms of spline function and trajectories in other joints are generated by calculating inverse kinematics. Besides, for the stable walking, fuzzy system is applied to a main con-

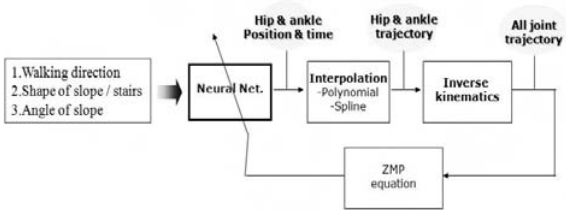

Fig. 7 Trajectory generation by using a neural network.

troller system for real time feedback. Fig. 8 shows the real-time motion control module by using fuzzy logic controller.

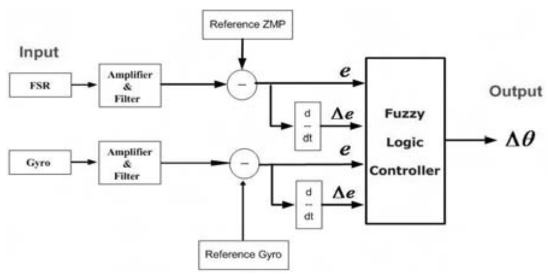

Fig. 8 real-time motion control module by using fuzzy logic controller.

As shown in Fig. 8, ZMP error and Gyro error are used as the input data and fuzzy logic controller calculates the angle to compensate the error. Fuzzy logic controller uses the Mandanic min-max product method as the fuzzy inference and uses the center of gravity as the defuzzification method.

3. EXPERIMENTS AND RESULTS

3.1 Recognition experiments for the compensation and the metric

First experiment is the recognition performance for the compensation and metric. The proposed system is evaluated by applying 150 periodic video streams. 50 periods are used as the training data, and the rest of them are used as the testing data. Training and testing data are selected randomly and experiments are performed under adaboost with 25x25 window size, PCA with 25 principal components, and hierarchical SVM with the polynomial kernel. Each experiment has seven trials. Fig. 9 shows the experimental results of recognition accuracy for the compensation. The top of Fig. 9 is the results of the recognition experiment for the wall, the middle image shows the results of the recognition experiment for the slope, and the bottom image also present recognition results for the stairs.

As shown in Fig. 9, recognition accuracies with compensation shows the better performance about 5% than recognition accuracies without compensation. Fig. 10 also shows the recognition results for the Euclidean and Mahalanobis metric. Upper image of Fig. 10 is the result with Euclidean metric and lower image is the result with Mahalanoobis metric. As shown in Fig. 10, the result of recognition having Mahalanobis metric with compensation shows the higher performance about 3%(average) than the ones of the recognition having Euclidean metric.

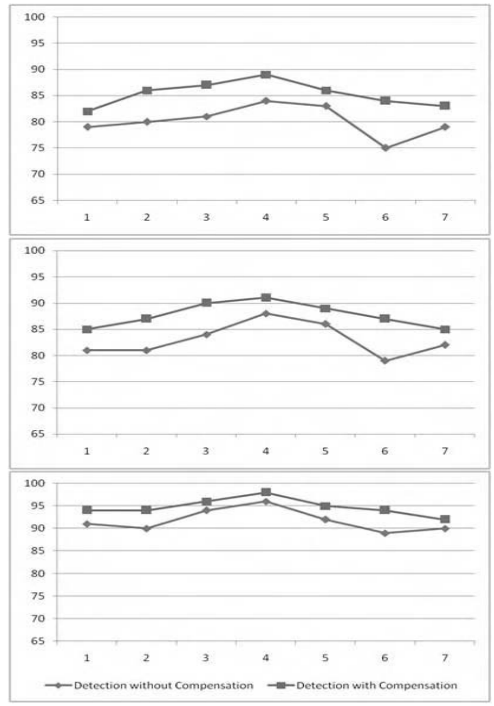

Fig. 9 Recognition results for the motion compensation.

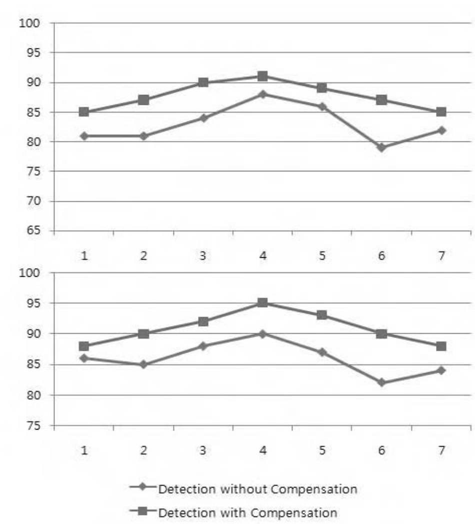

Fig. 10 Recognition results for the metric.

3.2 Recognition experiments for the compensation and the metric

Second experiment is the recognition performance for the kernel type(linear, polynomial, RBF) which belongs to hierarchical SVM, window size(25x25, 30x30) which belongs to adaboost, and the number of principal component(25, 50) which belongs to PCA.

From the evaluation in Fig. 11, the results of recognition performance show differences for the types of obstacles. Upper image in Fig. 11 is the recognition result using window with 25x25 in adaboost and lower image is the result using window with 30x30. Front numbers of SVM kernels mean the number of PC in PCA. In case of wall and slope, the region detection accuracy by daboost is relatively high, however they also have high false alarm rate. The total accuracies of both cases are about 85-89%, which is not satisfactory. On the contrary, the classification accuracy of stairs is approximately 93-98%. It is higher than the ones of other obstacles.

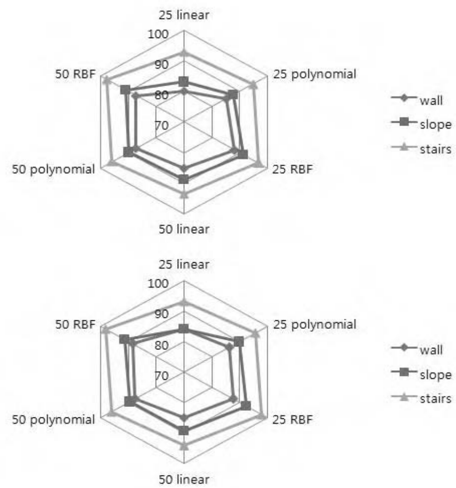

Fig. 11 Recognition results for the types.

4. CONCLUSION

We present the status control system of biped walking robot through the environment recognition and walking motion control. They are the mandatory conditions to make a robot autonomously recognize its surrounding environment and adaptively walk by generating its motion trajectories. This paper has the meaning of developing aid technologies for biped robot walking control. For the efficient performance, the environment system including a hierarchical SVM and the motion control system including neural networks and fuzzy method are proposed in this paper. This system is verified their effectiveness with a number of experiments by implementing them into a biped walking robot. Moreover there is a need of developing a stereo- vision system which works in a biped walking robot system itself, because the stereo-vision system offer the more various and detailed information regarding the environment. Motion compensation method which has the generality in the generation of the model is also needed for the biped walking robot.

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