SIMULATION OF NAVIGATION CONTROL AND OBSTACLE AVOIDANCE FOR AGV BY COMPUTER VISION WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The objective of this paper is to simulate the algorithm to control the vehicles based solutions to an Automated Guide Vehicle (AGV) guidance problem, namely to visual path and obstacle avoidance. Currently, AGV is a transport vehicle widely used in manufacturing industry. It can work automatically according to conditions, and the directions to destination are defined, but it cannot avoid obstacles in front by itself. The computer vision with artificial neural networks (ANN) can help the AGV can be seen and decide like a human. AGV guidance task is performed through neural networks, which has the ability to learn and memorize the route from the starting point to destination are defined by imitating the functions of the human brain. In this paper we use the Histograms of Oriented Gradient (HOG) to extract height objects feature from visual information in a hallway and the neural networks to identify the obstacles that are height object or non-height objects, then decide whether to hold or continue to be moved.

As a result, this paper presents the simulate the algorithm to control AGV that is flexible, which can work to destination are defined and avoided obstacles by computer vision with ANN as an alternative principle with high accuracy and reliability.

1. INTRODUCTION

One of the most important production is the flow of materials in the factory environment. The AGV is a transport vehicle widely used to move materials around a manufacturing facilities or warehouses. This system can also reduce labor costs in industry, as well as increasing the safety of its employees from working in dangerous environments. The navigation principles are different, such as markers or wires in the floor, magnets, lasers, or vision for navigation. It can transport materials and equipment to various locations in industry that work automatically according to conditions, and the directions to destination are defined, but it cannot avoid obstacles in front by itself. We can improve the performance of the AGV by making the AGV has the ability to see and recognize them like human beings.

The computer vision with ANN is mathematical for a computer that can imitate the function of human brain, which can help the AGV can see and recognize like a human. So far, many recognition and classification methods have proposed. When considering the actual AGV driving situation on the path, it is desirable to be able to recognize the preceding obstacles. In order to prevent a collision to the obstacles and the AGVs. Several works have been developed using neural networks for image analysis applied to obstacles recognition and classification, which is an important task in an automotive safety application. For examples, Marcos & Roseli (2006) proposed the objects detection and recognition of mobile robot, which is implemented by using sonar and a color classification method based on multi-layer perceptrons (MLP) neural networks. But this system can only be used to track objects of a specific color. One aspect has been neglected in previous studies is the obstacles do not know the exact shape, size and color. Guangyuan Zhang, et al. (2010) proposed the human detection system by using the HOG features to extract the specific features of the human by the distribution of intensity gradients or edge directions regardless of size or color of human. Then, the linear support vector machines (SVMs) is used as a classifier for the pedestrian detection. This process is a comparison and recognition, which can be applied to separate and identify the feature of pedestrian efficiently.

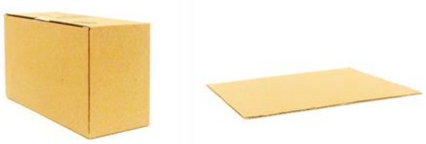
Moreover, Naveen Kumar Anumula et al. (2015) proposed an automatic road sign recognition to classify into six signs by using Multi-Layer Feed-forward ANN (MLF-ANN) with three layers, which classified into six signs. This method has the flexibility to specify the meaning of the traffic signs accurately in different lighting conditions, including different angle of views as well.

In this paper, we propose a combined computer vision system based on HOG features and ANN for simulate the algorithm to control AGV. The algorithm consists of three main states: pre-processing, feature extraction and classification.

2. EXPERIMENT

2.1 Experimental Apparatus

The aim of this experiment is to simulate the algorithm to classify the obstacles that are real obstacles or fake obstacles such as a painting on the floor, which most objects might be found in factories are simple boxes as in Fig. 1. We created an experiment to extract feature of the obstacles in the actual video images by using a HOG method and classify the obstacles by using neural networks (NN). These images were processed by using the black and white camera.



(a) a real obstacle (b) a fake obstacle

Fig. 1: The obstacle images.

2.2 Algorithm

In general, the AGV camera will take pictures in front looking directly at the object in the front view as in Fig. 2. However, even if the object is a three-dimensional object, but the camera images can be seen, it is a two-dimensional image based on the principles of an orthographic projection. An orthographic projection is a two-dimensional representation of a three-dimensional object, which two-dimensional drawing represents different s ides of an object. We can use this principle to analyze the specific features of the obstacles that need to detect.

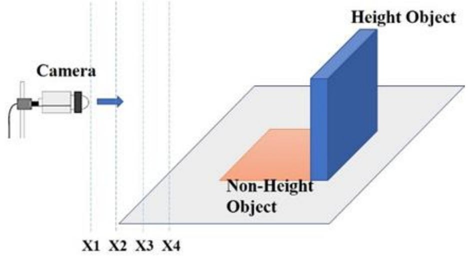


Fig. 2: Preview of the AGV camera is perspective and Xi: distances between the subject and the AGV.

2.2.1 Pre-processing

Prior to extract feature, training and testing a classifier, a pre-processing step is image enhancement applied to remove noise for highlight certain features of interest in the images, cropped to region of interest and downscale to 256x256 size. This provides better feature vectors for training the classifier. The most important thing is to detect and treat the edges of the object in the image.

The results of this experiment can detect the edges of the object in every shape, height and orientation of the height objects and the non-height objects as in Fig. 3 and Fig. 4 respectively.

Fig. 3: The examples of the edge detection: 1st and 3rd column shows the original images, 2nd and 4th column shows the edge of the height objects.

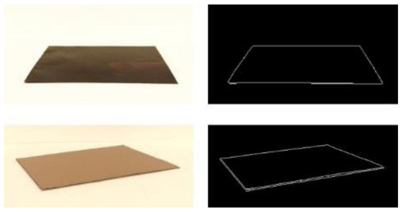


Fig 4: The examples of the edge detection: 1st column shows the original images and 2nd column shows the edge of the non-height objects.

2.2.2 Feature extraction based on HOG

Histograms of Oriented Gradient was first proposed by Dalal & Triggs (2005), devised a method to be used to detect humans. On the basic of HOG to use the features of shape. HOG counts occurrences of gradient orientation in part of an image hence it is an appearance descriptor regardless of size or color of the object in the image. By means of dividing the image into small cells. Each cell will contain the orientation of gradient, which is stored in the form of histogram, can be calculated by using 1D - discrete derivative masks in both the horizontal and vertical direction by equation (1). So, being given an image *I*, we obtain the x and y derivative. Each pixel in the cell will have the magnitude and orientation similar by equation (2), (3) respectively. To optimize accuracy, the histograms have been normalized for releasing the calculation of the indicators and the intensity of overlap of the cells within the block to reduce the impact of the illumination and contrast variation. Therefore, cells belonging to the same group will have the histogram value similar. When the calculation of the gradient and the direction of shape in image, then explain the image in histogram as in Fig. 5.

$$I_x = I * [-1 \quad 0 \quad 1],\ I_y = I * [-1 \quad 0 \quad 1]^T, \tag{1}$$

$$|G| = \sqrt{I_x{}^2 + I_y{}^2} \tag{2}$$

$$\theta = \arctan(I_y / I_x) \tag{3}$$

This experiment sets linear gradient voting into 9 orientation bins in 0 to 180 degrees, 2×2 blocks and 8×8 pixel cells. From the results, the feature length of each image is 34596 and a common features of many images of height objects is the northward vectors, aligned as a vertical line to narrow the boundary of the objects as in Fig. 6(a) and the non-height objects do not have the northward vectors, aligned as a vertical line as in Fig. 6(b). We can use this information for the obstacles classification.

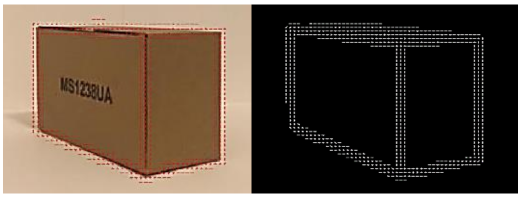
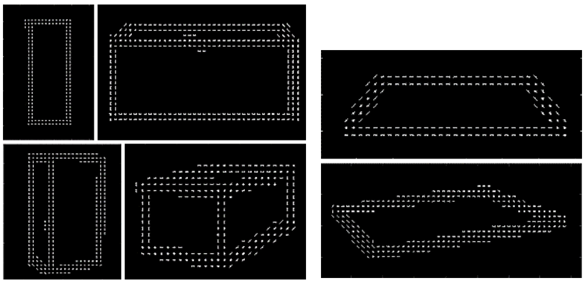


Fig. 5: HOG descriptor



(a) The real obstacles (b) The fake obstacles

Fig. 6: Preview the shape information of the HOG feature vector.

2.2.3 Classification with a Multiple Layers Artificial Neural Network (ML-ANN)

The artificial neural network is an attractive alternative due to the neural networks has the ability to learn on their own like human brain. The ANN is a mathematical model for information processing by calculating connectionist. The ANN has been developed as biological neural networks, which in an ANN consists of neurons are connected together to form a network which mimics a biological neural network. In a simple mathematical model of ML-ANN consists of nodes organized into three class called "Layer" include input layer, hidden layer and output layer, the effects of the synapses are represented by connection weights that modulate the effect of associated input signals. The hidden layer is responsible for the processing of the input signal by calculated the weighted sum of input signals, with the help of the transfer function as in Fig. 7. After that, the network will be classify by comparing the value of the weighted sum of the input signal and the threshold value, with using the activation function for converts a neuron's weighted input to its output activation.

In this paper, we want to classify the obstacles that are real obstacles or fake obstacles from the input image by themselves, can be performed by using ML-ANN, which the training process is supervised learning, the network learns by labeled examples. The Learning capability of artificial neurons is achieved by adjusting the weights in accordance with back-propagation learning algorithm.

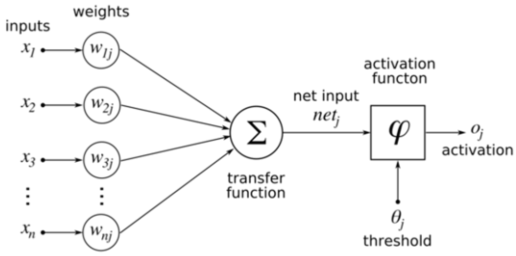


Fig. 7: A neuron in artificial neural network

The obstacles recognition system consists of a ML-ANN with three layers. The input layer consisting 34596 neurons, the hidden layer consisting 10 neurons with a sigmoid activation function and the output layer consists of two neurons. To the 34596 neurons will receive 34596 elements from HOG features as input and the ML-ANN produces 2 outputs for each input. Depending on the one of the two outputs of the network will be predominant that is represents the recognized obstacles. In this experiment, we gathered 120 images spanning around two different objects for training and validation. The obstacles classification testing by using actual video images. The resolution of the video images are 1920x1080 pixels and the frame rate is 30 frames/sec. The obstacle detection distance from the camera to the object is 50-120 cm.

3. EVALUATION

3.1 The results of the obstacles recognition system

The result of training process by ML-ANN, validation of neural network, and verification process can be observed that the network is stabilized in 100 epochs as in Fig. 8. The NN training confusion by using static data, 120 samples (70 obstacles and 50 fake obstacles) as show in Table. 1.

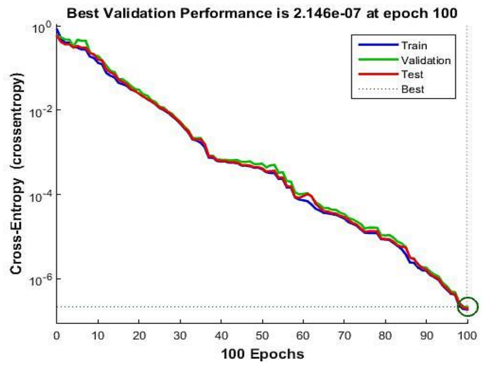


Fig. 8: The Neural network training performance.

Table 1. The Neural network training confusion.

Output class	Target		%Accuracy
	Obstacle	Fake Obstacle	(True/False)
Obstacle	70(58.3%)	0(0.0%)	(100/0.00)
Fake Obstacle	0(0.0%)	50(41.7%)	(100/0.00)
Accuracy (True/False)	(100/0.00)	(100/0.00)	(100/0.00)

3.2 The results of the obstacles classification

The result of the obstacles classification testing by using actual video images, 1,500 frame (the obstacles: 900 frames, the fake obstacles: 600 frames) as show in Fig. 9 and the accuracy as show in Table. 2.

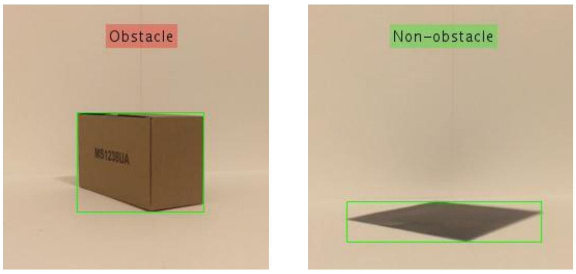


Fig. 8: The result of the obstacles classification testing by using actual video images.

Table 2. The accuracy of the obstacles classification testing by using actual video images

Output class	Target		%Accuracy (True/False)
	Obstacle	Fake Obstacle	
Obstacle	897 (99.67%)	3 (0.33%)	(99.67/0.33)
Fake Obstacle	1 (0.17%)	599 (99.83%)	(99.83/0.17)
Accuracy (True/False)	(99.67/0.17	(99.83/0.33)	(99.73/0.26)

4. DISCUSSION

The result of the obstacles recognition, 100% accuracy is achieved. From this result showed that the ML-ANN can recognize the obstacles by learning a features of the real obstacles, which is the orientation of the edges of the objects aligned as a vertical line from HOG features. Therefore, it can detect object of free size and free orientation in the image. This test is highly accurate because it is the static test. But the AGV is moving, we are tested by a mobile camera. The result of the obstacles classification testing by using actual video images have 99.73 % accuracy, with a false positive is 0.17%, but no damage. But in this experiment has a false negative is 0.33%, which is likely to cause damage. The distance used to test and classified the obstacles are 60 to 120 cm, which the AGV can brake without colliding with obstacles.

5. CONCLUSION AND FUTURE WORK

In this paper presents the simulate the algorithm to control AGV that is flexible, which can classify the obstacles that are real obstacles or fake obstacles such as a painting on the floor, which most objects might be found in factories are simple boxes and test in laboratory environment. The obstacles recognition system using ML-ANN with back-propagation learning algorithm by learning HOG features, 100% accuracy is achieved. The simulate of the obstacles classification by using actual video images have 99.73 % accuracy. The distance from the camera to the object that used to classified the obstacles are 60 to 120 cm, which the AGV can brake without colliding with obstacles. The method used in this paper can be further extended to recognize the obstacles by using shape variation rate due to this method can detect object in images by finding the orientation of the vector from HOG feature aligned as a line to narrow the boundary of the objects. When AGV moves closer to the height objects, we found that the size of the object has changed, but without changing the shape of the object. But when AGV moves closer to the non-height object, we found that the size and shape of the object has changed. We can use this principle to improve function classification object accurately and efficiently for AGV.

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