General Object Detection Method by On-Board Computer Vision with Artificial Neural Networks

Jittima Varagul 1)  Toshio Ito 1)

1) Graduate School of Engineering and Science, Shibaura Institute of Technology
307 Fukasaku, Minuma-ku, Saitama, 337-8570, Japan (E-mail: nb15504@shibaura-it.ac.jp)

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ABSTRACT: The objective of this paper is to find object based solutions for a collision avoidance system. In this paper, the authors present an algorithm for obstacle detection, from the actual video images taken by an on-board camera. The proposed technique is based on Histograms of Oriented Gradient (HOG) to extract features of the objects and classify the obstacles by the Time Delay Neural Network (TDNN). The experimental results showed that it can detect general objects, and is not restricted to vehicles, objects or pedestrians. It has provided good results along with high accuracy and reliability.

KEY WORDS: safety, automatic collision notification, image processing / neural networks, object detection

1. Introduction

Currently, there are many accidents that occur on the road. The most common cause is rear-end collisions and in several instances it is driver error such as fatigue, discomfort, or use of a phone while driving. These accidents can be reduced if these driver errors are eliminated. In recent years, there have been a lot of studies for a collision avoidance system, which is an automobile safety system designed to reduce the severity of a collision, namely to detect objects and obstacle avoidance. In the actual vehicle driving situation on the road, it is desirable to be able to recognize the preceding obstacles. In order to prevent a collision of the vehicles and the obstacles - of which we do not know the exact shape, size or color - it uses various sensors to detect the obstacles, such as optical sensors, radio detection and ranging (RADAR), sound navigation and ranging (SONAR), light detection and ranging (LIDAR), and laser sensor. After the detection is done, these systems either provide a warning to the driver such as a flashing dashboard icon, a beep, a tug from the seat belt or braking autonomously without any driver input when a collision is imminent. However, every detection sensor has both advantages and disadvantages.

The radar sensor system uses radio waves to determine the velocity, range and angle of an object. Radars can operate under all practical driving conditions such as rain, snow or fog. However, radar sensors suitable for the detection of large objects such as vehicles, may not suit small or narrow objects such as a pedestrian. In addition, the cost of the radar sensor is higher than a camera.

The lidar that measures distance using emitted light with high accuracy, which will work in every condition. Moreover, the minimum target size of lidar is a 1” square or larger. Therefore, it can detect objects of various sizes such as vehicles, motorcycles or bicycles. Nonetheless, due to lidar using light to detect objects, problems may arise when light is reflected from dark objects such as a black object, and they are still quite expensive.

The camera is a master of classification and texture interpretation, which has the cheapest and most widely available sensors of all three sensor types. Nowadays, cheap cameras with very high resolution are available. Furthermore, even a cheap camera has a resolution higher than lidar. It can detect every object, shape, size, and color. Therefore, it is able to understand things that can’t be learned from lower-resolution lidar and radar.

As a result, the authors would like to reduce the cost of the detector and improve the performance of the vehicle by making the vehicle has the ability to see and recognize the obstacles like human beings by computer vision system.

Many studies have been developed using computer vision with Artificial Neural Network (ANN) applied to obstacles recognition and classification, which ANN is mathematical model for a computer that can imitate the function of human brain. Hence, it can improve the performance of the vehicle has the ability to see and recognize like a human, which is an important task in an automotive safety application. For the objects that can be found on the road with several of sizes, shapes and colors. In particular, a detection of moving objects (pedestrians, cars, bicycles, etc.) as show in Fig. 1.

Fig. 1 The moving objects on the road

Such real-time obstacle detection by computer vision was crucial in that we often found fake obstacles such as a text, sign, or painting on the road. When the vehicle moves closer to the height object, as long t_1, t_2, t_3… as in Fig. 2, though the size of the
object has changed, the shape of the object has not changed. However, when the vehicle moves closer to the non-height object, the size and shape of the object have changed as in Fig. 3.

Fig. 2 Preview image of the camera perspective

We can compare this variation by calculating the ratio between the width and height of the object. The real obstacle has a low shape variation ratio. In contrast, the fake obstacles have a high shape variation ratio as shown in Fig. 4. As a result, we can take pattern of the shape variation of the obstacle to recognize the obstacles. So far, the object recognition by using TDNN have proposed. This neural network processes complete image sequences at a time instead of single images, which it is able to perform the described recognition tasks in a variety of real-world driving conditions on the road in a highly efficient and reliable manner.

In this paper, the authors proposed a combined computer vision system based on HOG and TDNN to improve general object detection method for the vehicle, which can classify the obstacles that are real obstacle or fake obstacle.

The outline of this paper is as follows. Section 2 discussed the conventional method. Section 3 describe overview the proposed method and present the design of the experiment. Section 4 present the result and evaluation of the experiment. Finally, section 5 is the conclusion of this paper.

2. Conventional Method

2.1. Related work

When considering the actual vehicle driving situation on the road, it is desirable to be able to recognize the preceding obstacles in order to avoid accident. Thus, one of the most important obstacle avoidance is the vehicle has to be able to detect, recognize and classify the obstacles that are real obstacles or fake obstacles. So far, many 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. In the following, we will briefly describe some recent approaches for the object recognition and classification.

In many works, the objects detection and recognition of mobile robot\(^{(1-2)}\), which is implemented by using infrared or sonar to detect obstacle of various shapes and color characteristic. In the image segmentation process, Multi-Layer Perceptrons (MLP) neural networks\(^{(1-2, 9)}\) used to track objects by a color classification method. The result of the classification is a defined color, separate from other colors of the image. However, this system can be used to track objects only a specific color. One aspect has been neglected in previous studies is when it cannot detect the exact shape, size and color of the obstacles. There are only a few works that can detect objects regardless of color, shape and size. The pedestrian detection system uses the Histograms of Oriented Gradient (HOG) method\(^{(3-4,12-16)}\) to extract the specific features of the human by the distribution of intensity gradients or edge directions regardless of the size or color of the human. Then, linear support vector machines (SVMs)\(^{(4)}\) are used as a classifier for pedestrian detection. This is a comparison and recognition process which can be applied to separate and classify the features of pedestrians efficiently. And also many works use HOG descriptors as features for classification such as the hand shape classification\(^{(5)}\), the classification of traffic signs\(^{(6)}\), and the handwritten digit recognition\(^{(7)}\). In addition to extracting the specific features of the object, recognition and classification are important functions in intelligent AGV. Automatic road sign recognition\(^{(8)}\) can detect and classify the traffic signs from complex scenes by using a Multi-Layer Feed-forward Artificial
Neural Network (MLF-ANN) with three layers, which is classified into six signs by learning from 500 images, and it gathers a wide range of data from the six signs. The MLF-ANN is used to label the signs. This method has the flexibility to specify the meaning of the traffic signs accurately in different lighting conditions, including different viewing angles as well.

For objects that can be found on the road in several sizes, shapes or colors, such real-time obstacle detection by computer vision was crucial we often found fake obstacles. Several works for object recognition use TDNN\cite{10-11}, and this neural network processes complete image sequences at a time instead of single images, for example, a pedestrian classification based on the typical criss-cross motion pattern of a pedestrian’s legs in sequences of gray-scale stereo images taken from a moving camera pair. The recognition is stabilized by feedback loops added to the feed-forward TDNN architecture.

2.2. Histograms of Oriented Gradients (HOG)

The aim of this paper is to detect the obstacles in front of a car. Real time object detection by computer vision was crucial in that fake obstacles may be found, such as text or a sign on the road. Therefore, this algorithm needs to recognize the difference of specific features of the obstacles, where the real obstacle is a height object and the fake obstacle is a non-height object. One method that is highly effective in the feature extraction of the object in the image is the HOG method.

The HOG method was first proposed by Dalal & Triggs\cite{3}, devised as a method to be used to detect humans. Basically, HOG used the features of shape regardless of the size or color of the object in the image. HOG counts occurrences of gradient orientation in part of an image hence it is an appearance descriptor. It is the most commonly used method to find an edge. It then divides the image into sub-images (block). Here’s how the image is divided into two types as in the Fig. 5(a), Rectangular-HOG type (R-HOG) and in the Fig. 5(b) is Circle-HOG type (C-HOG).

Each block is divided into small cells as in Fig. 3(a), and each cell will contain the orientation of gradient, which is stored in the form of a histogram. The computation of the gradient values can be calculated by using 1D - discrete derivative masks in both the horizontal and vertical directions. This method requires filtering the grayscale image with the following filter kernels by equation (1)-(2).

\[
D_x = [-1 \ 0 \ 1]
\]

\[
D_y = [-1 \ 0 \ 1]^T
\]

Hence, being given an image \( I \), we obtain the \( x \) and \( y \) derivatives using a convolution operation by equation (3)-(4).

\[
I_x = I \ast D_x
\]

\[
I_y = I \ast D_y
\]

Each pixel in the cell will have the magnitude and orientation similar to equation (5)-(6).

\[
|G| = \sqrt{I_x^2 + I_y^2}
\]

\[
\theta(x,y) = \tan^{-1}(I_x/I_y)
\]

The key parameter is bin, which is evenly spread over 0 to 180 or 0 to 360 degrees, depending on whether the gradient is “unsigned” or “signed”. The final feature vector includes all of the block in 1D matrix form. 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 by block normalization. The block normalizations are explored in four different methods for block normalization by Dalal and Triggs\cite{3}. Let \( v \) be the non-normalized vector containing all histograms in a given block, \( \|v\|_k \) be its k-norm for \( k = 1, 2 \) and \( \varepsilon \) be constant. Then the normalization factor can be calculated by one of the following as equation (7) – (9):

L2-norm:

\[
f = \frac{v}{\|v\|^2 + \varepsilon^2}
\]

L2-hys: L2-norm followed by clipping (limiting the maximum values of \( v \) to 0.2) and renormalizing.

L1-norm:

\[
f = \frac{v}{\|v\|_1 + \varepsilon}
\]

L1-sqrt:

\[
f = \frac{v}{\sqrt{\|v\|_1 + \varepsilon}}
\]
2.3. Time Delay Neural Network (TDNN)

As mentioned above, when the vehicle moves closer to the object, the shape variation ratio of each obstacle type is different. The real obstacle has a low shape variation ratio. In contrast, the fake obstacles have a high shape variation ratio. We are concerned about the difference in the shape pattern variation ratio of each type of obstacle. Hence, we can also use this relationship to learn the difference between height and non-height objects. Due to this, the pattern changes one sequence at a time. Therefore, we design it to use TDNN to recognize and classify the obstacle, where TDNN has the potential to work on sequential data.

The TDNN is an artificial neural network architecture whose primary purpose is to work on sequential data. The TDNN has the ability to recognize features of time-shifting and has a larger pattern recognition system. The general TDNN concept is well known from applications in the field of speech recognition. Currently, TDNN is commonly used in image-pattern shape or motion recognition tasks. When the vehicle moves closer to the height object, though the size of the object has changed, the shape of the object has not changed. However, when the vehicle moves closer to the non-height object, the size and shape of the object would have changed. For this reason, this system needs to recognize patterns of the obstacle shape variation ratio. The TDNN has the potential of learning to overcome the limitations of a multi-layer neural network, and complete image sequences at a time instead of a single image. It is appropriate in solving this problem.

The ANN is an attractive alternative due to the neural network’s ability to learn on its own like a human brain. The ANN is a mathematical model for information processing by utilizing connectionist calculations. The ANN has been developed as a biological neural network, and operates with multiple interconnected layers composed of clusters. These clusters are meant to form a network which mimics a biological neural network. In a simple mathematical model of TDNN like other neural networks, which consists of nodes organized into three layers of clusters including input layer, output layer, and the hidden layer which handles the manipulation of the input through filters as in Fig. 6, 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 calculating the weighted sum of input signals, with the help of the transfer function as in Fig. 7.

After that, the network will be classified by comparing the value of the weighted sum of the input signal and the threshold value, while using the activation function to convert a neuron’s weighted input to its output activation. In order to achieve time-shift invariance, a set of delays are added to the input so that the data are represented at different points in time such as audio files or sequences of images. An important feature of TDNN is the ability to express relations between inputs in time, which can be used to recognize patterns between the delayed inputs. Due to their sequential nature, TDNN’s are implemented as feed-forward neural networks, the flow of data in only one direction, forward from the input nodes through the hidden nodes and to the output nodes. There are no cycles or loops in the network. Supervised learning with a back propagation algorithm is generally the learning algorithm associated with TDNN.

3. Proposed Method

In this section, we will demonstrate our proposed method with the experiment we conducted. The aim of this experiment is to improve function, detecting objects to recognize and classify the obstacles that are real obstacles or fake obstacles such as a painting, sign or text on the road. For this experiment, we collected 150 samples of various obstacle that include 90 samples of real obstacles and 60 samples of fake obstacles as shown in Fig. 8. We propose a combined on-board computer vision system based on HOG features and TDNN. We created an experiment to extract features of the obstacles in the actual video images by using the HOG method. For obstacle detection, recognition and classification in real-time we use TDNN. These images were processed by using the sequences of video images taken by an on-board camera that was fixed on board the front of a vehicle. The experiment was done in a real environment. The experiment consisted of three main parts; pre-processing, feature extraction, and classification. The overview process of the experiment is shown in Fig. 9.
3.1. Pre-processing

The pre-processing process aims to prepare the data for the next stage. The output of this stage would be ready for the next stage to perform complicated image processing tasks on the data. Prior to extracting features, training and testing a classifier, a pre-processing step is image enhancement applied to remove noise to highlight certain features of interest in the images, cropped to region of interest. 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 simple pre-processing flowchart is given as in Fig. 10. 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. 11 and Fig. 12, respectively.

![Pre-processing Flow Chart](image)

![Fig. 10 Pre-processing Flow Chart](image)

3.2. Feature extraction based on HOG

In the extract feature part, we are interested in the difference of specific features of the obstacles, where the real obstacle is a height object and the fake obstacle is a non-height object. Thus, we need to learn and recognize the specific features of each type of obstacle be able to classify the obstacles. One method that is highly effective in the feature extraction of the object in the image is the HOG method. Therefore, we use the HOG method to extract features of the obstacles which can detect objects and shapes within an image by analyzing the distribution of the intensity gradient and edge direction, and then explain the image in a histogram as in Fig. 13.

![Fig. 13 The computation of the gradient values of HOG](image)
We created an experiment to analyze the characteristics of both types of obstacles by using the HOG feature method. This experiment sets linear gradient voting into 9 orientation bins in 0 to 180 degrees. Then it divides the image into sub-images by 2×2 blocks and 8×8 pixel cells as shown in Fig. 12. From the results, the feature length of each image is 34596 and the feature of the obstacles is as shown in Fig. 14. We will use these specific features as inputs to learn and classify the objects by TDNN.

Moreover, the classification test, we use 25 set of video images (the obstacles: 15 set, the fake obstacles: 10 set). This set of images used in this classification test is different from the set of sample used for training process.

Fig. 14 Preview the shape information of the HOG feature

3.3. Classification with a Time Delay Neural Network (TDNN)

In the recognition and classification part, we are concerned about the difference in patterns of the shape variation ratio of each type of obstacle when the vehicle moves closer to the obstacle. Therefore, we can also use this relationship and the feature from HOG to learn the difference between a height object and non-height object together.

We design the obstacles recognition and classification by using a TDNN, where the training process is supervised learning, and the network learns by labeled examples. The learning capability of artificial neurons is achieved by adjusting the weights in accordance with a back-propagation learning algorithm. This network consists of a TDNN with three layers.

For the training process, the process is to recognize the features of both types of objects. The first is the input layer, which is 150 sets of inputs and the 5 delays are extracted sequences of video images taken by an on-board camera which are feature of HOG. The resolution of the video images are 1,920x1,080 pixels and the frame rate is 30 frames/sec. The second is the hidden layer, to recognize and classify the obstacles consisting of 10 layers with a sigmoid activation function by learning the features from HOG and recognizing the difference in the patterns of the obstacle shape variation ratio when the vehicle is moving, where the real obstacle has a shape variation ratio lower than the fake obstacle. The last is the output layer, consisting of two neurons where the real obstacle and fake obstacle are as shown in Fig.15.

Fig. 15 The design of the object recognition and classification by TDNN

4. Evaluation and Discussion

The aim of this experiment is to detect the obstacles in front of a car by using a camera mounted in a moving car. We are only interested in the obstacles that are on the lane in front of the car. Therefore, we define the region of interest (ROI), which limits the processing area to the ground locations as shown in Fig. 16.

Fig. 16 The ROI to detect the obstacles.

4.1. The results of the training process

The results of object recognition, validation of TDNN, and the verification process can be observed as having a network that at stabilized in 97.33% accuracy, with a false positive error at 2.67%. The neural network training confusion is from using 150 sets of video images as in Table 1.
Table 1. The neural network training confusion.

| Output class | Target            | %Accuracy (True/False) |
|--------------|-------------------|------------------------|
| Obstacle     | Obscena           | 60.00%                 |
|              | Fake Obstacle     | 0.00%                  |
|              |                   | (100/0.00)             |
| Fake Obstacle| Obstacle          | 2.67%                  |
|              | Fake Obstacle     | 37.33%                 |
|              |                   | (93.33/6.67)           |
| Accuracy     | Obstacle          | (60.00/2.67)           |
|              | Fake Obstacle     | (37.33/0.00)           |
|              |                   | (97.33/2.67)           |

4.2. The results of obstacle classification

In the results of the obstacle classification testing by using actual video images, 25 sets of video images (the obstacles: 15 sets, the fake obstacles: 10 sets) have 96.67% accuracy as shown in Table 2.

Fig. 16 shows the results of the obstacle classification, where we define the ROI to limit the processing area along the dashed line. Moreover, the box with the solid line shows the detected obstacles.

Table 2. The accuracy of obstacle classification

| Output class | Target            | %Accuracy (True/False) |
|--------------|-------------------|------------------------|
| Obstacle     | Obscena           | 60.00%                 |
|              | Fake Obstacle     | 0.00%                  |
|              |                   | (100/0.00)             |
| Fake Obstacle| Obstacle          | 3.33%                  |
|              | Fake Obstacle     | 36.67%                 |
|              |                   | (91.67/8.33)           |
| Accuracy     | Obstacle          | (60.00/3.33)           |
|              | Fake Obstacle     | (36.67/0.00)           |
|              |                   | (96.67/3.33)           |

4.3. Discussion

The results of the training process for object recognition, validation of the neural network, and the verification process can be observed where the network is stabilized in 97.33%. This result showed that the TDNN can recognize the obstacles by learning the features of the obstacles from HOG and recognize the difference of patterns of the obstacle shape variation ratio when the vehicle is moving, where the real obstacle has a low shape variation ratio. In contrast, the fake obstacles have a high shape variation ratio. The results of this experiment show that it can detect obstacles of different sizes, shapes and colors (cars, bicycles, etc.) as shown in Fig. 17.

For the results of the obstacle classification testing, using actual video images have 96.67% accuracy, with a false positive at 3.33%. Fig. 18 shows a comparison of the error that occurred in this object detection method, where all of the errors are a false positive error. Although it will not cause damage, this system is not suitable for use with an automatic braking system because it can cause an accident with a vehicle that follows behind it. Therefore, this system provides a warning to the driver when there is an imminent collision in order to prevent an accident and reduce the severity of a collision. Those actions may start with warning the driver, such as through a flashing dashboard icon, a beep, or a tug from the seat belt. The distance from the real vehicle to the object that is used to classify an obstacle is up to 50 m, so the vehicle can be brake without a collision.

Fig. 17 The result of the moving object classification testing by using actual video images: (a) the obstacle (b) no obstacle

Fig. 18 Comparison of the error that occurred in object detection method.
5. Conclusion and Future Work

This paper presents the algorithm for vehicles to detect general objects, which can classify obstacles that are real obstacles or fake obstacles such as a painting or text on the floor. For the obstacle recognition system using TDNN by a features of the obstacles from HOG features and recognize the difference of patterns of the obstacle shape variation ratio when the vehicle is moving. The results of the training process is stabilized at 97.33% accuracy. Moreover, the results of the obstacle classification testing by using actual video images show that 96.67% accuracy has been achieved. The results of this experiment show that we can detect obstacles of various sizes, shapes and colors, which is not restricted to the vehicles, objects or pedestrians. The distance from the real vehicle to the object that is used to classify the obstacles are up to 50 m. Therefore, this method can be used to improve object function classification accurately and efficiently for vehicles by using TDNN in the sequence of video images. This system can be applied to provide a warning to the driver when there is an imminent collision in order to prevent an accident and reduce the severity of a collision. The method used in this paper can be further extended to detect the obstacles in bad weather such as fog or rain. In particular, a detection of moving objects is available to realize safer path planning, a form of informative support for the driver. We expect this research will lead to more control over vehicles to avoid oncoming obstacles automatically and efficiently.

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