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Effects of image size reduction and gray level compression in Support Vector Machines

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Abstract. Support Vector Machines (SVMs) are being increasingly applied to automatic video-based object detection and traffic scene analysis because of their remarkable performance in real-time pattern recognition. However, the performance of SVMs is highly dependent on the property of input vectors. Studies have shown that the predictive performance of ANNs could be improved by preprocessing the original raw data. The purpose of this study was to investigate the predictive performance of SVMs with preprocessing methods, such as image size reduction and gray level compression. Experimental results from SVMs were compared with those from ANNs. This study showed that preprocessing techniques, which have been widely used to improve performance in various learning models, tend to undermine the predictive accuracy in SVMs learning model.

Keywords: Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), image size reduction, gray level compression

1 Introduction

Over the last twenty years, there has been an increase in the number of studies on image processing technique for automatic traffic data collection such as vehicle counting [2, 7], congestion [9], vehicle tracking [1], and incident detection [3]. However, detection accuracy is still far from perfect when it comes to complicated backgrounds. Furthermore, the application of learning models such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) has grown tremendously, and they have been successfully applied in traffic scene analysis because of their remarkable ability to achieve high precision. The property of input vectors as well as the learning algorithm greatly influences the predictive performance of a model. It is important to select a good source of input vectors in order to achieve high performance in learning models. Preprocessing techniques, such as image size reduction and gray level compression of pixels, create new input vectors for learning and reduce the computer [1]memory requirement and computing time. A previous

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research [4] has shown that preprocessed data could be much more efficient than the original image data in pattern recognition and can improve the performance in terms of computing cost and prediction accuracy for independent test sets not used for training in Back-propagation neural network model [8]. The aim of this study is to investigate the impact of various preprocessing methods on the predictive accuracy of SVMs. Experimental data were obtained from real-world traffic scenes where the task was to detect vehicle image patterns, and the results were compared with those from Back-propagation, which is the most popular neural network model.

2 Image size reduction

In this method, an image is shrunk by selecting every other pixel. It can be formulated as follows: i.e. $f(x, y) = g(2x-1, 2y-1)$, for the first shrinking and $h(x, y) = f(2x-1, 2y-1)$, for the second shrinking, where g( ) is the original image of size x × y and f( ) is the shrunken image (x= 1, 2, 3, ..., n and y = 1, 2, 3, ..., m). The function h ( ) in equation (11) represents the twice-shrunken image (x= 1, 2, 3, ..., i and y = 1, 2, 3, ..., j), where $i = n/2$ and $j = m/2$.

3 Compressing gray levels of each pixel

The original image data of road traffic scenes were 24-bit RGB color images. Since grayscale images are sufficient for many tasks, more complex and difficult-to-process color images were unnecessary. Therefore, color images were converted to 256 (2^8) gray levels using the following equation [6] in order to reduce the dimension of input vectors and improve performance and efficiency in learning models. Gray = 0.30 × R + 0.59 × G + 0.11 × B, where R is red, G is green, and B is blue. In this equation, the grayscale intensity is stored as an 8-bit integer giving 256 possible different shades of gray; however, the grayscale intensity can be changed to 128 gray levels or 64 gray levels by converting it to a 7-bit or 6-bit image, respectively.

$$L_g = 2^n \begin{cases} n = 8, & \text{if bit depth is 8 bit} \\ n = 7, & \text{if bit depth is 7 bit} \\ n = 6, & \text{if bit depth is 6 bit} \end{cases} \tag{1}$$

where L_g is the number of gray levels per pixel, and n is the number of bits per pixel. In the above equation, if n is 8, the pixel values are integers that range from 0 (black) to 255 (white). If the gray levels are reduced from 256 to 128 by selecting a 7-bit depth, then the pixel values are integers that range from 0 (black) to 128 (white). Similarly, the pixel values are integers that range from 0 (black) to 64 (white) if a 6-bit depth is selected.

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4 Experiments and Results

For the experiments in this study, all the data sets are the same as those of the previous research [5]. The task is to classify three different patterns in traffic scenes: Pattern A, Pattern B, and Pattern C. Figure 1 shows the preprocessed image data where Pattern A corresponds to the front part of a vehicle, Pattern B corresponds to the top of a vehicle, and Pattern C is an image of the road with no vehicles. The number of data sets for training and test are 230 and 700, respectively.

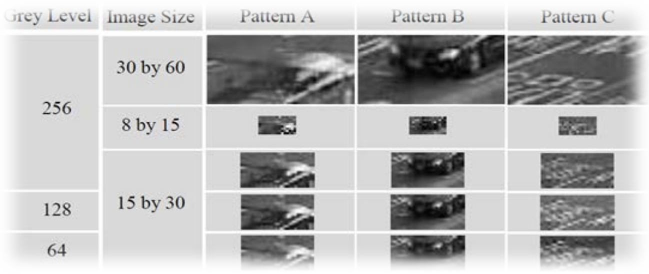

Fig. 1. Various grey level and image sixe of three patterns

Table 1 shows the predictive performance of SVMs on the test data sets using three different sizes of the image. In the 30 × 60 size, there were 12 prediction errors in a test of a total of 700 data sets. However, the number of prediction errors increased with reduction in image size. In the 15 × 30 and 8 × 15 sizes, there were 15 and 30 prediction errors, respectively. In addition, Table 1 shows the predictive performance of the second preprocessing, which was to compress grayscale. In the 256-grayscale image, there were 15 prediction errors in a test of total 700 data sets. However, the number of prediction errors significantly increased with grayscale compression of the pixels. In 128 and 64 grayscales, there were 100 and 103 prediction errors, respectively. The overall experimental results showed that preprocessing of image data may significantly reduce the predictive performance in the learning algorithm of SVMs. However, the results are different from the previous study by Kim [4] in which Back-propagation has been used on the preprocessed image data. Preprocessing resulted in considerably less prediction errors with Back-propagation than SVMs in this study.

Table 1. Performance on the shrunken image and variant gray level

	Image Size			Gray Level		
	30 × 60	15 ×30	8 × 15	256	128	64
C	1.0	1.0	1.0	1.0	1.0	1.0
Gamma (γ)	0.02	0.04	0.2	0.04	0.03	0.006
Mean Squared Error	0.0171429	0.02143	0.0428571	0.02143	0.177143	0.172857
Prediction error	12	15	30	15	100	103

	Image Size			Gray Level		
	30 × 60	15 ×30	8 × 15	256	128	64
Prediction accuracy (%)	98.2857	97.86	95.7143	97.86	85.71	85.2857

5 Conclusion

Preprocessing plays an important role in learning models with complex input vectors. Some preprocessing methods, such as image size reduction and gray level compression of each pixel, may improve the predictive performance, such as in Back-propagation, but it does not do so in SVMs learning model. SVMs performed better with the original input vectors than with the preprocessed data. This implies that SVMs are more useful in complex input vectors than other learning algorithms. A back-propagation learning algorithm for feed-forward neural networks, called Back-propagation, shows high sensitivity to noise. However, SVMs may provide more immunity against noise than Back-propagation. While preprocessing makes the network simpler and reduces (or eliminates) image noise, some important information for pattern recognition, such as the geometric relationship of objects and pixel grayscales, might be lost. In conclusion, preprocessing is not an efficient method for improving the predictive performance of SVMs learning model.

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