A Neural Ensemble Approach for Segmentation and Classification of Road Images

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Abstract. This paper presents a novel neural ensemble approach for classification of roadside images and compares its performance with three recently published approaches. In the proposed approach, an ensemble neural network is created by using a layered k-means clustering and fusion by majority voting. This approach is designed to improve the classification accuracy of roadside images into different objects like road, sky and signs. A set of images obtained from Transport and Main Roads Queensland is used to evaluate the proposed approach. The results obtained from experiments using proposed approach indicate that the new approach is better than the existing approaches for segmentation and classification of roadside images.

Keywords: Artificial Neural Networks, Support Vector Machines, Hierarchical Segmentation, Classification, Clustered Ensemble.

1 Introduction

Recently, both automatic road objects detection and recognition have been the subject of many studies. Roadside objects recognition is important for detecting the various risk factors on the roads and improving the overall safety of the road. Many factors need to be taken into account in an automatic traffic image recognition system. The objects appearance in an image depends on several aspects, such as outdoor lighting conditions, camera settings and camera itself. Also the images taken from moving vehicles can produce blurred images because of the vehicle motion.

Many roadside objects do not have specific shapes and the color also varies which create problems during segmentation and classification. The problems considerably affect the segmentation step, which is the initial stage in detection and recognition systems. In this paper, the aim of segmentation is to extract the road objects from the images, as this is crucial in achieving good classification results. Many segmentation methods have been presented in the literature using various image processing techniques.

A quantitative comparison of several segmentation methods used in traffic sign recognition is presented in [1]. The methods presented are colour space thresholding, edge detection, and chromatic decomposition. A simple and effective method that accurately segments road regions with a weak supervision provided by road vector data is presented in [2]. A factorisation based segmentation algorithm is applied to achieve this. An algorithm for real time detection and recognition of signs using

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geometric moments is presented in [3]. A video segmentation algorithm for ariel surveillance is shown in [4]. It uses a mixture of experts for obtaining the segmentation results. A method for detection, measurement, and classification of painted road objects is presented in [5]. The features are extracted using dark light transition detection on horizontal line regions and robust method. An active vision system for real time traffic sign recognition is presented in [6]. The recognition algorithm is designed by intensively using built-in functions of an off-the-shelf image processing board for easy implementation and fast processing. A method to develop a computer vision system capable of identifying and locating road signs is explained in [7].

A fast and robust framework for incrementally detecting text in road signs is presented in [8]. The framework applies a divide and conquers strategy to decompose original task to sub tasks. It presents a novel method to separate text from video. A new adaptive and robust method for colour road segmentation is presented in [9]. A fitting and predicting approach is used to extend the features to the whole image. A system to detect and interpret traffic signs in colour image sequences is presented in [10]. The colour segmentation of the incoming images is performed by high order neural network. Various methods to evaluate segmentation methods are shown in [11].

A method for developing a computer vision system capable of identifying and locating road signs using colour segmentation strategy is shown in [12]. A method that combines the decisions of weak classifiers is shown in [13]. It presents a road sign identification method based on ensemble learning approach. The methods mentioned above are mainly meant for images with high quality and the objects to be separated are road signs.

In this paper, we discuss a new approach based on neural ensemble to segment and classify roadside image into different class of objects. The ensemble learning process combines the decisions of multiple classifiers created by clustering. The images used in the experiments were provided by Queensland Transport and Main Roads and were obtained from Australian countryside highways.

The remainder of this paper is organised as follows. Section 2 explains the proposed neural ensemble approach. Section 3 presents the methodology adopted using proposed neural ensemble for extraction and classification of road objects. Section 4 briefly describes the previous approaches used for road image segmentation. Section 5 describes the data collection part and experiments. Section 6 details the comparison of experimental results between various approaches. Section 7 details the conclusions from experimental analysis and directions for future research.

2 Proposed Ensemble Approach

The proposed approach for generating ensemble of classifiers is based on the concept of clustering and fusion. The initial task is to cluster the road images into multiple segments and use a set of base classifiers to learn the decision boundaries among the patterns in each cluster. This process of clustering partitions a dataset into segments that contains highly correlated data points. These correlated data points always tend to stay close together geometrically. Also these data points are difficult to classify when patterns from multiple classes overlap within a cluster. When clustering is applied on datasets associated with a class, two types of segments are produced atomic and non-atomic. An atomic cluster contains patterns that belong to the same class whereas a non- atomic cluster is composed of patterns from multiple classes.

Following the clustering process, classifiers are trained based on the patterns of non-atomic clusters and class labels are assigned for the atomic clusters. The class of a test pattern is predicted by finding the suitable cluster based on its distance from the cluster centres and using corresponding class label for atomic cluster and then by using suitable classifier for non-atomic cluster. So clustering helps in identifying difficult to classify patterns. Once clustering operation has been performed and clusters are identified a neural network classifier is trained for each cluster grouping.

In k-means clustering the assignment of pattern to a cluster can be different based on seeding mechanism (initial state of cluster centres) where the number of k-means clusters is different to the actual number of clusters in the data. If multiple clustering can be performed with different seeding points then pattern might go to different cluster each time. When a new clustering operation is performed with different initial seeding it is called layering and these clusters form a layer. This cluster alignment will be different from one layer to the next. So a classifier can be trained on these non-atomic clusters for each layer and the result of the classifiers fused together by the majority vote algorithm to create an ensemble. Thus the layers provide a means of introducing diversity in ensemble and making it easier to classify non-atomic patterns.

3 Research Methodology

The proposed research methodology adopted is shown in Fig. 1 followed by explanation of each step done in the process. In this paper we focus on the classification of road objects like road, sky as well as road signs. It is hard to classify roadside images as there are multiple objects in a single image and also many objects scattered and mingled with one another.

3.1 Segmentation

During segmentation, we take into account the characteristic features related to change in the colour components. The first step of segmentation is to measure the colour features. At first the road images are segmented into two colour channels: white and non-white. In this approach k-means is used with k=2 for road image segmentation. Segmentation produces white segments for lanes, sky, dry vegetation and road signs. The non white segment contains road, coloured road signs and green vegetation. In this stage the potential road objects are located by their position in the image. The road extraction process is done by block based feature extraction method on bottom part of the image. The sky region is separated by confining the search to top section of the image.

3.2 Feature Extraction

The segmented image is then subjected to block based feature extraction. At first a block size of 64*64 is defined and using the defined block size the image is divided

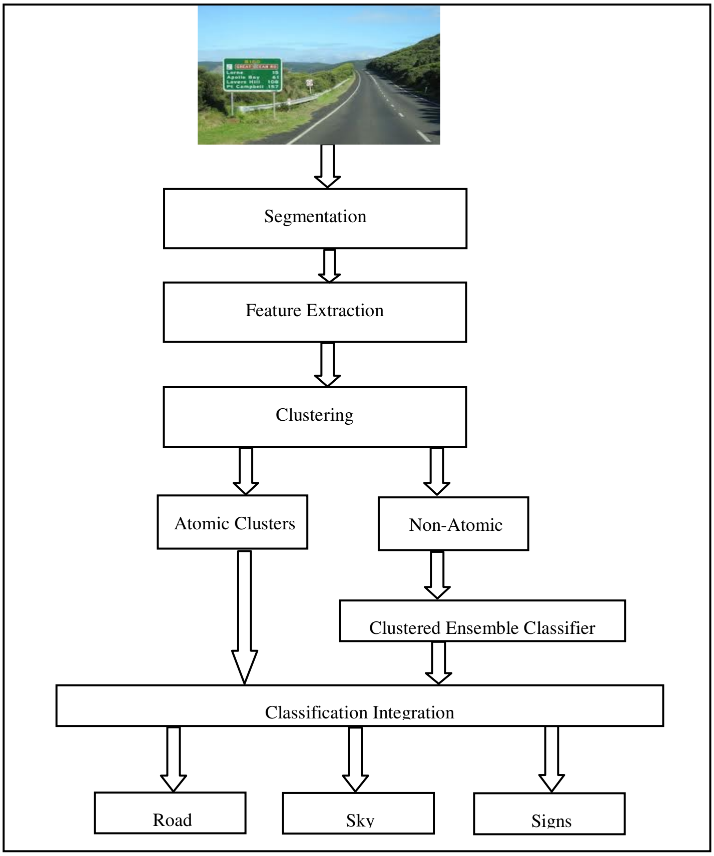


Fig. 1. Research methodology using proposed ensemble approach

into equal no of blocks. For road segment extraction the image is divided at the bottom part of image. Then each block is labelled into different classes as road, non–road, and background. Features are then extracted from each block.

For sky segment extraction the image is divided at top of the image. Then each block is labelled as sky, non-sky and vegetation. Finally feature extraction is performed. Following types of road signs were extracted from the image: green signs, light blue signs, yellow signs, and speed signs. Colour ranges are used to extract regions from the images. Then the boundaries of the regions are extracted. The regions are then further filtered by comparing the signature of each blob with those obtained from the reference shapes.

3.3 Clustering and Classification

The dataset for the road images is clustered by using k-means clustering algorithm. This produces both atomic clusters where only one class membership exists and non-atomic clusters where more than one class is present. A neural network is then trained on the non-atomic clusters and this produces a layer (a trained classifier based on a particular dataset created through training). This process is repeated for a number of clustering operations where the cluster initialization point (seeding) is different. So each classifier layer can be trained to recognize different decision boundary for the non-atomic clusters.

After the training operation is completed the network is tested. The ensemble classifier during testing evaluates as to which class a test pattern belongs in two steps. In the first step the cluster membership is determined by examining the said patterns distance to the cluster centroid. If the pattern belongs to an atomic cluster then the class label for that cluster is returned. If the pattern belongs to a non-atomic cluster then the class label from trained network is obtained. Finally a majority vote is used to return the decision from the ensemble classifier.

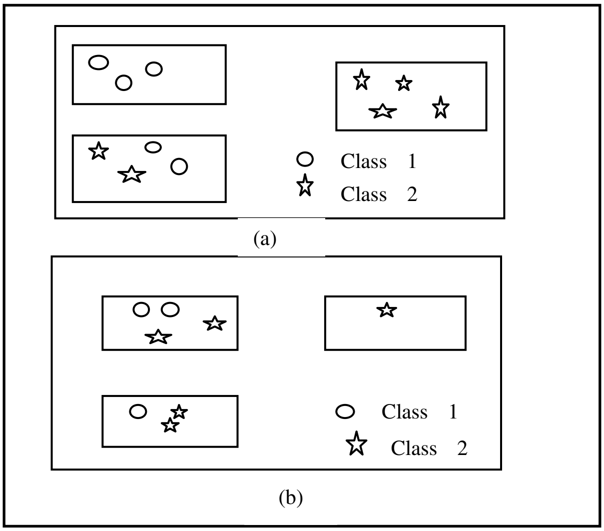


Fig. 2. Same dataset clustered at two layers

Fig. 2 shows the method of layering that occurs by varying the seeds of the cluster centers. In Fig. 2(a) three clusters have been defined and the class membership indicates that two atomic clusters and one non-atomic cluster have been formed. The non-atomic cluster contains multiple classes so a neural network classifier needs to be trained on this cluster. The atomic clusters are easier to classify and their class labels signify the classifying test patterns. In the second part of diagram Fig. 2(b) the cluster seeding are changed and the layer produces three clusters and cluster memberships are very much different to the previous layer. This difference in patterns creates diversity during neural network training which helps improving performance of ensemble classifier.

3.4 Classification Integration

The outputs obtained from different neural networks trained on each clustered layer are integrated by majority vote as this mechanism improves the overall output when compared to the individual accuracy of each classifier. The majority vote selects the output with highest number of votes.

4 Existing Classification Approaches

This section describes the previous approaches used in the experiments to extract the different road objects and compare the results with proposed ensemble approach. The different approaches for road objects extraction are detailed in the following sections.

4.1 SVM Classifier Approach

In this approach [14], experiments were performed to extract the road objects using SVM classifier. SVM classifier determines the linear separating hyper-plane with largest margin in high-dimensional feature space. In SVM classification we extract the feature vector on each pixel of the input image and then each vector is classified by the trained classifier.

4.2 Hierarchical Segment Learning

This approach [15] is based on hierarchical segment extraction and classification of segmented objects using a neural network. In this approach we extract different objects such as sky, road, sign and vegetation in hierarchical stages and classify them using a neural network classifier. This approach improves classification accuracy over SVM approach while extracting different road objects from the road images.

4.3 Clustering Based Neural Network

This approach [16] combines clustering and neural network classifier for the classification of road images into road and sky segments. This approach first creates clusters for each available class and then uses these clusters to form subclasses for each extracted road image segment. The integration of clusters in the classification process is designed to increase the learning abilities and improve the accuracy of the classification system.

5 Data Collection and Experiments

The road images were extracted from TMR videos using Matlab version 7 on Windows platform. The original videos are in avi format with MJPEG codec. The videos were converted into avi format with MPEG codec using Prism Software. The image frames obtained were saved as JPEG files and subjected to different processing methods. All the images used in our experiments have a resolution of 960 × 1280. We need to identify the best segmentation method. The best segmentation method is considered to be the one which gives the best recognition results. For good recognition results we have defined criteria as high recognition rate, low number of lost signs, high speed, and low number of false alarms. To test the performance more than 400 images were obtained from different sequences while driving at nominal speed. A database was constructed from the images which were taken under different settings and lightning conditions. A sample set of images used is shown in Fig. 3.

Fig. 3. Sample set of roadside images

In the hierarchical approach [15], a neural network is used for segmentation and classification of road objects. A block size of 64× 64 and (960× 1280)/ (64 ×64) segments per image was used. The images are then subjected to clustering and feature extraction process. The extracted features are used to train classifiers to classify the different road objects. Matlab neural network toolbox was used for neural network training by varying the number of hidden units. In the experiments using SVM classifier [14] we replaced neural network by SVM classifier and performance was evaluated.

In clustering based neural network approach [16], clustering is used to create clusters or sub classes within existing classes and integrates these clustering based new classes with the training process. The classifier used in this approach is a multi-layered perceptron classifier with a single hidden layer. The classifier is trained on each cluster and results are integrated. Training of the weights was achieved using the backpropagation learning algorithm. The following parameter setting was used during the training process for all datasets: 1) Learning rate = 0.01; 2) Momentum = 0.2; 3) Epochs, i.e., no. of iterations = 55; and 4) RMS goal = 0.01. The best parameter settings on datasets were found by trial and error.

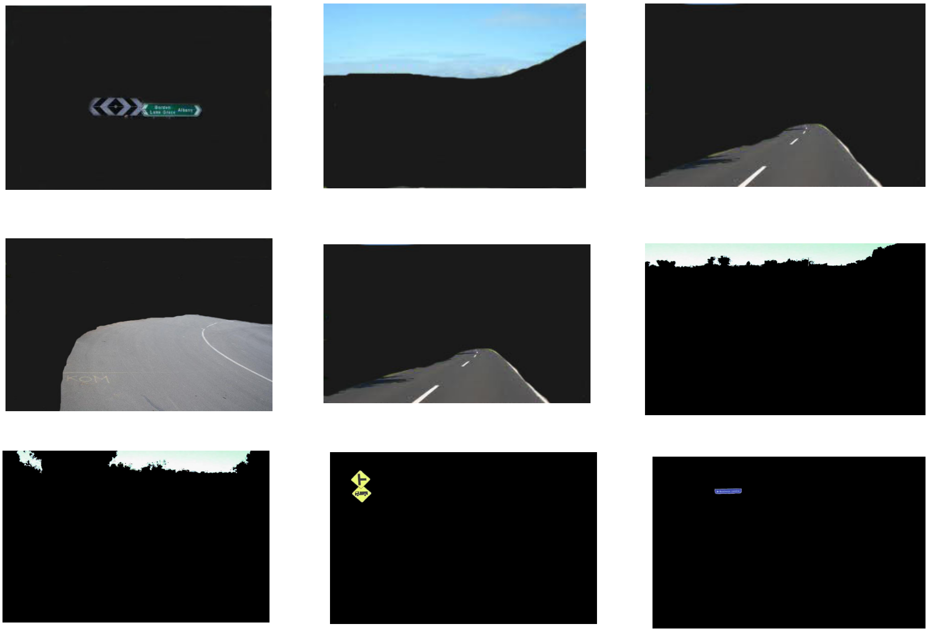


Fig. 4. Sample set of extracted road objects using proposed ensemble

6 Results and Analysis

Many images from videos on different routes and under different lightning conditions were captured. Each sequence includes hundreds of images. To analyse the different situations and the problems encountered, we extracted several sets, including some frames that were difficult to segment.

Each set represented different problems in segmentation like low illumination, rainy conditions and similar background colour. For results in this paper, a total of 400 images selected from thousands of 960×1280 pixel images were analysed. These sets are representative of the segmentation problems that arises during segmentation. Various methods to measure segmentation performance are shown in [11] but they do not specify a standard. They also cause excessive execution time.

In this paper we propose an evaluation process based on the performance of the whole classification system using four measures /criteria. The criteria or measures for evaluation are described below.

1) Rate of correct classification: The sum of all correctly classified objects divided by the total number of objects. The value of 100 indicates that all possible objects were correctly classified.

2) Number of lost objects: This relates to number of objects that were not classified in any way.

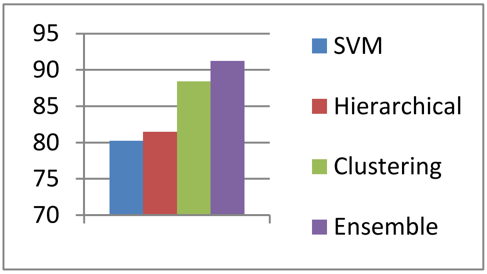
3) Number of maximum scores: This indicates the number of times a method achieved maximum score.

4) False recognition rate: This represents percentage of objects wrongly classified by a method with respect to number of total objects classified.

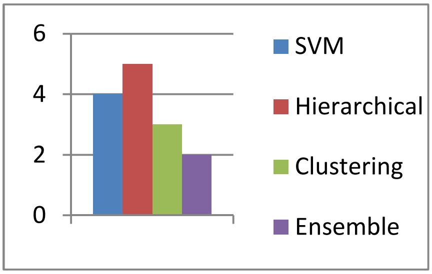
The experiments were conducted using the above measures and results were compared for proposed and exiting approaches. As shown in Table 1, the classification rate is higher in the ensemble learning approach which is around 91.2%. It shows considerable improvement when compared to other approaches. The number of objects lost and falsely detected is also lower in the case of ensemble approach. Fig. 4 shows the sample set of extracted road objects. Fig. 5 indicates the comparison between the approaches for the various measures.

Table 1. Performance measures of various approaches

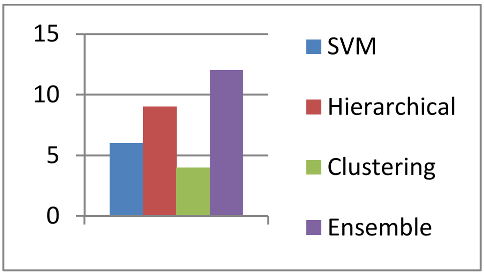
Measures	SVM	Hierarchical	Clustering	Ensemble
Classification (%)	80.2	81.5	88.4	91.2
Lost	4	5	3	2
Max	6	9	4	12
False (%)	2.34	3.4	2.1	0.00



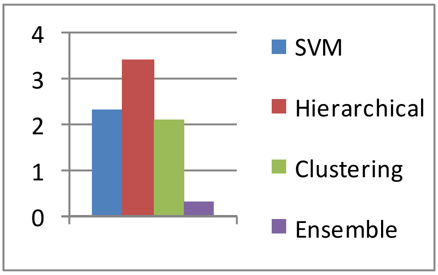
(a) Rate of Correct Classification (%)



(b) Number of Lost Objects



(c) Number of Maximum Scores



(d) False Recognition Rate

Fig. 5. Comparative analysis of results using various approaches

7 Conclusions

In this paper we have presented an ensemble technique and evaluated it on the roadside images provided by TMR. The tests prove the significant improvement in classification rate over existing approaches for roadside image segmentation and classification. The proposed approach uses different seeding points to partition data into various layers and generates clusters with different patterns at each layer. A classifier is trained on each cluster for each layer. The outputs are fused using majority vote to create an ensemble clustered network. The experimental results show that the proposed approach using clustered ensemble can correctly segment and classify different road images and extract the objects with classification rate of 91.2% which is higher than the classification rates obtained by existing approaches for roadside object extraction. In our current work, we have conducted evaluation for road, sky and sign objects so further experiments and evaluation with more roadside objects at different conditions (cloudy, rainy and night) will be conducted in future research.

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