Multi-Clustered Neural Network for Improved Classification of Road Images

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Abstract—This paper presents a new multi-clustering neural network approach for classifying road image into road, sky, signs and vegetation segments. The proposed approach at first creates clusters for each available class and then uses these clusters to form subclasses for each extracted road image segment. The multiple clusters integrated into the classification process increase the learning abilities and improve the accuracy of the classification system. The experiments using multi-clustered neural network classifier have been conducted on the set of images obtained from video data obtained from the department of Transport and Main Roads Queensland. The experimental results demonstrate that the approach is capable of achieving reasonably high accuracy.

Keywords- neural networks, image segmentation, classifiers, multi-clustering.

I. INTRODUCTION

The essential aspect of an intelligent transport system is a vision based system that can analyse the images obtained by cameras. There are a range of benefits from analysis of road images from video using an automated system. An automated road object recognition system can play an important role in alerting drivers of road conditions making driving safer. An automatic road recognition system should be able to first detect, and then identify a set of road objects from within images. Such a system should be able to analyse the road image captured by the camera, extract the road objects region and make intelligent decisions. In addition, it must appropriately alert the driver of the road hazards ahead. Automated road object recognition is a difficult task. There are a number of important issues that need to be taken into consideration. These include: illumination conditions, direction of sign’s face, status of paint on signs, placement of multiple signs near each other, shape of objects, obstacles such as tree, image sensor’s properties, car vibrations, etc.

Analysis and processing of roadside video data has lot of potential for improving road safety. Computer processing and analysis of video in an automatic way using advanced segmentation, identification techniques would improve the degree of accuracy and play a vital role in improving road safety. Several algorithms have been developed for road signs extraction but very few algorithms on road image segmentation.

The spatial compactness and colour homogeneity are two desirable properties in unsupervised segmentation which leads to image-domain and feature-space based segmentation techniques. In [1] Autonomous Driving Robot performs detection and classification of traffic signs based on analysis of images.

Image segmentation algorithm based on background recognition and perceptual organisation is shown in [2]. A three level road marking algorithm is explained in [3]. It automatically extracts the parameters for repainting. A real time detection and recognition algorithm of main groups is shown in [4]. The classification is done by computing geometric moments and appropriate shape factors. The sign symbols are recognised using an artificial neural network. A method to detect and segment road and traffic signs using colour space is shown in [5]. This method is tested under different light conditions and backgrounds and show very good robustness. A method for detection, measurement, and classification methods for painted road objects is presented in [6]. Dark light dark transition detection on horizontal line regions and robust method for colour road segmentation are used to extract features. Gray level segmentation is used to refine colour. The road sign recognition system using neural network is presented in [7]. This is based on a system which consists of two modules detection and classification. The detection module can segment the image in the intensity colour space, and detects road signs using multi-layer neural network. The use of colour thresholding to segment the image and the use of shape analysis to detect road signs from the image is presented in [8]. The shape of a particular sign is identified by RGB segmentation. An automatic extraction method using one-class support vector machine is presented in [9]. The proposed method has higher computational accuracy than pixel based SVM classification and is much effective. A new method which is both adaptive and robust for colour road segmentation is presented in [10]. A fitting and predicting approach the features are extended to the whole image. A dynamic region growing technique is shown in [11] to enhance colour segmentation. The results show good detection and recognition rate with real outdoor scenes using several light conditions. New approaches based on image colour segmentation and distance oriented classifiers for road sign detection are proposed in [12-14]. A colour segmentation strategy to locate and identify road signs using a vision based system is shown in [15]. A Sematic segmentation of objects in a road scene using bag of textons is presented in [16]. An hierarchical approach using a support vector machine as a classifier for segmentation and classification of road images is discussed in [17]. Classification of road signs using various algorithms in RGB colour space is explained in [18-24].

In this paper, we present a new approach by combining multi-clustering with a neural network to improve the training process as well as accuracy when we classify the road image into road, sky, signs and vegetation segments. The new approach uses clustering to create clusters (sub classes) within existing...
classes (road, sky, signs, and vegetation) and integrates these clustering based new classes within a training process.

This paper is organised as follows. Section II of this paper explains multi-clustering based neural network approach. Section III explains the data collection and experiments. Section IV shows results obtained with the proposed approach and analysis of the results. The conclusions and directions for future research are presented in Section V.

II. MULTI-CLUSTERING BASED NEURAL NETWORK APPROACH

The proposed approach in this research is to utilise a combination of multi-clustering and neural network classifier to determine if the classification accuracy of the system can be improved through enhancements of clusters to the classifier. An overview of the proposed approach is presented in Fig. 1 below, followed by an explanation.

![Multi-Clustering based neural network approach](image)

**Figure 1. Multi-Clustering based neural network approach**

**A. Feature Extraction**

We make use of colour feature clustering to perform image segmentation, here we take into account the characteristics features related to change in the colour components. The first step during segmentation is to measure the colour features. To extract these features we compute the response from a Gabor filter oriented at the prominent direction of the neighbourhood of a pixel. We use the International Commission of Illumination (CIE) \( L^*a^*b^* \) representation of the colour image because this colour space can independently control colour and intensity information. The \( L^*a^*b^* \) space consists of a luminosity layer \( L^* \), a chromaticity layer \( a^* \) indicating where colour falls along the red-green axis, and a chromaticity layer \( b^* \) indicating where the colour falls along the blue-yellow axis. All of the colour information is in the \( a^* \) and \( b^* \) layers, so that the colour features are extracted from \( a^* \) and \( b^* \) components as features for image segmentation.

**B. Multi- Clustering**

Multi-Clustering involves the partitioning of a set of data into smaller similar groups to find the natural groups based on similarity of input features. This process is achieved through evaluating the distance between a point and the cluster centroid. After extracting all the features for an image of size \( M \times N \), we have a set of \( L = M \times N \) feature vectors, which are regarded as points in a 2-D feature space. To group these points, we use a \( K \)-means clustering algorithm. In the proposed approach we take the level of abstraction by recognising subclasses within road, sky, signs and vegetation classes. By clustering the road we arrive at a number of target sub-classes (e.g. \( R_1, R_2, \ldots, R_n \)). The process is repeated for sky class (e.g. \( S_1, S_2, \ldots, S_m \)) and for sign and vegetation classes which are our target subclasses for our training and classification purposes. These subclasses represent the target output class for our classifier during training and testing process.

For multi-clustering, we produce an image of \( K \) levels after encoding the pixel cluster relationships, where each pixel value is replaced by the cluster label deduced by the \( K \)-means algorithm. The clustered image is smoothed spatially by the repeated applying a mode filter until the number of pixels that are different between images is less than one percent.

At this stage, all the blobs in the segmented image are inspected by a verification process, and some of them are discarded with respect to their size and aspect ratio (i.e., the height-to-width ratio). We also impose some limits on the size of the objects that we are trying to obtain. The limits for both criteria, i.e., size and aspect ratio, are derived by a trial-and-error method based on the experiments on the images. The thresholds for the size criterion are selected at specific percentages with respect to the dimension of the images being analyzed. For road segment this process is done at bottom part of image and for sky at the top part of the image. The process is again repeated on the remaining part of the image which contains signs and vegetation. Once the segmentation process is completed we obtain the ROIs, possible candidate road, sky, sign and vegetation segments.

**C. Neural Network Classifier**

It is through the training process that the input/output data is applied, weights are updated and through this process the network acquires knowledge in the problem domain in question. Once trained, the network is then able to generalise using the acquired knowledge to solve different problems possessing similar characteristics. Thus a neural network maintains knowledge about the problem domain by the weighted interconnections that were used to train the network. Neural networks are able to capture the complex relationship of variables better than many other models because they can capture the non-linear relationship of the training data.

However the literature also demonstrates that neural networks can suffer from various problems which restrict their efficacy. Traditionally MLP style networks would be utilised in a classification approach such as this where a backpropagation...
of an error component (such as Root Mean Square -RMS) is passed back in order to adjust the network weights. Once the error is reduced to a threshold value the network is trained. However it has been noted that a reduction in RMS error doesn’t always lead to an improvement in the classification accuracy of the network.

The neural network classifier that has been employed in this research is a multi-layer perceptron style classifier. There is only a single hidden layer, the number of neurons being determined experimentally so as to ascertain the optimal configuration. In the proposed approach, during the feature extraction process for road, sky, sign and vegetation segment extraction, features corresponding to each object are extracted. From the features the training data is generated. The training data is used to train the neural network based classifier. The weights of the neural network define the relationship between the input features and the road objects classification. The same process used to generate the training data is used to generate the test data. Then we generate predicted labels for the test data using the trained classifier model. Finally the test accuracy is calculated by comparing the predicted labels with known labels of the test data.

III. DATA COLLECTION AND EXPERIMENTS

The road images for conducting experiments to evaluate the proposed method were obtained from TMR videos using Matlab version 7 on Windows platform. The original TMR videos are in avi format with MJPEG codec. The videos were converted into avi format with MPEG codec using Prism Software. The frames obtained are saved as JPEG files for easy processing during the experiments. We have used set of 15 images for training purposes and set of 10 images for testing purpose. In total we have made use of database of 25 images for preliminary experiments and these images were subjected to segmentation process as shown in Figure 1. The images are subjected to feature extraction and the clustering process. The extracted features are used to train the clustered neural network classifier and extract road, sky, sign and vegetation objects. We have used neural network training function (trainrp) which updates weight and bias values according to resilient backpropagation algorithm. The experiments were repeated for different cluster values in the neural network classifier.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Matlab neural network toolbox was used for training the classifier. We have used accuracy as well as sensitivity, specificity as performance measures. Sensitivity is the True Positives / (True positives + False Negatives) and represents the probability of correctly detecting road, sky, signs and vegetation segment. Specificity is the True Negatives / (True Negatives + False Positives) and represents the likelihood of correctly not detecting road image sky segments. Segmented road, sky, sign and vegetation images obtained using the proposed approach is shown in Fig. 2 and Fig.3. In the extracted sky segment some part of signs and poles are visible. The colour features have high similarity between signs and sky. Hence pole is misclassified as sky. The performance of the neural network classifier by varying cluster values for road object is shown in Table 1. Similarly the performance of the classifier for sky, signs and vegetation segments are shown in Table 2, Table 3 and Table 4 respectively. The proposed framework of combining clustering and classification was able to correctly classify various road segments and achieve better performance for road image segments. Table 5 details the performance of multiple clustered classifiers over single clustered classifier for road segment. Table 6, Table 7 and Table 8 show the improvement of multiple clustered classifiers over single clustered for sky, signs and vegetation segments. The results show significant improvement in performance. So the proposed method provides a mechanism for improving the accuracy for extracting both road, sky, sign and vegetation segments.
Figure 2. Results (extracted road and sky segments) using the proposed approach
Figure 3. Results (extracted sign and vegetation segments) using the proposed approach
### TABLE 1. PERFORMANCE OF CLUSTERED ANN FOR ROAD SEGMENT

<table>
<thead>
<tr>
<th>Clusters</th>
<th>Performance of the Proposed Approach [%]</th>
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<tbody>
<tr>
<td></td>
<td>Accuracy</td>
</tr>
<tr>
<td>1</td>
<td>86.2</td>
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<td>2</td>
<td>84.6</td>
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<td>88.1</td>
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<tr>
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<td>10</td>
<td>87.0</td>
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<td>89.5</td>
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</table>

### TABLE 2. PERFORMANCE OF CLUSTERED ANN FOR SKY SEGMENT

<table>
<thead>
<tr>
<th>Clusters</th>
<th>Performance of the Proposed Approach [%]</th>
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<tr>
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### TABLE 3. PERFORMANCE OF CLUSTERED ANN FOR SIGN SEGMENT

<table>
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### TABLE 4. PERFORMANCE OF CLUSTERED ANN FOR VEGETATION SEGMENT

<table>
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<tr>
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<td></td>
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<tr>
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### TABLE 5. PERFORMANCE IMPROVEMENT OF MULTI-CLUSTERED CLASSIFIER OVER SINGLE CLUSTERED CLASSIFIER FOR ROAD

<table>
<thead>
<tr>
<th>Clusters</th>
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<tbody>
<tr>
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<td>Accuracy</td>
</tr>
<tr>
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<td>+1.9</td>
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<tr>
<td>5</td>
<td>+0.4</td>
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<td>+0.8</td>
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<tr>
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<td>+3.3</td>
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### TABLE 6. PERFORMANCE IMPROVEMENT OF MULTI-CLUSTERED CLASSIFIER OVER SINGLE CLUSTERED CLASSIFIER FOR SKY

<table>
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<tbody>
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<tr>
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<td>+2.5</td>
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<tr>
<td>20</td>
<td>+2.9</td>
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</tbody>
</table>

### TABLE 7. PERFORMANCE IMPROVEMENT OF MULTI-CLUSTERED CLASSIFIER OVER SINGLE CLUSTERED CLASSIFIER FOR SIGN

<table>
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<tr>
<th>Clusters</th>
<th>Performance Improvement [%]</th>
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<tbody>
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<td></td>
<td>Accuracy</td>
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<tr>
<td>4</td>
<td>+3.1</td>
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<tr>
<td>5</td>
<td>+3.4</td>
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<tr>
<td>10</td>
<td>+3.9</td>
</tr>
<tr>
<td>20</td>
<td>+5.2</td>
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### TABLE 8. PERFORMANCE IMPROVEMENT OF MULTI-CLUSTERED CLASSIFIER OVER SINGLE CLUSTERED CLASSIFIER FOR VEGETATION

<table>
<thead>
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<th>Performance Improvement [%]</th>
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<td>+2.6</td>
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<tr>
<td>20</td>
<td>+2.8</td>
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V. CONCLUSIONS

A multi-clustered neural network approach has been investigated and presented in this paper. This approach uses multi-clustered neural network for classifying roadside data into road, sky, signs as well as vegetation segments. Several existing road image segmentation methods were studied. Next, the development stages of the proposed system were presented. Finally, the performance of the proposed multi-clustered neural network classification system was evaluated extensively. The experimental results show that the proposed approach can correctly segment and classify roadside data into road, sky, signs and vegetation segments with a significant improvement in accuracy. Overall accuracy has significantly improved when compared to the single clustered classifier approach. This work will be further extended by conducting experiments for more roadside objects in the future.

REFERENCES