Accurate Real-Time Traffic Sign Recognition Based on the Connected Component Labeling and the Color Histogram Algorithms

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Abstract—**Image processing such as Traffic Sign Recognition (TSR) plays a key role in Intelligent Transportation Systems particularly in Traffic Sign Recognition (TSR) which aims at increasing driver safety. Several studies have proposed TSR systems based on different image processing and machine learning algorithms. However, the efficiency of the proposed TSR algorithms requires improvement to enable real-time alerts on onboard devices which have limited computational power. Further improvement on accuracy of TSR is also required mainly in unstable weather conditions or when multiple signs exist on one pillar. This research proposes an improved model for Automatic TSR (ATSR) consisting of improved Connected Components Labeling and color histogram. Firstly, images are captured in real-world conditions in Palestine. The region of interests is detected using the improved Connected Components Labeling algorithm combined with Vectorization to reduce computational time. Secondly, the local features of detected images are computed using the color histogram. The results of the research show that combining the Connected Components Labeling with Vectorization reduces the computational time. Also, the Connected Components Labeling algorithm followed by histogram increase the accuracy of recognition. The low computational cost and the accuracy of the model enable us to use the model on smart phones for accurately recognizing traffic signs and alerting drivers in real time.**

Index Terms—**traffic sign recognition, region of interest, connected components labeling algorithm, location histogram**

I. Introduction

Traffic signs are designed to reduce traffic accidents and improve safety on roads. However, drivers sometimes do not follow traffic signs because they cannot see them due to obstacles, or they do not pay attention to them. Nowadays, automotive suppliers integrate TSR with vehicular technologies to increase driving safety. Although existing technologies and studies have proposed several traffic sign recognition systems, these systems are limited to the recognition of speed signs, children signs, and turn ahead signs. In addition, TSR remains a challenging task as it can be changed easily depending on its relative location and angle of view against camera and surrounding condition such as weather and daytime [1].

Previous studies have outlines the process of TSR and identified several factors affecting TSR [2]-[6]. Usually, the identification of the road signs can be achieved through two main phases: detection and recognition (e.g. [2]). In the first phase, each captured image is pre-processed, improved, and then the Regions of Interest (ROI) is segmented based on the signs attributes such as shape and colors (e.g. [7]). The output of the segmented regions should represent the possible road signs. Indeed, accuracy and speed of detection play an important role in obtaining accurate and fast recognition process. Although the previous studies provide fundamental framework for TSR algorithms, the accuracy and efficiency of TSR algorithms can be improved to fit with the requirements of on board real time systems such as alerting drivers.

This research proposes an improved TSR model that integrates the traditional Connected Component Labeling (CCL) algorithm [8] with the Color Histogram algorithm [9]. To improve the efficiency of CCL, we combine CCL with vectorization technique which is borrowed from the MatLab. Vectorization replaces the for and while loops and reduces the computational time [10]. The proposed model consists of detection phase and recognition phase in which an image captured from a video taken by a smart phone camera is examined.

The results of this research are promising as the proposed model outperforms the traditional CCL in terms of accuracy and efficiency. Therefore, the proposed model can be used on smart phones for accurate TSR which enables alerting drivers in real-time. The proposed model is able to recognize written information on traffic sigs such as maximum speed or other guiding texts. It can also work in different traffic conditions such as clear, dusty and foggy weathers. Further, it is able to recognize multiple signs simultaneously. The results of this project

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benefit the field of ITS in the safety domain. Further, we will integrate these results to tune the parameters of traffic flow prediction proposed in [11]-[13].

Section II presents the proposed model and explains how the proposed model is used. Section III shows the results of the proposed model. Section IV concludes the paper and outlines the future work.

II. Current Approaches

According to previous studies, the identification of the road signs requires two main phases: detection and recognition [2]-[6]. Traffic signs can be detected either by shape or color. Shape based detection algorithms use techniques such as the Hough transform to detect lines and identify the shape of the road sign [14], [15]. However, the existence of non-traffic similar shapes on roads affects the accuracy of this algorithm. Further, the extraction of shape usually consumes large computational time.

Color based algorithms are a color segmentation of Red, Green and Blue regions in the given image [16]-[19]. These algorithms are well enough for segmenting traffic signs in ideal illumination condition. Further these algorithms need defining many threshold values for the colors. Color based detection employs transforming images to HIS or HSV color spaces. The transformation is computationally demanding and therefore researchers moved to the RGB color space in order to speed up the detection procedure.

Regarding to classification of colors or shapes, the Support Vector Machine (SVM) is often used as in [20], [21]. The SVM shows good accuracy when images are rotated. Other classification approaches include the Artificial Neural Networks (ANN) as in [17]. The normalized correlation-based pattern matching was also used to classify signs based on colors [22]. In these approaches, it is possible to represent regions of interest based on illumination values (pixel based approaches) or on image features (feature based approach). Despite the good accuracy of the TSR that utilize these classification techniques, their computation performance is not suitable for real-time recognition on onboard devices which have limited computational resources.

The K-nearest neighborhood (KNN) has been also used in traffic sign classification [23]. The KNN is a machine learning technique, and it is widely used in pattern classification. In some cases, the KNN outperforms the SVM for real time TSR system. The KNN is borrowed to our research for increasing the accuracy and reducing the computational time.

III. Proposed Model

The model used in this paper is based on two main algorithms that are the Connected Component Labeling and Histogram. The connected component labeling algorithms is the core of image detection since it widely used in image processing field and shows good performance. The histogram technique is used for image recognition by comparing colors between the captured images and the stored images.

A. Connected Component Labeling

The Connected Component Labeling (CCL) algorithm is used for region extraction from an image. In binary images, CCL decides that adjacent pixels are connected if they have the same label. It contains two passes within one image [8]. First it gives a label (value) to each pixel in the image by processing the image from left to right and top to bottom. The labels are stored in a pair of arrays. In other words, the first pass phase takes a pixel p and scans its 4-nieghbours (four directions around p Left, right, top and down). If p=1 and all values in 4-neighbours are 0, assign a new label to p. If only one value in 4-neighbours is not 0, assign its values to p. If two or more values in 4-neighbours are not 0, assign one of the labels to p and mark labels in 4-neighbours as equivalent expressed as a binary matrix. In the second pass, the CCL compares each label with labels of adjacent pixels' and replaces each label by the label assigned to its equivalence class.

The traditional CCL was criticized by having large computational time mainly in the second pass [24], [25]. To increase the performance, we integrated CCL with vectorization technique. Vectorization is used in MatLab to increase the performance of loop-based operations [10]. All while and for loop operations can be given as vector operations which run faster than the while or for loops. Vectorization enables one programming command (single line of code) to run on the entire array.

B. Color Histogram

Color histogram is used to represent the distribution of colors in images and determine the range of colors in an image [9]. It can be formed by counting the number of pixels that contains a specific color. An important characteristic of color histogram is determining color proportion without focusing on the space where the color was found. This enables us to compare images even if they were rotated for some angle.

Color histogram can be used to find the similarities between images by color matching [26]. An image I_1 can be compared to another image I_2 quantized and stored in a database. Each image should have the same color range k, e.g. k =16 colors, 64 colors or 256 colors. Each image also has color palettes where for the first image the palettes is $P_1 = \{c_i, i=1, 2, \ldots, k\}$ and the second image is $P_2 = \{b_j, j=1, 2, \ldots, k\}$. Histograms H_1 and H_2 can be created for the two images. The goal is to match each of the colors in P_1 to a color in P_2.

The matching process starts by finding the Euclidean distance between colors c_i and b_j and this distance is stored in a matrix $D(i,j)$ of size kXk. Then a list of color indices which contains the order of increasing Euclidean distance is created based on matching each color in P_1 to a single color in P_2. Then the entries in P_2 are reordered according to the list of color indices which gives a new palette P_{2n}. The two palettes P_1 and P_{2n} are compared using histogram intersection to find the histogram similarity. The histogram intersection utilizes the distances between the matched colors as weights to reduce the effect of poorly matched colors on the similarity calculation. The similarity can be calculated as:

$$S(P_1, P_{2n}) = \sum_{m=0}^{k} min[P_1(m), P_{2n}(m)\ ]w(d_m)$$

where S is the similarity, d is the distance between colors c_m and b_m, and w is the weight for color similarity measure and it is given by:

$$w(d) = \begin{cases} 1 - \dfrac{d}{d_{max}}, & d < T \\ 0 \quad\quad\quad , & d \geq T \end{cases}$$

where T is a threshold on color similarity and it can be set to d_{max} [9], [27].

C. Method

The flow of our proposed model is shown in Fig. 1 which shows that the proposed model includes other techniques that are: video framing, enhancement, and transforming images to binary image. Initially, video framing is used for capturing an image from video taken by a smart phone camera mounted in the car. Then, the image is enhanced through Weiner filter and histogram equalizer which remove noise from image, improve contrast, and convert image to the daylight mode. Both histogram equalizer and Wiener filter do not affect the efficiency of the model since both require linear time computational complexity.

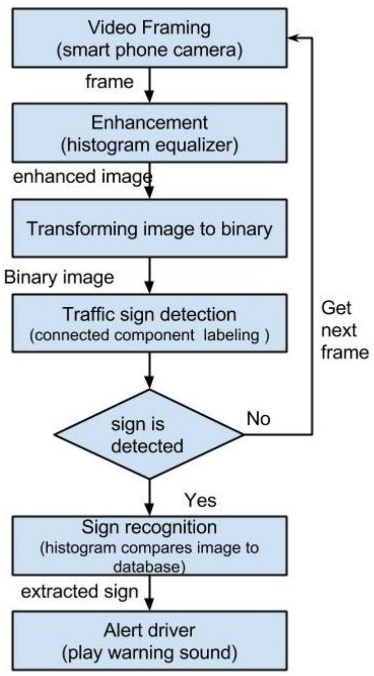

Figure 1. The flow chart of the proposed model.

After that the image is converted to binary (black and white) based on the RGB value of traffic sign color. We define the color set $C = \{R, B, G, Y\}$ according to the colors of traffic signs available in the country which are Red, Blue, Green, and yellow). Examples of traffic signs are shown in Fig. 2. Let $x \in C$, the algorithm searches for x in the image and converts it and other colors to black.

Figure 2. Examples of some traffic signs of different colors.

The traffic sign detection stage starts when the CCL combined with vectorization is applied to identify the connected components. The output of CCL is different shapes formed by connecting the white color points. Let U be the set of traffic sign shapes: Circle, Triangle and Rectangle, such that U = {Cr, Tr, Rr}. Let y be the CCL output that belongs to U. We have different cases of the CCL output:

- The output is not a shape that belongs to U, this shape will be discarded,
- The output may contain y plus other irregular shapes e, the algorithm extracts y and discards e,
- The output may contain multiple y_n:$n=1,2,\ldots$ mainly when multiple traffic signs exist in one image, these multiple signs will be extracted and added to a queue so that an alert corresponding to each detected sign will be sent to the driver.

To deal with the previous cases, the CCL is accompanied with a pre-classify stage to eliminates irregular shapes e, and a classify stage that extracts y using edge detection and extreme point algorithm.

The traffic sign recognition follows the detection stage. We use the histogram to match the detected image with other images stored in the database. The recognized image is the one of the best similarity.

IV. Experimental Results

The settings of the experiment incorporate the hardware part and the software part. We aim to reduce the hardware by allowing the entire system to run on one device. Instead of taking photos by a camera and then transfer them to another computer for analysis, we use a smart phone with a high speed processor (A8 processor 64-bit architecture) and a high resolution camera (photo resolution=8 megapixel and video rate =30 frame/second). The software part is IOS operating system. We use MATLAB and MATLAB coder to write the code and convert it to C code. The C code can be easily integrated in the IOS environment.

The process of recognition starts by applying our proposed model on every image (video frame) captured by the camera. The histogram equalizer and Wiener filter enhance the contrast of the image and produce noise-free image. The image then is converted to binary. After that the CCL algorithm detects the traffic sign and the histogram recognizes it. We examined our model on images with different resolutions. To ensure the reliability of the proposed model, our sample images include real photo captured from real time video in different weather conditions. An example of our results is shown in Fig. 3 which shows the input image in (a), the detected red color in (b) and the extracted traffic signs in (c).

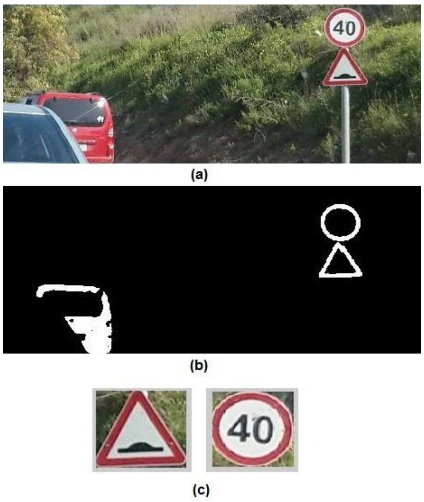

Figure 3. An example of detecting multiple traffic signs of red color.

Figure 4. Examples of two recognized traffic signs in different weather conditions.

Figure 5. Examples of two a recognized traffic sign that contains written information.

Fig. 4 shows an example of two recognized traffic signs in different weather conditions. The upper image shows no overtake situation and the image was captured during clear view, while the lower image shows turn right and the image was captured during foggy weather. Our model can also identify traffic signs with written information on them. Fig. 5 shows an example of a sign with maximum that displays the maximum speed on road.

The accuracy and the efficiency (running time) of the proposed model are very high as shown in Table I. We notice that in nice weather, traffic signs can be recognized from far distance with high accuracy, while in foggy or dusty weather the distance is shorter. The Table also compares the proposed model which utilizes CCL combined vectorization with the traditional CCL showing that the proposed model has better accuracy and efficiency.

TABLE I. A COMPARISON BETWEEN TWO ALGORITHMS IN TERMS OF ACCURACY AND EFFICIENCY DURING DIFFERENT WEATHER CONDITIONS

model	accuracy		Efficiency (time in seconds)	
	clear	foggy	clear	Foggy
CCL	89%	81%	2 sec	2.2
CCL+vectorization	98%	94%	0.47	0.63

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed an improved traffic sign recognition model that consists of Connected Components Labeling algorithm and Color Histogram. The model is tested in real conditions and shows high performance in terms of accuracy and efficiency. The model can work in different weather conditions including clear, foggy, and dusty weathers. Written information on traffic signs such as maximum speed or guiding texts can also be recognized. The high performance of the model makes it appropriate for real time driver alert system in which a smart phone is used to capture signs, identify them and alert the driver using sound effects.

Different ways can be used in further studies to extend this research. A final step of fine-tuning can be introduced using back-propagation instead of using rough features as illustrated in [28]. However, using the rough features makes the algorithm fully incremental avoiding the adaptation to a specific domain. The strict separation between the construction of the feature space and the classification allows considering other classification problems sharing the same feature space. Our future work will also include employing a novel machine learning approach based on Deep Belief Network based on Restricted Boltzmann Machines (RBMs) and Contrastive Divergence [29], [30]. To our knowledge, this approach has not been investigated yet. This approach is under testing and it is expected to achieve better performance.

Moreover, the future work will also include prioritizing traffic signs particularly when more than one sign are detected. Prioritizing can be performed based on the distance between the car and the sign or based on the importance of the sign. This would make our system more intelligent by giving alerts to drivers according to the importance of the sign.

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