Intelligent Vehicle Recognition based on Wireless Sensor Network

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Abstract

One of the main requirements of any intelligent transportation system is to be able to identify vehicles in the traffic. This paper presents an intelligent vehicle identification system used within a complete solution for a traffic monitoring system thatusesa novelwireless sensor network architecture to monitor traffic. A novel wireless sensor network architecture to monitor traffic is proposed where a visual sensor node captures images of the traffic and sends them to the traffic control center for processing. Also, this paper compares between three main localization and recognition algorithms. To locate the vehicle logo in the traffic image a symmetry detection algorithm is used to detect the inherent symmetry in vehicle frontal images. A fine location of the logo is identified using three different methods in the region marked by the symmetry line. After locating the logo three feature sets are extracted and presented to the classifier to correctly identify the type of the vehicle. The results of the localization and recognition algorithms show the efficiency of the presented system in identifying vehicle types with a recognition rate over 90%.

Keywords*:vehicle logo recognition, traffic control systems and wireless sensor network*

1. Introduction

The massive increase in automobiles as one of the most important modes of transportation has facilitated human life but it introduces different types of problems as traffic congestion, parking problems and traffic accidents.Researchers are pursuing solutions through developing intelligent transportation systems to solve these problems. An intelligent transportation should be able to manage, monitor and direct users to a safer and more coordinated transportation. Primarily, an intelligent transportation system has to correctly identify, recognize and track vehicles in real-time [1]. This paper presents a solution to monitor traffic using Wireless Sensor Networks (WSN).

Wireless Sensor Network (WSN) is a network of small Sensors Nodes (SN) that could communicate between themselves and/or base location using a wireless communication system. A sensor node usually consists of a sensor unit, a computing and a communication unit. Currently, researchers are increasingly using WSN due to its variety in function flexibility in development and numerous potential applications [2].

The architecture of a typical WSN contains a large number of SN and one or more Access Points (AP). The access points have higher computational power, enhanced communication capability and larger power source. In general, sensor nodes are small nodes that measure environmental conditions, deployed with a spatial density and at a high sampling rate that is defined by the application. The sensor nodesprocess the raw sensor data to extract useful information which is transmitted to the access point using the communication system. The access points could process the data collected from the sensors in the network to extract more relevant information then sends the data collected to the traffic operators or the traffic control system through the internet [3].

In traffic surveillance application, as shown in figure1, sensors are positioned at predetermined locations on the pavement; their job is to gather the magnetic signature of vehicles travelling over the sensor nodes. The nodes use vehicle detection algorithms to process these signals. The detection events are then generated and transmitted to the base station from the entire network. Based on this collected information, the base station computes the vehicle count, occupancy and speed of the traffic flow and in turn transmits it to the control center. The traffic management center (TMC) uses this real-team information for road monitoring and traffic signals control [3].

This paper presents a complete system to monitor traffic and gather vehicle information using wireless sensor networks. The proposed system introduces the main architecture of the traffic control system. It provides a solution to traffic monitoring and vehicle identification using non intrusive sensor network. The vehicle identification system is presented and explained in details on this research as one of the main modules in traffic monitoring and surveillance system. Our proposed vehicle identification system is divided into logo localization and recognition.

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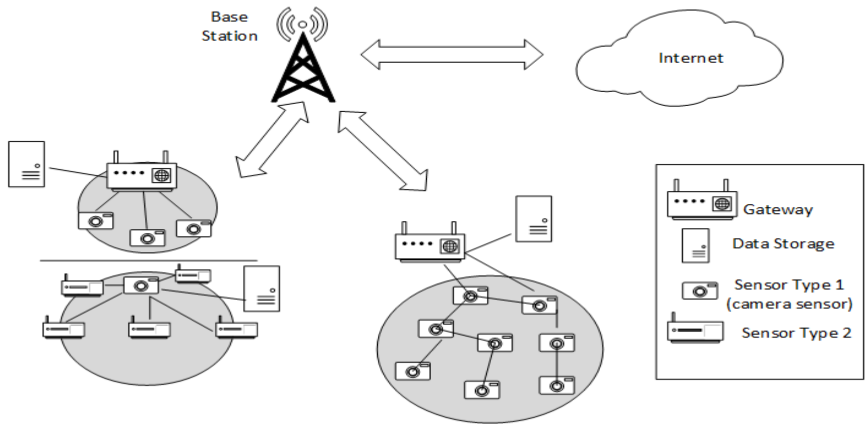

Figure 1: Typical wireless sensor network architecture

Vehicle logo localization locates the logo image in the input image and detects the fine location of the logo [4,5]. Firstly a course location of the vehicle logo is extracted from the input image by detecting bilateral symmetry of the vehicle front image. Next, the system tries to remove the background or vehicle grille using various textural analysis and edge detection methods. Based on the analysis of the previous step the fine location of the logo is detected the output of the vehicle logo localization is a fine location of the logo image [6]. The recognition of vehicle type from the logo image is divided into feature extraction and classification.

The rest of this paper is organized as follows; section 2describes the different methods which used in traffic control using WSN and its challenges. Section 3 provides an overview about Bilateral symmetry detection and Section 4 provides a description of the proposed system and focuses on the vehicle detection and recognition strategies, focusing on the details of the algorithm's implementation. A set of experiments was used to evaluate the method's performance. The analysis of the results, achieved under various test conditions, is presented in section 5. Finally, section 6 presents the conclusions drawn from the work developed and highlights possible directions for future work.

2. Relatedworks

In this paper, a vehicle logo recognition algorithm for the wireless sensor traffic monitoring system is presented. In the next section, current research in traffic control using wireless sensor network is presented then various vehicle logo recognition algorithms is discussed.

2.1 Wireless Sensor Networks

Different architectures of WSNs in intelligent transportation system are demonstrated in [7]. The survey explains the difference between main architecture and presents a summary of traditional vehicle detection and surveillance technologies. One of the most notable systems is Sensys networks [8] Wireless Vehicle Detection System (WVDS). WVDS sensors are placed in the middle of a lane and transmit information to a repeater which is located near the traffic control cabinet. To increase the lifetime of the sensor and network an efficient communication protocol [9] is used. Traffic center gathers information from the access points to process it and analyze traffic real-time.
Using wireless sensor networks for traffic monitoring is investigated in [1] to provide data for Intelligent Transport System (ITS). They presented a case study in the freight village of Turin to evaluate the performance of a vehicle detection system based on magnetic sensors. WSN-based framework for traffic information collection according to the user requests is presented in [10]. Two key processes associated with the traffic information acquisition and delivery were specified using three types of sensor nodes. They used a two-layer hierarchical communication channel to establish communication among these sensors. A user-customizable data-centric routing scheme is proposed for data delivery, in which an efficient routing method is adopted for the routing decision-making. A real time intelligent transportation system capable of providing prompt information was presented in [11] based on acoustic arrays and powered by effective post-processing.
An adaptive traffic control system using WSN is presented [12] based on controlling traffic on single and multiple intersections. The first part of this algorithm is a traffic sensor node installed on the roadside that collects periodically the traffic data from vehicles. The second part is a communication system algorithm that finds and

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controls the communications between the sensor and the base station.

2.2 Vehicle Logo Localization

The vehicle logo localization is the first step in any logo recognition algorithms. The process is divided to coarse localization of the logo location then followed by a fine detection of the logo region. The coarse location of the logo is detected using priorinformation then a background and grille removal algorithm is used to finally detect the fine location of the logo. There are two main methods usually used in coarse location of the logo. The first is relative to the license plate location and the second is relative to bilateral symmetry line of the car. Various texture and morphological methods are used in background removal and fine location of the logo. The next section describes each method in more details.

2.2.1 Relative to the License Plate

Based on the prior knowledge that the logo usually located over the license plate, the course location of the logo is detected relative to the location of the license plate. Figure 2 shows a frontal image of a vehicle and the relative position of the logo to the license plate [3,13,14]. The approximate location of the logo is identified by an equation similar to Equation (1) .

$$\begin{cases} X_1 = X_{left} \\ X_2 = X_{right} \\ Y_1 = Y_{up} - N * width \\ Y_2 = Y_{up} \end{cases} \quad (1)$$

where X_{left} and X_{right} are the left and right position of the license plate, width is the width of the license plate and Yup is the upper boundary of vehicle license .

Figure 2: The relative position of Vehicle logo to the License plate

Liu [4] presented this solution in his system which starts by locating the location of the license plate. After applying Equation 1 a coarse location of the vehicle logo is detected. A texture recognition algorithm is used to detect the type of the grille of the vehicle. Liu categorized the grille to be horizontal, vertical or both. The next step is to remove this background based on which type of grille detected in the previous step. The final step uses morphological operators and vertical and horizontal projection to detect the fine location of the logo.

However, the aforementioned for License Plate Recognition (LPR) based approaches face the general problems caused by the viewpoint variation and/or non-symmetric frontal license plate as shown in figure 3. In essence, a universal solution to license plate recognition is still not available, it is highly dependent on prior knowledge about aspect ratio, background/character color and symbol types of the license plate, thus license plate recognition, in general, does not generate satisfactory results in countries or regions where vehicles have diverse license plates which might be issued by various authorities. Therefore, vehicle logo localization will eventually fail due to the incorrect LPR result [6].

Figure 3: Example of non-symmetric frontal license plate

2.2.2 Symmetry Detection

An easily recognizable feature of the front view of the vehicle is the air-intake grille which is mounted on most vehicle's front. It usually has a regular shape grid or horizontal/vertical bars which is easy to detect, co-occurring with vehicle logos and shares the same symmetric axis with the vehicle. Therefore, by detecting the symmetry line of the air-intake grille the potential position of the vehicle logo can be efficiently determined [6] .

This method is used in some systems as used by Zhou [6] who presented a system that relies on the feature-match based symmetry detection algorithm [15] for detecting bilateral symmetry in the image. Then used Hough transform to detect vertical and horizontal grille lines from the phase congruency edge image. The final location of the logo is detected using a sliding window inside the grille region.

(a)The original image

(b) Coarse location

(c) Vehicle logo image

Figure 4: The Result of Vehicle Logo Localization Phase

This method is more robust than localization relative to the license plate location but it has lower recognition rate. In this research we adopt this method and try to improve it using various background removal and fine localization of the system. The experiments implemented provided in section 5 an analysis of the achieved improvements.

2.3 VehicleLogo Recognition

The second step after localization of the vehicle logo is classifying the vehicle for a specific brand (Toyota, Ford ... etc.). This step includes extracting features from the logo image and comparing it to the logo against a database of known brands, and using the calculated similarities to decide the most likely manufacturer. Feature extraction is one of the key operations in any classification system. In vehicle logo recognition most systems either use moments or Feature Matching Schemes. This section illustrate how different systems used these feature extraction to identify vehicle types .

Moments are a certain weighted measure of image intensity which could be scaled, translation and orientation invariant. There is a different type of moment like Zernike moment, Hu moments and Legendre moment used in various recognition problems including gesture recognition and 3D object recognition [2]. Hu moments define seven invariant moments to scale, orientation and translation. Unfortunately they have data redundancy problem because Hu moments are not orthogonal moments. Dai [2] used Tchebichef moments invariant as features for vehicle logo recognition. He compared Tchebichef moment with Zernike moment and Hu moment invariants.

Some promising approaches to detect foreground objects from images have been published: Scale Invariant Feature Transform (SIFT) [16, 17] that introduced in [18], Speeded Up Robust Features (SURF) [19]. Both methods detect interest points called features and propose a method of creating an invariant descriptor for these features. The authors of SURF claim to be a superior to SIFT in term of runtime execution while it is still providing good results with regards to feature point quality [16]. The created descriptor is used as a vector, uniquely identifying the found interest points. It has to be distinctive and robust for various scale-space deformations. Vectors can be used for matching indetecting interest points even under a variety of disturbing conditions like scale changes, rotation, changes in illumination and viewpoints or image noise. The invariance is the most important ability of these key-point detectors.

Different classification method was evaluated in vehicle recognition systems. In [20], a comparison between various classifiers and classifier fusion methods is presented. They compared between Support Vector Machine (SVM), Back propagation Neural Network and K-nearest neighborhood classifier as they present the most used classifiers. Others used Euclidean distance measure to match key point of the input logo to the key points of the database [17]. In the next section we will present a necessary background information about the main algorithms used in this research. The bilateral symmetry algorithm and SIFT feature.

3. Bilateral Symmetry detection

The first step in the system is bilateral symmetry to detect the symmetry in the vehicle front image. This process was first adopted by Zhou [6] based on symmetry detection presented by [15]. The algorithm is divided into three main steps : SIFT descriptor computation, symmetry descriptors detector, symmetry line estimation. The first step in the algorithm is computing the SIFT features an extracting the descriptors for keypoints (see next section3 for details of the algorithm).The next step starts by finding similar or mirror keypoint based on the values of the SIFT descriptor. The process removes all key points that do not have mirror feature in the image. This step also includes grouping keypoints to a set of mirrored keypoints. The final step starts by constructing small symmetry lines between each two pairs of mirrored points and then tries to detect symmetry line by generating a Hough transform of all the symmetry line from all mirrored keypoints. More than one symmetry line could be detected and so a confidence value is associated with the symmetry line based on the strength and number of the mirrored keypoints.

3.1 Scale Invariant Feature Transform (SIFT)

Matching features across different images in a common problem in computer vision. When all images are similar in nature (same scale, orientation, etc.) simple corner detectors can work. But when you have images of different scales and rotations, you need to use the Scale Invariant Feature Transform.

Scale Invariant Feature Transform (SIFT) is an image descriptor for image-based matching developed by David Lowe [21]. This descriptor as well as related image descriptors is used for a large number of purposes in computer vision related to point matching between different views of a 3D scene and view-based object recognition. The SIFT descriptor is invariant to translations, rotations and scaling transformations in the image domain and robust to moderate perspective transformations and illumination variations. The approach is efficient on feature extraction and has the ability to identify large numbers of features.

SIFT is implemented as the following stages: Creating the Difference of Gaussian Pyramid, Extreme Detection, Keypoints Elimination, Orientation Assignment and Descriptor Computation. Firstly, a Gaussian scale space $D(x,y,\sigma)$ is constructed from difference of Gaussian images from the convolution of input image $I(x,y)$ with Gaussian filter with different widths or (sigmas σ) . Next the goal of extrema detection is to find the extrema points in the DOG pyramid. To detect the local maxima and minima of $D(x,y,\sigma)$, each point is compared with the pixels of all its 26 neighbors. If this value is the minimum or maximum this point is an extrema.

Key point elimination attempts to eliminate some points from the candidate list of key points by finding those that have low contrast or are poorly localized on an edge [21]. Next, the orientation assignment step, assigns consistent orientation to each key point based on the local image properties. The key point descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation. SIFT is orientation based on the orientation histogram which is formed from the gradient orientations at all sample points within a circular window around the key point. Each sample added to the histogram is weighted by its gradient magnitude and by a Gaussian-weighted circular window with a three times that of the scale of the key point. The orientation histogram has 36 bins covering the 360 degree range of orientations. The final step, descriptor computation is computed for the local image region that is as distinctive as possible at each candidate key point. The image gradient magnitudes and orientations are sampled around the key point location.

4. System Description

This paper presents a wireless sensor network architecture to monitor traffic using a vision based algorithm. Figure 5 shows the architecture of the proposed system. The figure shows that the traffic is monitored using two types of sensor nodes a small sensor nodes mounted on each streetlight and more powerful access points mounted on the traffic light of each street. The network depends on non intrusive sensor nodes that gather traffic and vehicle data to reduce the cost of installation on current traffic systems. The sensor will basically build based on acoustic sensor implementing a vehicle detection algorithm similar to [11]. The sensor nodes transmit information from the sensors to the access points which contain a camera sensor, higher communication unit and more powerful computing unit. The data are transmitted using LLEAP routing protocol [22]. The access points detect the activity in the street by utilizing information from the neighborhood sensors. The access points transmit the data to the traffic control unit when activity is detected in the street. The traffic center relieves street and vehicle images and sensor data gathered from the whole network to extract full traffic monitoring information and statistics. The first step our automatic monitor system is vehicle logo recognition algorithm to detect the vehicles in camera feeds from the data in the traffic monitoring center.

One of the main identifying features of the vehicle is the vehicle logo. It contains the information about the vehicle model and manufacturer which could not be replaced easily. This provides an important basis for identifying and tracking vehicles accurately. Vehicle logo recognition is mostly divided into two main steps logo localization and vehicle logo recognition. Although vehicle logo localization seems an easy problem however the inherit particularity of vehicle logos makes accurate localization a more challenging problem.

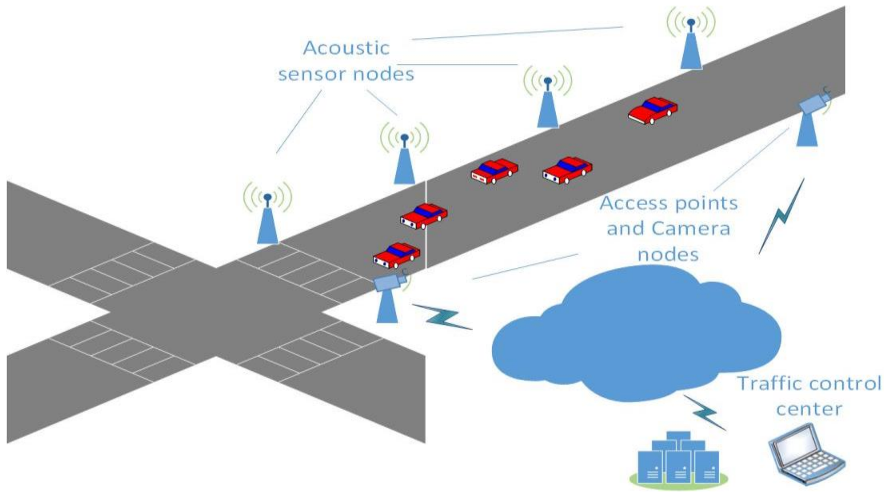


Figure 5: Traffic monitoring system

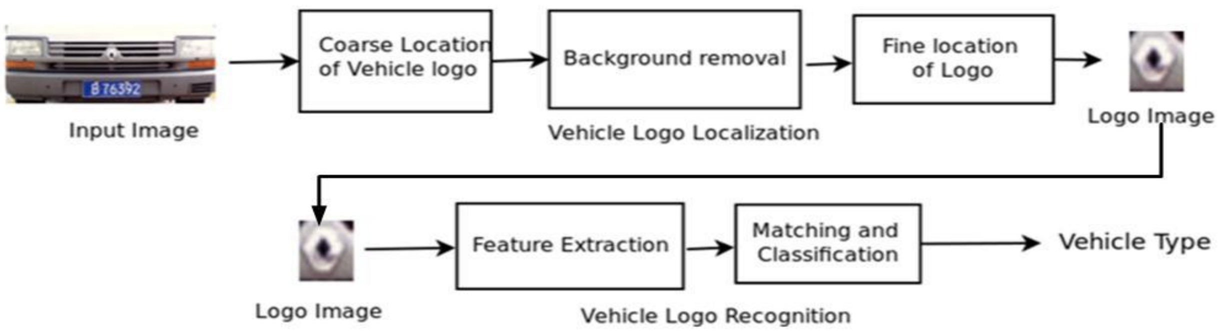


Figure 6: Basic Block diagram for any Vehicle Recognition System.

The next section presents in details the vehicle logo recognition system that identifies vehicles captured by a camera sensor in our traffic monitoring system. Figure 6 illustrates the main steps in any vehicle recognition system; the first step is vehicle logo localization which locates the logo image in the input image. The second step, vehicle logo recognition, classifies the a logo image to one of known vehicle types. In most systems vehicle logo localizations is divided into coarse location of logo, background removal and fine location of logo [4,5]. Firstly the coarse location of the vehicle logo is extracted from the input image. Next, the system tries to remove the background or vehicle grille using various textural analysis and edge detection methods. Based on the analysis of the previous step the fine location of the logo is detected the output of the vehicle logo localization is a fine location of the logo image. The recognition of vehicle type from the logo image is divided into feature extraction and classification.

4.1 Localization

The system is divided into logo localization and logo classification . Figure 7 shows the block diagram of the localization algorithm. The first step in the localization algorithm is the bilateral symmetry detection which detects SIFT features and use it to detect the symmetry. The bilateral symmetry algorithm is similar to implemented by Zhou [6]. The algorithm uses SIFT features to detect major features in the image. The next step focus on matching the mirrored features together and removing all non mirrored. The mirrored featured are matched and a rough symmetry line for each set is drawn into the images. Hough transform is used to detect the symmetry line with the highest confidence in the image.

Figure 8 shows different stages of the bilateral symmetry algorithm. The first figure shows the SIFT key features extracted from the image. The next picture shows only the matched mirrored features after removal of all non mirrored features (the green lines in the image). Figure 8 (a) shows the symmetry axes of each two matched features. This image is used as input for the Hough transform which produce output similar to figure 8 (b) . This image shows the main matched mirror features along the symmetry line with the highest confidence. The next step after detecting the symmetry axis of the image is locating the logo in the input image. The system is based on the assumption that the logo is directly over the grille and that we are detecting the logo from the front of the image. The easiest method of locating the logo from the input image is to crop the input image based on a margin of the symmetry line. The result of this cropping is illustrated in the following figure9.

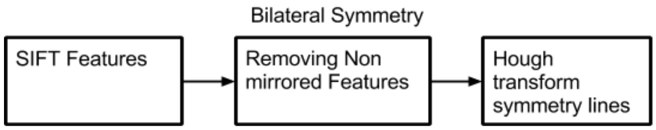
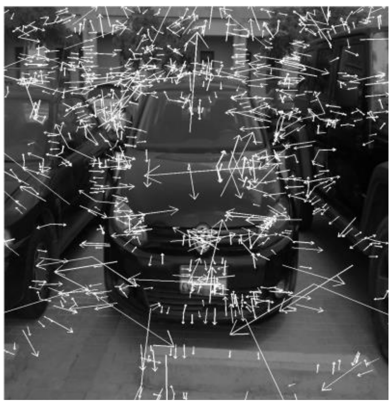
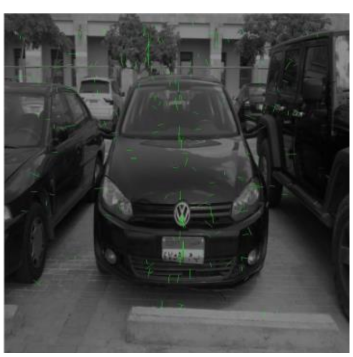


Figure 7: Block diagram of the localization algorithms



(a) SIFT features

(b) Mirror Features



(c) Symmetry Points

(d) Final stage

Figure 8: Stages of Bilateral symmetry detection

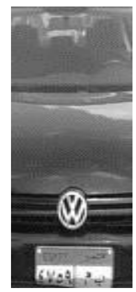


Figure 9: Final symmetry axis detected

4.1.1 Hough Transform based algorithm

A variation of the method presented in [6] was implemented where Hough transform is used to locate the region of the grill and then a horizontal and vertical filter applied in this region of interest to fine detect the logo location. Figure 10 shows sample of the output of this system on the dataset, these result confuse the background grid and buildings with the requested car grill location and move the solution location from beside the symmetry line to a wrong location. A different approach was used to solve the problem in [6] algorithm.

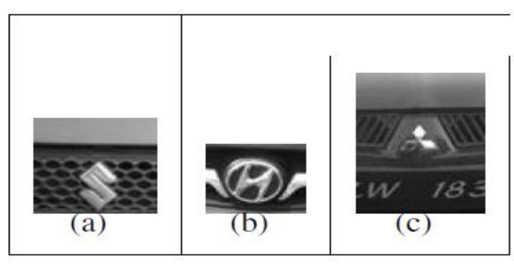


Figure 10: Result of Hough transform to detect the grill and then gradient to detect logo location

4.1.2 Texture analysis algorithm

The second method that was implemented extracted the textural features of the grill in location beside the symmetry line. In this experiment we used some Gabor filters [23] and then use a k-means clustering algorithm to divide output of the 2D Gabor filter into different textural regions. Each region is then examined to check if it contains the grill. This examination is applied using sliding window and a horizontal and vertical line detection mask. Figure 11shows sample of the result extracted using this procedure.

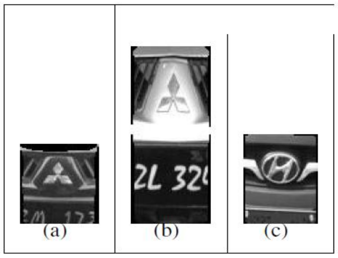


Figure 11: Example of the output of the Gabor filter texture analysis

4.1.3 Gradient algorithm

The third algorithm used to fine locate the logo image is a gradient based searching of the grille. After detecting the course location of the logo from the symmetry line. The system applies two gradient filters one to detect horizontal line and the second to detect vertical lines. After the filters are applied the system undergoes some morphological operations to fill the gaps and create a better mask for the air grille in the image. The final step is searching for the location of horizontal and vertical lines in the mask images. This final step produce and image with the location of the logo and the grille clear from the background. Figure 12 shows samples of the result extracted using this procedure.

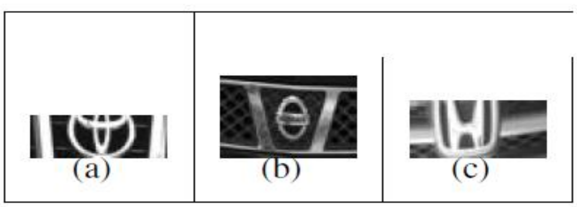


Figure 12: Example of the output of the gradient algorithm

4.2 Recognition Algorithms

After the vehicle logo is located in the input image and a final logo image is extractedbythe logo localization algorithm. This is the image that is used as an input for the next phase of the feature extraction and classification. A composite set of features is used to generate a three main feature vector. The following list describes each feature vector in details.

4.2.1 Scale Invariant Feature Transform

SIFT features is used to extract the key points from the logo image, the SIFT has an advantage to be robust to changes and will generate similar features for small and large images. This is helpful as the logo image may contain some other background. The SIFT feature are then concatenated into single features. To solve the problem of unbalanced features from different Images and types we only use the largest N[2] features in all input images and if the number of key descriptorsis less than N we add a dummy zero value feature to the feature vector.

4.2.2 Gradient Operators

These features use global gradient with Gaussian mask*:* The gradient of the image is measure of the intensity and direction of the image. The systems starts by applying a simple gradientoperator then computes the direction in 8 different sublayers finally each sublayer is convolved using a gaussain mask to generate the final feature set.

4.2.3 Wavelet

Our proposed solution uses wavelet transform to extract key features in the logo image. *2D wavelet transform:* A transform that captures both frequency and location information.

After computing the features, the symbol is introduced to the classifier as a feature vector. The system uses Support Vector Machine (SVM) classifier with Linear kernel [24]. An OVO classifier structure (object versus object) is used to handle the multi - class problem.

5. Results

This section presents the experiments conducted on the system and explain the obtained results. The dataset used in testing system was gathered as a dataset for license plate [25]. It consist of 708 frontal car images and 710 rear car from 8 different car manufacturers. We only used the frontal car images because the main constraints of detecting the logo on top of the grill. After the first few experiments we found that the dataset has images of cars without an identifying logo. A manual removal of images with no logo or when the logo is too small with respect to the car in the image. We also collected a set of 50 images to increase the dataset and compensate for removing images. Finally, we had 560 images that constitute our dataset used in localization and recognition.
In the experiments we conducted on the localization algorithm the test set implies that whole 560 images. In the recognition phase, we divided the data set into 70% training and 30% testing dataset.

Figure13 shows a result of the bilateral symmetry block with the line of symmetry and the main symmetry featured marked on the input image. In all the images the number of images that the logo is located in the image is 93.82%. The

[2] Empirically determined to by 74 feature

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figures below show examples of a correct and an error locating of the symmetry line and cropping of the logo. Most errors in detecting the symmetry lines are due to confusion between the car symmetry features and dominate symmetrical background features. Other errors include two short or a too long symmetrical line in the front of the car.

Figure 13: Sample of Correct localization

Figure 14 shows the results of localization using the different algorithms. The table shows the best result achieved by the system is 93.82% using Simple cropping.

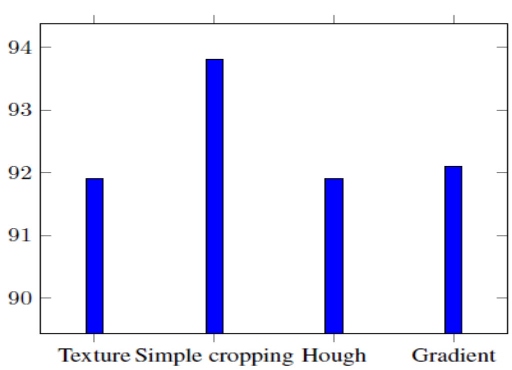

Figure 14: Final Localization Results

In Recognition phase, the dataset is divided into training, and testing is setto 70, 30 % respectively. A linear Support Vector Machine SVM classifier is used as a classifier for the system. The results presentd for the SIFT Features are similar to the 91% in [17]. Figure 15 shows the result of each feature extraction method. It is clear from the table that gradient provide better results than raw wavelet and SIFT features. This is natural as the gradients are powerful sets of feature and capture the local difference with more accuracy than wavelet features.

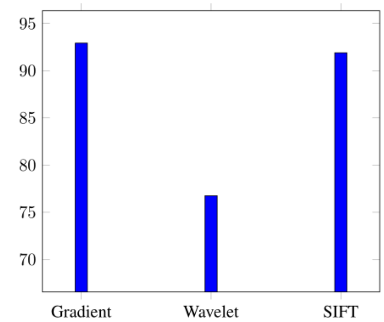

Figure 15: Final Recognition Results

6. Conclusion and Future Work

This paper presented a vehicle identification used in a traffic monitoring system using wireless sensor network. The architecture of the system consists of a wireless sensor network monitoring the traffic using various types of non-intrusive sensors. Acoustic and basic sensor nodes are mounted near each streetlight. These nodes has minimum processing power that sends information to larger access nodes. The access modes are installed on the traffic lights and will contain a camera sensor, larger processing unit and wireless access point to connect to the traffic control center. The access node process the information from sensor nodes and camera sensor to detect vehicles. The detection of vehicles triggers the transmission to the traffic monitoring center. This paper focus only on vehicle localization and recognition algorithms that are used in our traffic monitor system.

The vehicle logo localization algorithm based on the symmetry of the frontal image of the vehicle as well as the air-intake grille as the dominant features has been presented. The system uses SIFT key features to detect the mirror features along y-axis in the image. This symmetry line is line with the most number of mirrored features in the image. Three different logo localization algorithms are presented to fine locate the logo in the image. The first is just simple cropping with some empirically margins. The second uses gradient horizontal and vertical masking to detect horizontal and vertical lines in the grill. The third algorithm scans the input window and tries to detect vertical and horizontal lines using Hough transforms. A comparison of the three algorithms is presented in the result with final accuracy rate of 93.82% , 92.18%, and 91.97% respectively. The recognition of the logo is tested using SVM classifier with

two different features set, gradient and wavelet transform. The final recognition rate of the system is over 90% which is better than current vehicle logo recognition systems.
This paper represents a proposed architecture for a wireless sensor network to monitor traffic with the a detailed investigation of the vehicle recognition algorithms. The research focus on introducing vehicle logo localization and recognition algorithms to identify vehicle type in the traffic monitor procedure. Further work on the system will start by building the sensor and access point nodes. After building the nodes the next steps will include various simulations of power consumption and various vehicle detection algorithms using acoustic and magnetic sensors.
Further simulation of the wireless sensor network is needed to test the power consumption and effective distance between nodes. Also, further improvement to the current vision system could be included for testing other feature extraction methods and implement a more domain specific features. This will enable fast feature extraction that will improve execution time. Another improvement is to extend the system to deal with logo localization for a vehicle with irregular shaped air grille, back view of the vehicle instead of frontal view only

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