Automated Detection for Road Marking Quality, using Visual Based Machine Learning

Firas.Habbal [a], Fawaz.Habbal [a], Abdulla.Alnuaimi [b], Shafya.Alkheyaili [b], Ammar.Safi [b]

[a]Department of Management College of Business,
International learning institute, United Arab of Emirates
[b]Ministry of Infrastructure Development, United Arab of Emirates
E-mail: firas.habbal@iqli.net, fawaz.habbal@iqli.net, Abdulla.alnuaimi@moid.gov.ae,
Shafia.Alkheyaili@moid.gov.ae, ammar.safi@moid.gov.ae

Abstract –

Most of the cities road marking inspection is performed manually and considered an ideal candidate for automation because it is a labour-intensive process. We propose a solution based on automated quality assessment tool for road marking to detect and qualify road marking characteristics. Our data inventory and data collection approach work on images collected from a camera mounted on vehicle or drone. We use an automated procedure to choose images suitable for inspection based on road marks conditions. From the selected data we segment the ground and detect three different parameters; road markings conflicts, missing road markings, and road marking reflectivity.

We describe convolutional neural network and image classification algorithms that identifies road marks conflicts, visibility, missing road markings. We also discuss the problem of evaluate the quality of the existing road markings, conserve human and financial resources that is caused by on-site inspections, reduce improper manipulation of road marking (human errors), and prompt jobsite management to focus on promoting fine workmanship of road marking during the execution and train the classifier. We present results from the prototype that shows the detection of the three trained parameters mentioned above. Finally, we show results computed using our method over a subset of a citywide urban and non-urban road network.

Keywords –

Road Marking; Road Detection; Automated Roads Evaluator; Focal Point Detection

1 Introduction

For at least two decades, the development of transportation systems has led to the development of embedded applications allowing to improve the driving comfort and to minimize the risk level of hazardous areas. More specifically, the researches in intelligent and Advance Driving Assistance Systems have provided a great number of devices on many types of automatic vehicle guidance and security systems such as obstacle detection and tracking [1], road visibility measurement [2], pedestrian detection, road departure warn- ing systems. However, one of the first embedded system that was studied is probably the lane detection system. This application is usually based on road marking detection algorithms. [3]. This system is also one of the most important sources of information in order to build a local perception map of an environment surrounding an ego-vehicle. Indeed, this information provides relative vehicle location information to all other perception systems (obstacles, road signs, ...) that need to know the road and lanes attributes. For this reason, the system must be as robust as possible. Moreover, for several year, it appears evident the automation of the driving task is probably a solution in the reduction of the road injuries. But for automated or partially automated driving task, the road marking and lane localization are very important and provide a critical information. This information needs to be really accurate, certain, reliable in order to achieve some manoeuvers like lane changes or generate safe path planing (co-pilot) [4].

The research and the study proposed in this paper are directly dedicated to this important topic of road markings detection and tracking, and lanes estimation for automated and/or partially automated driving applications. Our objective is to provide an assessment of the road surface attributes (road markings attributes, type of road marking, number of lane and characteristic of lanes). This method is based on use of one or several embedded cameras.

Most of the algorithms are basically based on a three-step scheme summarized as follows. First, images are processed in order to extract road marking features. Second, extracted primitives are analyzed in order to extract point distributions corresponding to a road marking. And finally, in a third step, extracted and validated points are used to extract lane shape. In some previous work [5], the first extraction part has been studied, tested, and evaluated in order to determine the best way to extract road marking primitives. In this paper, a double extraction strategy is proposed to achieve the discrimination of the points for marking points and non-marking points. To guaranty the robustness of our approach, we proposed in addition a performance evaluation protocol for the first road primitive's extraction stage based on the use of the SiVIC platform, which is presented in [6]. This protocol provides an accuracy measurement of the clustering and robustness relatively to a clustering threshold.

In this paper, we present several significant improvements of the original method proposed by S. S. Ieng and D. Gruyer in [7]. The global scheme is the same one, but some enhancements have been done in each part. For instance, the combination strategy of several extractors, the management of the primitives in the detection stage, and the lane and markings estimation in the lane estimation part has been modified. In addition, instead of imposing a very discriminative threshold into the extraction part, we propose the use of the intensity of the extracted point into both the detection and the estimation parts. Lane marking detection, originally based on the study of a histogram containing projected points, is now made by using the same type of histogram but where the projected point is weighted in function of their uncertainty. Moreover, the poly-fitting mechanism has been replaced by a weighted poly-fitting, for the same reason. Higher is the extracted intensity points, more strongly weighted are these points in the estimation process. To robust our approach and avoid false alarms, distribution points which are not satisfying very discriminative criteria for peak clustering are submitted to a robust weighted poly- fitting.

2 Literature Review

2.1 Image Amendment

Because of the point of view impact, it is troublesome and dreary to discover the path of the street just from the first front view. To relieve this issue, we utilize differentiate viewpoint imaging strategies to make an all-encompassing perspective in the city. To do this, we have to figure the homograph network that maps the picture in the essential plane (essential camera pivot) to the vertical virtual camera. This transformation to IPM depends on the alignment boundaries of the network camera, the tallness of the camera over the ground, and the perspective of the camera comparative with ground. This implies the IPM is good with all camera designs in light of the fact that the homograph lattice is evaluated. Take these boundaries as indicated by [19] and change them separately for each shading channel of the picture. On the off chance that the skyline is known, the piece of the picture that contains the sky territory doesn't contain any valuable data identified with the street sign and is evacuated for additional thought.

2.2 Image Improvement

We improve feathered creatures eye picture differentiate by changing over shading esteems utilizing versatile limited complexity histogram evening out (CLAHE). This progression is important to evacuate the difference in the picture brought about by over the top sunlight-based light or. Nonetheless, the improved street picture may in any case experience the ill effects of extreme plan data, which might be unseemly for identifying street signs and may prompt mistaken street mark region proposition. To mitigate this issue, we utilize a snappy two-dimensional channel with portrayed advancements to expel structure data from perception while safeguarding edge data. From that point forward, we propose to use on-board data to improve street marker limits. Such an improvement would improve street marker recuperation results for various lighting conditions and assurance settled street mark zone recommendations at the territory identification stage. Along these lines, a top-notch edge map is separated utilizing the quickest edge locator proposed by Dollar et al. This edge discoverer depends on organized backwoods; it works at 60 fps and is impervious to different light conditions. In spite of the fact that this presents a method of producing material suggestions from edges, this calculation doesn't exhibit the precision of item recommendations good for our specific reason. Therefore, we propose an elective way to deal with recommendations of adjoining territories for recognizing street markings.

2.3 Recognizing Regions

Before we proceed onward to the subtleties of the last period of the field recommendation calculation [10], first depict a portion of the highlights that are helpful for expelling guide zones from the street surface.

1. Street signs are normally light and, in this manner, have a higher incentive than their sides. This expands their permeability and the probability that the driver will really feel them. Likewise, traffic signs are typically geometric and here and there painted in various hues.
2. Traffic signals are typically neighbourhood inside the road with long numbers (which are bigger than the width) to make it obvious to the driver in spite of the fast.
3. Some traffic signs have a lot of signs or text.

For this situation, all their contacts are near one another to guarantee that their mediator will be equivalent to the street checking. Keeping these properties in mind helps us to develop a robust road marking detection algorithm.

Our zone helps cut the picture of ROI discovery in zones that are acceptable possibility for street signs. Traffic scene symbolism, particularly in urban zones, includes a ton of things, for example, vehicles, individuals, trees, which are not important to us, wiping out most zones where street signs are not noticeable. Improves framework execution. We depend on the distinguishing proof of fascinating territories; street signs are in every case splendid around them since they are intended to look simple. For this reason, we utilize Fixed Additional Areas (MSER) to distinguish territories of intrigue that are street markers for our situation. The MSER is an associated locale, and the pixels in the districts are consistently more splendid or darker than the pixels inside the range. There are compelling calculations for processing MSER. We identify MSER in precise road see pictures. Alongside certain regions of different pieces of the scene, practically all zones with street signs were found. Be that as it may, these phony disclosures don't cause any issues in our calculation as they are detached at a later stage. MSER is steady in splendid and recognizable changes. In the writing, variable similitude of direction is acquired by adding circles to MSER areas, changing over curved districts into roundabout districts, and finding nearby element vectors. For our situation, in any case, rotational shakiness is unfortunate since it causes discovery. Street signs on the contrary roadside.

2.4 Focal Point Detection

We separate a lot of highlight focuses from the districts of intrigue registered as clarified previously. To empower constant calculation without the utilization of GPUs, we utilize the FAST corner locator proposed by Rosten et al [18]. Quick has been accounted for to be around multiple times quicker than the Harris corner locator, and multiple times quicker than SIFT. Repeatability of highlight discovery is accounted for better than, and even under the least favourable conditions practically identical to, the SIFT key focuses indicator. We apply the FAST corner finder on the locales of intrigue recognized on the redressed pictures.

2.5 Highlight Extraction

Every POI is gravitated toward an illustrative descriptor. We figure the histogram of the objective expressive (HOG) for every POI. The descriptor of the HOG comprises of a quality vector with 128 measurements, determined utilizing the "best" approach at picture scales around explicit scales and POIs. Deciding these best scales and bearings is a long count. Given the necessary speed, we draw the HOG work vector with 3 fixed scales and 1 fixed bearing. For each scale, a 128-dimensional trademark is determined for every POI. By taking a gander at the included highlights at various scales, we get the last 384-dimensional element vector for every POI. For every single model picture, the arrival on speculation with traffic signals is gotten from reality on troublesome ground. Following the upgrades, POIs in the ROI named the pictures all things considered. From that point onward, the component vector is utilized for all POIs. All highlights are put away as vector reconciliation model pools and related POIs [20].

2.6 Solid twofold picture

The significant data of primary property on how we can expel street signs [11]. Since the street signs are more brilliant than the territory around them, the top channel utilized in it tends to be utilized to feature territories of intrigue. The top warmth channel has the state of a rectangular progression capacity and channels the closest neighbour. Practically speaking, nonetheless, the top warmth channel produces inadmissible outcomes when seen to some degree because of obscure or outrageous light conditions. Furthermore, the channel is delicate to reaction boundary settings.

2.7 Merging of Regions

The third property gives us bits of knowledge into the reconciliation of recommendations in the region. We can see that some sign-based street markers have numerous associations. While some examination sums up territory recommendations by depicting bunch requirements and others treat every area exclusively, we propose a superior answer for this test. Specifically, we use commotion (DBSCAN) with nearby thickness-based bunching of uses created by Torr et al. Basically, DBSCN is a grouping calculation that makes bunches from high-thickness models dependent on the local range, where searches are performed and the base number of explicit focuses in the group less TS. This calculation accomplishes the base number of focuses by choosing any point in the informational collection and imitating the current group from the current bunch point with the minP ts limitation. At the point when the calculation leaves the focuses to be added to the group, any new point is at long last chosen and the procedure is rehashed. Be that as it may, the calculation becomes flimsy when the limit purposes of neighbouring groups are recognized. The depicted places of business this issue and shows the exhibition of visual execution contentions for information with neighbouring bunches. This makes thickness based grouping a powerful acclimation to accomplish a lot of locales that have a place together and have a place with a similar class. The grouping calculation is applied to the inside directions of the considerable number of proposals of the street checking zones in the wake of separating the wrong regions. The utilization of thickness-based grouping disposes of the need to consider every locale separately and combine districts utilizing experimentally decided imperatives.

While path identification has been seriously read for a considerable length of time, the recognition of other street signs, (for example, representative and finished) has pulled in little consideration. To tackle the issue of finding street signs, numerous strategies depend on starter data about the area of paths. In any case, path exactness may antagonistically influence the acknowledgment of other street signs. Tao et al. He noticed the requirement for autonomous distinguishing proof of street signs and proposed an elective calculation to recognize and distinguish street signs. This methodology influences the recently applied IPM procedure to manage point of view impacts. From that point forward, numerous ROIs are recovered as MSER.

In this way, the FAST component identifier is utilized to remove the objects of intrigue, and the arranged inclination histogram (HOG) is utilized as a handle to make an example for each class. The layout picture is then contrasted with each picture in the format, and the class mark is doled out by looking at the vectors of the test highlights and each picture in the layout. Despite the fact that the creators report victory, this strategy depends on the precision of an exceptionally quick FAST finder and extricating substantial HOG capacities is computationally costly. On the other hand, [15], Perform low-level preparing to remove ROI from IPM pictures to distinguish target street signs. Recuperated ROIs are breaking down and distinguished dependent on rakish direction and bead size. In spite of the fact that this work has yielded good subjective outcomes, no quantitative appraisal is justified. Moreover, another calculation ought to be liable for recognizing a specific sort of street marker, which brings about lower adaptability. Correspondingly, it tries to expand the unwavering quality of the calculation by separating street markers into text and representative street markers. Text-markers are recognized utilizing the optical character acknowledgment calculation, while character-based markers are distinguished by extricating the HOG highlights ordered utilizing the support vector machine (SVM). In any case, a slight improvement in the proposed calculation doesn't legitimize the need to process street markers independently, prompting computational repetition.

In contrast to physically made assignments, whose exhibition relies upon their planned reason, classifiers have demonstrated their dependability for some PC vision applications dependent on fake neural system extraction (ANN) devices and AI. Various works have endeavoured to utilize neural systems to improve the discovery and recognizable proof of street markers. For instance, [17] the creators propose to utilize the coordinating edge in the IPM picture to discover likely contender to submit to a prepared neural grouping.

This strategy shows great quality against various states of light, climate and street surface. This is the primary method to utilize completely associated neural systems to perceive street signs. Rather than completely associated neural systems, virtual neural systems (CNN) have performed better in characterization results because of their capacity to remove increasingly powerful portrayal highlights. Be that as it may, with current ExxonMobil or VGGNET models, such a profound CNN as a rule requires a great deal of preparing information and is regularly executed on costly GPUs, permitting the vehicle circuit but there is more weight. Following this rationale, Chen and so on. Proposed a calculation that utilizes the Being Object Detector to give proposals to various potential areas with similitudes to the district's images. These up-and-comer territories are additionally grouped by the PCA Network (PCENT). PCN8 is a sort of profound learning system that utilizes PCA channel bank as opposed to confounding layers like CNN. As a rule, PCANet is a lightweight rendition of CNN that is basically basic and has demonstrated to be a compelling technique for picture arrangement. The impediment of the proposed approach is that a fixed number of BNB lines (30 offensive up-and-comers) are drawn per outline, which frequently prompts computational repetition, as the quantity of street signs from the survey perspective never increments. Doesn't reach such huge numbers of locales.

Another disadvantage is that the street markings are not set accurately and regularly the determined bouncing box contains other disconnected articles. Simultaneously as our work, Hyeon et al. We have built up an elective framework for perceiving and perceiving street markings. This technique varies from multiple points of view. Extraction of associated sets is finished utilizing Gaussian diff rather than MSER. Locale put together gathering is accomplished based with respect to curved conditions while depending on thickness-based gathering. Arbitrary woodland is utilized for characterization errands. Rather, utilize further developed AI strategies. Likewise, this paper groups perceived regions into image based or text-based street markings, however the client needs to accomplish more acknowledgment. This technique, then again, treats all street markings similarly and perceives an unmistakable class of all street markings presented. Intrigued per users are urged to think about this synchronous work too. To beat the previously mentioned downsides of the current techniques, we propose a calculation that gives superior on complex datasets. Our commitment comprises of three sections.

We give a framework that dependably recognizes street markings in pictures. Wireframes process a few pictures in equal without expanding the calculation time. This commitment guarantees that street markings are distinguished under various lighting conditions and uses thickness-based bunching to amass street markings. These disposes of the need to process character and text territories independently and utilizes AI procedures to perceive street markings. Notwithstanding PCANet, it proposes a little CNN and gives an iterative answer for improve and keep up the steadiest districts.

2.8 Runtime Template Corresponding

We presently go to the execution coordinating calculation that improves the score. The means recorded in the past areas. Amendment, MSER check, sharp edge location and HOG-explicit computations are performed on each test symbol. The test pictures are uncovered based on POI after indication discovery. In the road see picture, there might be a wide range of traffic signs. What's more, one sort of image can show up in numerous spots in a picture. In this way, each example may have more than one comparing patch in the test picture. Moreover, P.O.I. The identifier doesn't have a redundancy of 100 reiterations, subsequently, a portion of the POI tests found in the test picture don't show up in the example, etc. Accordingly, the test picture for the most part has a similar POI substrate as the POI substrate in the example. There are two stages in our calculation to ascertain this comparability. In the first place, we acquire a positive POI coordinate dependent on their component vector, and second, we improve the outcome utilizing an auxiliary coordinating calculation that coordinates the 2D geometry of the POI in the street sign [3].

3 Research Methodology

Our aim of this research is to develop an automated road marking detector based on multi-deep learning algorithms to detect and qualify the road marking conditions in which is evaluated the best selected road marking that fulfil the future autonomous vehicles needs and requirements, by utilizing deep learning algorithms. Using convolutional neural network and image classification technologies, the proposed prototype system first receives digital images of finished road marking surface and do the images processing and analysing to capture the road marking characteristics.

Those characteristics are then evaluated to determine the quality level of road marking conditions. System will be trained by multi-real cases as well as demonstrated through three real cases to show how it works. In the end, a test comparing the assessment results between the proposed system and expert inspection will be conducted to enhance the accountability and accuracy of the proposed mechanism.

Our system consists of training and testing phases. The input to the training phase is a set of images with ground truth masks and labels of the road markings as shown in Figure 1.

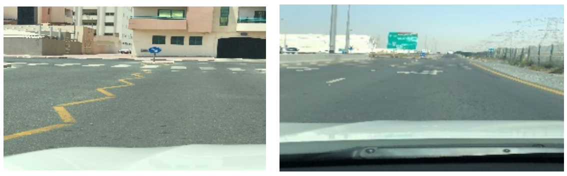

Figure 1. Template Images

We will call these training images as template images henceforth since these are used as templates for the road marking detection.

For each template image, we first perform rectification to compensate the lens and perspective

distortions. Within the regions of interest containing the road markings, a set of points of interest (POI) are detected, for which we use FAST corner detectors [15]. A Histogram of Oriented Gradients (HOG) [16] feature vector is extracted for each POI and the template set is built using the locations and the feature vectors of the POIs extracted from all template images for the particular type of road marking.

During runtime, the same steps are repeated for each frame of the testing video, captured pictures and a set of POIs and their feature vectors are extracted, except that the regions of interest are detected automatically. Subsequently, we find multiple matching candidates for each POI in each template image. Lastly, a convolutional neural network and image classification algorithms are employed to test if a subset of the matched POI pairs forms a road marking the same as the ones in the template images.

3.1 Image Rectifications

The camera we use is mounted on a rooftop rack and focuses to the front of the vehicle. Because of this low perspective, there is a huge point of view contortion with separation. We correct the picture utilizing a reverse point of view change that altogether diminishes this mutilation. Converse viewpoint changes have likewise been utilized widely in past work on street stamping identification [16], [4]. The reverse point of view change is a lattice which just relies upon the camera adjustment, the tallness of the camera over the ground, and the review edge of the camera θ regarding the ground Figure 2. Applying the lattice changes an information picture to a feathered creatures eye see. A case of such a fowl's eye see is appeared in Figure 3. Note that the change boundaries are adjusted beforehand accepting the ground is level, as opposed to aligned in real-time. Subsequently the paths might be not ideal equal in the winged animals eye see when the vehicle is on slopes or has pitch and move developments. Acquiring the flying creatures eye see permits us to legitimately figure the slope on this picture to get the HOG descriptors. Without the winged creatures eye see, we would have been compelled to utilize an anisotropic angle administrator to represent the point of view twisting.

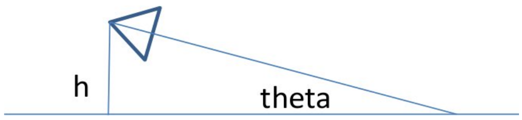

Figure 2. The setting of Cameras

Figure 3. Image Detection multi views

3.2 Region of Interest Detection

Our region of interest (ROI) detector helps prune the image to portions which are good candidates for being road markings. Since a traffic scene image, especially in urban areas, will contain many objects such as vehicles, people, trees etc., which are not of interest to us, removing most of these areas where road signs are not likely to occur improves the efficiency of our system considerably.

We base our recognition of interesting regions on the perception that street signs are consistently more brilliant than their prompt environmental factors since they are intended to be seen without any problem. To this end, we utilize Maximally Stable Extremal Regions (MSERs) [17] to identify locales of intrigue, which are putative street markings for our situation. A MSER is associated district that is extremal as in the pixels inside the locales are consistently more splendid or darker than the pixels on the limit. Proficient calculations for processing MSERs exist. We recognize MSERs on the redressed street scene pictures.

MSERs are steady across brightening and perspective changes. In the writing, perspective invariant coordinating is accomplished by fitting circles to the MSER areas, changing the oval districts to roundabout locales, and extricating nearby component vectors [15]. Be that as it may, for our situation, the subsequent revolution invariance is bothersome as it would prompt discovery of street markings in the contrary roadside too. A model is appeared in Figure 4, where there is a left go sign in the contrary path. Subsequently, we don't change the MSERs into circular districts.

3.3 Runtime template matching

We currently continue to the runtime coordinating calculations that perceive the street markings. The means referenced in the past areas viz. correction, MSER identification, Quick corner discovery, and Hoard descriptor calculation are performed on each test picture. The signs in the testing pictures are then recognized and distinguished dependent on the POIs.

In a street scene picture, there might be numerous diverse street signs. Additionally, a solitary sort of street stamping may show up at different areas in a picture. In this way, every layout may have numerous coordinated fixes in a test picture. Furthermore, since the POI identifier doesn't have 100% repeatability, a portion of the POIs distinguished in the test picture may not be recognized in the layout picture and the other way around. Subsequently, there is generally a subset of POIs in the test picture that coordinate a subset of the POIs in the layout. Our calculation to process this coordinating comprises of two stages. Initially, we find putative coordinating sets of POIs dependent on their element vectors, and second, we refine the outcome through an auxiliary coordinating calculation that coordinates the 2D geometry of the POIs inside the street checking.

4 Dataset

To the best of our knowledge, currently there is no dataset that is designed for evaluating the performance of road marking detection and recognition. Hence, we collected our data using a mounted camera on a rack of a vehicle or drone and facing forwards. The vehicle was driven on urban and non-urban roads in Dubai and Sharjah Emirates, UAE under various road conditions. We manually annotated a subset of the road markings appearing in the captured images. We hope that this extensive dataset will provide a fruitful benchmark for other researchers working on this problem. An example of an annotated template image is shown in Figure 4.

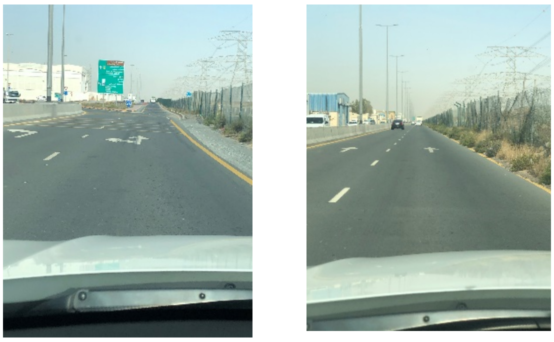

Figure 4. Annotated template

5 Experiments & Findings

We tested our algorithm on the dataset described above. Our algorithm uses OpenMP for parallelization in the feature extraction stage. A value of 1.3 was used for the α threshold from (1), while the value for the β parameter from Section IV-B was set to 0.01.

Figure 5. Detection Segments

Fig. 5 Unqualified Detected Segments left side the wrong road marking and right side the template images

Our system currently depends on two manually selected threshold values, the α parameter of (1) and the β parameter of section IV-B. It is future work to automatically select these parameter values and adapt them online for different test conditions. We currently observe that the values used in our experiments presented above are applicable in a wide range of scenarios including large variations in road marking conditions.

Our system works robustly for complex road markings, but the false positive rate is higher for simpler markings such as forward arrows. Finding a tighter cost function that alleviates this problem is part of future work.

In our experiment, we select several images as the templates, which contain different types of road markings including pedestrians' crosswalks, intersections, and roundabouts. Our algorithm achieves a true positive rate of 90.1% and a false positive rate of 0.9%, indicating that false positive detections occur only very rarely. We found that our algorithm could also detect and recognize road markings clarity in case of sand dunes / snow accumulation.

In our system, we trace and obtain several segments that contains unqualified road markings as shown in figure 5.

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