Feature Extraction Analysis, Techniques and Issues in Vehicle Types Recognition

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Abstract— The Vehicle Type Recognition is one of the applications in the Intelligent Transportation System that has implemented in wide range areas such as intelligent parking systems and automatic toll collection system. The system is recognized and classified the vehicle based on vehicle types such as car, bus and truck classes. Most of the system's accuracy depends on the features which represent the information from the data and the process of feature extraction whether to use single features extraction technique, a combination of single features techniques or based on deep learning methods. However, this paper focuses on feature extraction technique based on deep learning which is a Convolutional Neural Network. There are issues in the system that limit the capability which caused by overfitting, underfitting and intra-class issues. The intra-class issue occurs due to lack of features data and imbalanced dataset which is used for vehicle type classification. It happens when the recognition is applied to the vehicles with the almost similar appearance of the vehicle structure, for different vehicle type classes. To conclude, this paper discusses the related findings based on feature extraction techniques and issues in Vehicle Type Recognition; and used for a further research study to learn more about deep learning methods and data augmentation technique to improve the vehicle recognition and type classification especially in intra-classes.

Keywords— Vehicle Type Recognition; Feature Extraction Technique; Convolutional Neural Network

1. INTRODUCTION

There are lots of development in the Intelligent Transportation System (ITS) [1],[2],[3] that have published since 1996 [4]. ITS is an integrated application of advanced technologies that used communications, computer and advanced sensors to provide great quality, safe and efficient systems to manage and improve the transportation management [2],[5]. It uses detection, tracking or recognition method to applied in the transportation management system to provide a smart city. Vehicle recognition is one of the applications in ITS. It consists of a method that vehicle type will be recognized using the vehicle features either sensor-based or camera-based applications. However, this paper focuses on vehicle recognition using camera-based because it is more practical to be used compared to the sensor-based approach. It is due to the advantages of the camera-based have, for instance, low cost for maintenance and practical to applied in the system [6],[7]. It also can give an accurate measurement when the Artificial Intelligence technique(s) imposed in the system [8], [9].

The vehicle recognition divided into four categories of classification [10] which are vehicle type that known as vehicle type recognition (VTR) such as car, van, minibus, and truck classes; vehicle model or logos such as Toyota, Ford, and Nissan; vehicle license plate and vehicle color such as red, blue and yellow. Nevertheless, VTR is one of the approaches in the ITS applications that have implemented in wide range areas such as traffic flow statistics, intelligent parking systems, automatic toll collection systems, and vehicle counting [11], [12]. For example, in the automatic toll system whereby the toll rate can be automatically determined based on the automated recognition of vehicle type. The purpose of VTR is to recognize and classify the vehicles accurately and efficiently, according to the vehicle type whether inter or intra-classes using the extracted features [13], [14]. Intra-class is a group contain few classes that have a resemble appearance and lead to a high percentage of similarity features between classes. While inter-class is a group of classes that contain different features in each class. However, the method has a difficulty to recognize and classify for the specific vehicle due to the almost similar appearance of the vehicle. Due to this limitation, the majority works applied deep learning methods such as Convolutional Neural Network (CNN) to maximize the learning features [9], [15], [16]. However, to extract the unique features in this research area leads into the system complexity such as overfitting and underfitting[17], [18]. This paper will focus on VTR studies by reviewing the feature extraction analysis and techniques; and also, the challenges and issues in this research area referred to the existing works.

In this paper, we organize the review into three parts which are feature extraction techniques, the challenges and issues and the conclusion. In Section 2, the feature extraction analysis and proposed techniques that have been used in VTR will be discussed in two subsections; single features extraction technique and the combination of single features extraction based on deep learning methods. Followed by Section 3, the challenges and issues in VTR are provided and discussed. Finally, Section 4 concludes a summary of findings and a discussion of important future research directions.

2. FEATURE EXTRACTION TECHNIQUES IN VTR

The VTR can categorize into two types; static-based or motion-based. Both methods have almost similar process steps, however, using different types of input and pre-processing. It uses shapes, edges or other appearance features to recognize from the image. The static-based method uses the static vehicle appearance as an input data for the recognition [19], [20]. A static vehicle appearance is an approach that used to distinguish the vehicles in an image from the static background or static objects such as trees or road. It applied to static background application such as parking lot system and automatic toll system. Whereas, the motion-based is to capture the input data of a moving vehicle from a video [13], [21]. It applied in many applications such as traffic control system and traffic census. The moving vehicle distinguished from a background in the video either static background or dynamic background. The static background captured from a camera that is located at particular positions using a fixed angle. Whereas, the dynamic background has a changeable background due to the motion angles of the camera. Most of the researchers fully utilized the extensive use of traffic surveillance cameras in capturing the image in VTR [22].

However, this paper will focus on VTR using the static image based on the static-based method. It is due to the motion-based that applies to use in live applications and still convert the input data from the video to a static image using from the video frame for the recognition process [21]. Hence, to do VTR, the vehicle features will be recognized and classified based on the vehicle type classes such as car, van, bus, ambulance, and truck. The first step is data acquisition which is to put the input into the system. Then, the pre-processing will be applied to remove the noises, prior to the next processes which are feature extraction, feature selection, and classification. Feature extraction is used to extract the features from the input data such as edges, shape, texture, colour, and others. Commonly, the accuracy of the system depends on the features information while the classification used to classify the data and generate the results into image classes. In this review, we focus only feature extraction process and techniques that have applied in the VTR based on existing works. The feature recognition is using the information that extracted from the data to do matching recognition. In order to get an accurate result for VTR especially for intra classification, unique features need to be extracted from the data. However, to learn and extract the unique features, it became an issue for feature extraction process in VTR.

The feature extraction divided into two categories of features analysis. First is a single features extraction method which based on global features or local features. The second features analysis is the combination of the global and local features method [23]. Global features are used to describe the images as a whole to generalize the entire object. Meanwhile, the local features are used to describe the key points of the image object. The example of the single feature extraction techniques such as Principal Component Analysis (PCA)[24], Histogram of Gradient (HOG)[25] and Scale Invariant Feature Transform (SIFT)[25]. While the works that used combination feature extraction, using either combination of the single features technique or based on deep learning. The example of deep learning methods is such as Convolutional Neural Network (CNN)[26] and Deep Belief Network (DBN)[27], [28]. Table 1 shows the overview of feature extraction in VTR. This table consists of two sections, first section is single feature extraction method and second section is combination of single extraction method based on deep learning.

Table 1: Overview of Feature Extraction in VTR

i.Single Feature Extraction Method				
References	**Techniques**	**Advantages**	**Limitations**	**Result**
Irhebhude et al., 2016 [29]	CENTROG Support Vector Machine (SVM)	It practical during daylight and night-time	Limit type classes in the classification	Day: 97% Night: 100% accuracy

Chantakamo & Ketcham, 2015 [7]	Blob K-Nearest Neighbors (KNN)	Use low-level features Low-cost	Real-time surveillance	88% accuracy
Kafai & Bhanu, 2012 [6]	Blob, GMM, SFFS Algorithm, DBN	Use low-level features, low-cost, tolerate noisy feature	Error in the classification of vehicle type	95.68% accuracy
Chen, et al., 2011 [14]	Polygonal boundary Random Forest SVM, model-based classification	Low cost Easy to applied	Time-consuming, High Performance	96.26% accuracy
Khan, 2010 [30]	Hog SMD - Salient Match Distribution Matrix	The dataset consists of vehicle images from various viewpoints	Occlusion issue Intra-class issue	80% accuracy
ii.Combination Feature Extraction Methods based on Deep Learning				
References	**Techniques**	**Advantages**	**Limitations**	**Result**
Zhuo, et al., 2017 [31]	CNN, Caffe Software	Work well with big databases, illumination and view angle	Occlusion and limited data issues	98.26% accuracy
Kim & Lim, 2017 [32]	CNN, Data Augmentation, Bagging	Work well with big data; able to improve the imbalanced data issue; improve the performance	Intra-class issue	97.84% accuracy
Yao, et al., 2017 [9]	CNN, Data Augmentation, Softmax Classifier	Apply to inter and intra-class Robust against various translations, rotations, and noise variance	Error in intra-class Shadow issue Severe occlusion issue	92-94% accuracy
Huang & Zhang, 2016 [25]	CNN, ROI	Improve the vehicle features by localizing the corresponding parts	Error in classification	88.34% accuracy
Wang et al., 2016 [33]	CNN, ROI, Extreme Machine Learning (ELM)	Effective to applied on real surveillance	Not specific on vehicle type classes	85.56% accuracy
Asaidi et al.; 2014 [34]	Integrated Neural Network Bayesian classifier, Color histogram	Shadow Remover Low cost	Intra-class issue	96.96% accuracy
Dong et al., 2014 [12]	CNN, Softmax Classifier	Effective in classifying vehicle type using unsupervised data	Error in intra-class	92.89% accuracy

A. Single Feature Extraction Technique

For the first section in Table 1 shows the overview based on single feature method and the applied techniques based on existing works. Based on Irhebhude et al. [29], they proposed Census Transformed Histogram Oriented Gradient (CENTROG) feature and SVM technique for vehicle recognition at daylight and night times. They can classify into two types of classes in night-time which are car and truck; while three types of classes in daylight which are car, jeeps, and truck. They also used frontal angles to do recognition and achieved 97.2% of accuracy at daylight and 100% of accuracy at night-time result. Next, Chantakamo & Ketcham [7], they proposed hybrid Blob and KNN techniques by getting low-level features to apply in the multi-vehicle recognition. From their work, they can classify the vehicle types into three classes which are car, pickup, and truck; using rear side view and achieved an 88% accuracy result.

For Kafai & Bhanu [6], they proposed low-cost approaches, which used blob analysis and Bayesian network for vehicle classification. They classify the vehicle based on the rear view of four classes which are sedans, pickups, SUVs and unknown classes using tail light pattern features. From the proposed work, they able to produce a method that tolerates to noise from low-level features, and get 95.68% accuracy in recognition result. Next, Chen et al. [14], they have proposed vehicle type categorization by making a comparison of classification schemes using polygonal boundary, random forest, SVM and model-based classification. The proposed technique can classify the vehicle types into four classes which are cars, bus, van, and motorcycle; by using frontal view and able to get 96.26% of accuracy result. Lastly, for Khan [30] he has proposed a technique using Hog, Salient Match Distribution Matrix (SMD) for 3D model-based vehicle classification in aerial imagery. They proposed a technique that can classify the vehicle types into nine types of vehicle classes based on inter and intra-classes which is a full sedan, mid sedan, a compact sedan, coupe, station wagon, van, SUV, compact SUV, and truck. From the recognition based on the 3D view, they achieved 80% of the accuracy result.

B. Combination Features Extraction Technique based on Deep learning

Next, for the second section in Table 1 shows the overview of the combined features methods based on deep learning; and also applied techniques based on the existing works. According to Zhuo, et al. [31], they used CNN and Caffe software to do vehicle type classification based on inter and intra-classes from the large-scale traffic surveillance video. They proposed a technique that can classify the vehicle types into six classes, which are car, van, motor, minibus, bus, and truck; by using frontal angle and achieved 98.26% of accuracy result. Next is Kim & Lim [32], they proposed to use CNN, data augmentation such as flip and rotation and bagging for vehicle type classification on multi-view surveillance. They proposed a technique that can classify the vehicle types into seven classes, which are car, van, pickup truck, articulated truck, pedestrian, bicycle, and motorcycle; by using multiple view angles. From their proposed work, they able to process big data and able to improve the imbalanced data issue from proposed post-processing thus improve the system's performance and achieved 97.84% accuracy result. Next, Huang & Zhang [25] work has proposed to use CNN and region of interest (ROI) technique to do fine-grained vehicle model recognition. From their proposed work, they able to improve the vehicle features by localizing the corresponding part and achieved 88.34% accuracy result. Based on Wang et al., 2016 [35], they have proposed CNN, ROI and Extreme Learning Machine (ELM) to classify the vehicle into three categories which are compact, middle size and heavy duty. Their proposed method is effective to be applied to real-time surveillance and able to get 85.56% accuracy result.

For Asaidi, et al. [34], they proposed an integrated neural network with the Bayesian classifier and colour histogram to eliminate the shadow and classify the vehicles types in traffic video surveillance. This proposed technique can remove the shadow element in the image and low-cost implementation and able to classify into three categories, which are car, van, and truck; by using front view and achieved 96.96% of accuracy result. Based on Yao, et al. [9], they proposed to use CNN and Softmax classifier to classify the coupled multivehicle with the prior objectless measure. From the proposed technique, they can locate and classify the vehicle types accurately between inter-class and intra-class, decrease searching time, robust against various translations, rotations, and noise variance also adapted to the multi-vehicle environment. Their work also can classify the vehicles into three classes which are bus, car, and taxi. They also used frontal images and able to get 92% to 94% accuracy based on vehicle types. Dong et al. [12], they proposed vehicle type classification using CNN and Softmax Classifier. From this work, they were able applied their work to unsupervised data into the vehicle type classification and also able classify the vehicle into six types of classes which are bus, microbus, minivan, SUV, sedan, and truck; using frontal view and achieved 92.89% of accuracy result. For the limitation in Table 1 overview of both sections will be discussed in Section 3 which challenges and issues in VTR.

Based on the existing works, the single feature extraction method is a feature extraction process based on local features or global features method. This method has widely used in many existing works which mostly used in the early methods for vehicle verification [9], [25], [36]. Most works used global features such as PCA technique used to extract the vehicle images [19], [37]; while HOG technique used for vehicle verification based on the gradient features [38], [39]. For local features such as SIFT [40] and LBP [3], [41] techniques, it describes the image patches by computing multiple points in the image. The selection of the combination approach is because of the limitation of the single feature extraction technique. The purpose of VTR is to classify and recognize the specific vehicles accurately and efficiently under the unconstrained and complex environment [13], [14]. Unfortunately, the single feature extraction technique is only extracting the single features either local or global features extraction. Plus, the single feature extraction limits the system to classify into small classes such as vehicle and non-vehicle. In order to increase the accuracy results along with the complex and variation of vehicle type classes, the combination of the single feature extraction technique approaches is a strategic method to extract features in the VTR. The example of the combined single features method such as a combination of PCA and LDA technique [14], [42]. Although this method was claimed to perform well for vehicle recognition [3], [6], [30], due to the lack of unique features, it has caused the difficulty of classification process for intra-classes and leads to an inaccurate result [9], [43]. Intra-class is a group class that contains a different vehicle type but has a high percentage of similarity features between each other classes such as car and taxi; or van and minibus. In order to reduce high similarity features**,** the combined features based on deep learning will be selected to be the focus of this paper. This combination of deep learning methods is used to enhance the feature extraction process to gain unique features.

The selection of deep learning methods has been used by many existing works and able to increase the results accuracy and reduce the process time. The advantages of using deep learning are able to deal with big data features in the system [31], [35]. It also enhances the feature learning process to increase the accuracy result by searching the features and find the correlated features [9]. Besides, its feature learning process helps the system to find new or uniqueness features in the limited set of features data [16]. The deep learning methods have widely used in the recognition research area such as for human face, fingerprints and vehicle recognition. There are four types of deep learning model which are Deep Belief Network (DBN) [26], Deep Boltzmann Machine (DBZM) [24], Autoencoder [44] and Convolutional Neural Network (CNN)[15], [45]. DBN is a model that used the feed-forward neural network with a deep architecture. It used to learn the feature and suitable for unlabeled data. However, it cannot use to extract higher-level features which are used to getting unique features. Next, DBZM is a generic model with the potential of learning complex internal data. This model can use to extract high-level features of complex data. However, the DBZM cannot predict accurately because of the random distribution technique that applied in this model. For Autoencoder, it is a deep learning model with one hidden layer that using an unsupervised learning algorithm to compress and encode the data. Plus, it also used as a noise remover. However, this model is not suitable to use in this VTR study because the model is not deep to learn the features critically. Plus, for DBN and DBZM model is not suitable for this study because of both models suitable for unsupervised data and data clustering. While for CNN, this model has many hidden layers to deep learn the features and able to extract the unique features which are an issue for single feature extraction method. This paper will focus on CNN method because of it is suitable for supervised data and data classification especially for this VTR study.

3. THE CHALLENGES AND ISSUES IN VEHICLE TYPE RECOGNITION

From the overview in Table 1 in the previous section, there are lots of issues and limitations in VTR. For the first issue in VTR is a real-time issue. It happened when the proposed system cannot work well in the real-time environment and caused Chantakamo & Ketcham [7], and Khan [30] works get a low percentage of accuracy result. Next limitation in VTR is an error in classification. This issue occurs in single feature extraction works when the works are classified into many classes. Based on Khan [30] has proposed the work and has an issue in intra-class features cause limitation in the vehicle recognition. He used various 3D viewpoints to adapt the complexity background image. However, their proposed technique also has a limitation which it avoided the texture fewer regions like the centre of the roof or hood. For instance, sedan types have more overlaps with other classes. The proposed works able to classified the vehicle into 70% mid-sedan, 12%, full-sedan and 6% compact-sedan, respectively. Similarly, the recognition of van classification is frequently misclassified when comparing with SUV or Station Wagon because of the vehicle structure. Besides, his work also has occlusion issue which limits the robustness. Whereas, for Chantakamo & Ketcham [7] and E. Irhebhude [29] works also are limited into classification thus make their high percentage result was not practical if applied into complex data classification especially for intra-class. Also for Kafai & Bhanu [6] work, their limitation is an error in the classification of vehicle type because of the limitation of features data. The solution to these limitations, the system needs to apply multiple or combination features to increase the result of performance. However, the high performances work also leads to another limitation which is time-consuming like Chen et al. [14] work. It is because the system will be complex when a function with a combination of two features extraction techniques to extract the features from the input data.

Next limitation in VTR that to focus on this paper is an intra-class issue. Even though there are many enhancements of deep learning methods in VTR, there are still lots of limitations based on CNN. For example, Zhuo et al. [31], their proposed technique is applied in vehicle type classification based on inter-class and intra-classes from the large-scale traffic surveillance video. The intra-classes which are known as groups class that have a high similarity feature between each other. While for inter-class is a group of class with obvious different vehicle structure and has a low percentage of similarity features between each other. Their proposed technique is compatible with working with databases that contain various changes illumination and view angle. Also used for limited dataset by enhancing using fine-tuning. However, their work is limited to occlusion issue because of they only focus on single vehicle from front angle to recognize and extract features from the input. Next, Kim & Lim [32] work is limited in intra-classes issue which is hard to classify the vehicle that has the almost same appearance and features. For example, is the classification between a pickup truck and articulated truck because both trucks have almost the same vehicle structure. Besides, the imbalanced dataset in vehicle classes cause limitation of unique features especially in intra-class leads to inaccuracy result in the classification process. While for Asaidi, et al.[34], the limitation in this research work is the classification focused on inter-classes thus limited to apply in the intra-classes classification. It is due to some error in the detection of vehicles from spatial image resolution, which affects the robustness of moment invariants. It also indicates that moment invariants perform well and not suitable to apply in intra-classes which have high similarity for vehicle features. Next, for Yao et al.[9] work, the limitation of this work is the proposed work also has some error in intra-class, which it misclassify between a red car and red taxi because of the almost same vehicle features between both vehicles. It is also due to the issues in the input data that they used. Besides, it also cannot overcome the issues in the data such as poor colour resolution, illumination, occlusion, and shadow. Next, Wang et al., [33] the work limitation is it not specific to classify for vehicle type classes. It classifies the vehicle by groups of compact, middle size and heavy-duty size thus make this work has an issue with intra-class. However, for Huang & Zhang [25] work, their proposed work had an error in classification for vehicle model due to the models have almost similar vehicle features in each class. Lastly, based on Dong et al.[12] work, the limitation of this work is it cannot classify accurately in intra-class due to the limitation of unique features in the training dataset. It has caused the classifier in the proposed technique to learn the features discriminately and caused misclassification.

From the overview, there are lots of limitations in the VTR such as shadow, illumination, occlusion, computational complexity and classification problem in the inter and intra classes of the vehicle [2], [46], [47]. However, since the deep learning is a method that fits the purposed of the VTR, the limitation of this method is critical in intra-classes issues because of the limited features in the dataset. Other than that, the unbalanced features in the vehicle type classes also lead to overfitting and underfitting issue.

Overfitting is known when a statistical model describes the random error. It happens when the deep learning methods memorize the features training data and not learning the correct features; thus, giving a low training dataset and high validation error. While underfitting occurs when a statistical model cannot capture the underlying trend of the data because of the deep learning algorithm does not learn the data correctly. Next limitation in VTR is in the VTR classification, and this paper focuses on the intra-class issue; for examples such as between standard car and taxi, or between SUV and minivan [9], [43]. The problem of misclassification is because of the almost same features of the vehicles types and also limited features in the dataset lead to a mismatch in the classification process. Plus, it also leads to time-consuming, system's error and produces an inaccurate result in the VTR.

4. CONCLUSION

From the overview in this paper, there are many techniques have proposed in VTR works. The feature extraction divided into two types of feature analysis which is single features method and the combination of single features method. The single feature extraction method is the approach using either global or local features. It is a simple approach to be applied to the system. However, it only extracts the single features and suitable to be applied in small classification such as vehicle or non-vehicle. While for the combination feature extraction technique, it uses both global and local features method to extract more features from the input data. It is a good approach to be applied to VTR because it can extract both global and local features from the input data. However, since it is a combination technique, it will make the system complex to learn the features. It happens when the combination techniques want to extract more features from the input and to processes a big database. However, this paper focuses on the combination features method based on the deep learning which is CNN. This method is a complex model; it can extract both global and local features in the same network [9], [11]. Plus, this model also can search the features and find the correlated features. Then, it also learns by finding new or uniqueness features in the limited set of features data. Also, practical to be applied to the big database and varied classification. This paper also reviews the feature extraction techniques, the challenges and issues in the VTR based on the existing works. For feature extraction technique, three techniques can be used for either single feature extraction, a combination of single features or based on deep learning. From the existing works, shows that the accuracy results in VTR from using CNN based on deep learning methods have higher accuracy than using other techniques. However, there are still lots of issues in deep learning that need to be improved such as shadow, illumination, and occlusion which based on the image; and also, the proposed solution techniques from the existing works. However, the main issue is an intra-class issue which caused by overfitting and underfitting in CNN model. It is because the model does not learn the features correctly. Also, the other issues are the limitation of features in the dataset and an imbalanced dataset of vehicle classes that affect the classification process. On the other hand, from the observation based on existing work, by implementing data augmentation technique in the CNN, it can reduce the imbalance in the training dataset. Thus, improve the limitation features in the training dataset and increase accuracy results in the VTR. In the future, we will learn more about deep learning methods and data augmentation technique to improve the vehicle recognition and vehicle classification, especially in intra-classes.

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