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A REVIEW OF VEHICLE ANNOTATION METHOD FOR URBAN TRAFFIC SURVEILLANCE

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Abstract. *At the beginning of its presence, the Intelligent Transportation System (ITS) played a significant role in assisting vehicle surveillance because of its ability to recognize a vehicle license plate. However, in conditions of dense urban traffic, license plate information can be challenging to obtain. Since license plate information probably cannot be obtained, the vehicle's fine-grained features such as color, model, year, and manufacturer, are considered necessary. However, the effort to obtain fine-grained feature information manually is exhaustive. Some researchers have begun to develop a method to obtain these attributes more efficiently, namely vehicle annotation method. This paper provides a review of the vehicle annotation method and the preprocessing method and dataset characteristics commonly used in vehicle annotation method research. Besides highlighting some of the methods compared, we will also discuss issues found in current research and future research to address existing issues at the end of this paper.*
Keywords: Intelligent transportation system, License plate, Vehicle's fine grained features, Vehicle annotation, Urban traffic

1. **Introduction.** The number of vehicles around the world continues to grow. This situation then gives negative impacts on daily traffic conditions such as longer congestion [1-3], frequent red-light running violations [4], and the increasing number of vehicle accidents [5,6]. One of the solutions to overcome these impacts is to develop an Intelligent Traffic System (ITS) [41]. The main module of ITS was the automatic vehicle license plate recognition. After several studies, the automatic license plate recognition method shows very satisfactory results [7-9]. However, ITS had another problem when deployed in urban traffic. Urban traffic is a traffic condition where various vehicles such as cars, motorcycles, and bicycles are located on a single road segment in massive amounts [10]. This situation then potentially causing the module is not working correctly because of the license plate area occluded by other vehicles or any other object near the road [11]. When the module is not working correctly, ITS should use other attributes such as vehicle color, type, speed, direction, and model instead of the license plate. However, to get the other attributes, it costs more significant efforts. Vehicle annotation aims to make this process easier and more effective. Vehicle annotation is a subtle appearance variation that can distinguish vehicles from the same class [12].

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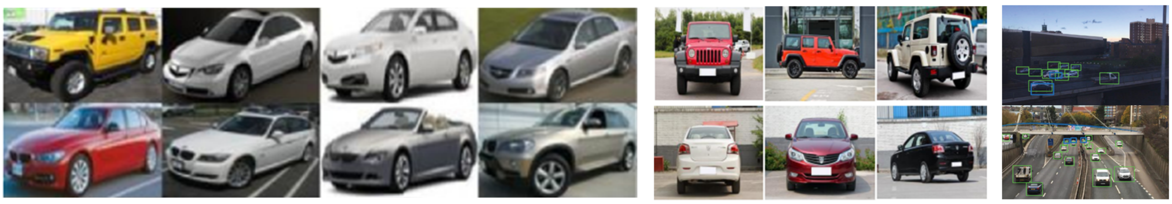
The rest of the paper is organized as follows. In the next section, we present frequently used datasets and their characteristics. In Section 3, we present preprocessing methods that are commonly used in vehicle annotation research. Section 4 reviews the advantages and drawbacks of the latest research on vehicle annotation methods. In Section 5, we discuss and outline some issues found from reviewed methods and give an overview of future work in this research field. Finally, we conclude the paper in Section 6.

2. Dataset in Vehicle Annotation Research.

2. Dataset in Vehicle Annotation Research. Dataset plays a very vital role in the vehicle annotation system. Generally, there are two types of the dataset that researchers frequently use in developing a vehicle annotation system, i.e., a dataset that only contains a vehicle image and a dataset containing a general object image. This section will discuss some commonly used datasets in the vehicle annotation research field.

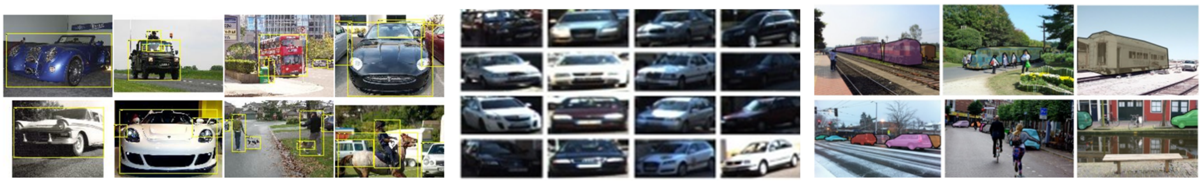
2.1. Vehicle only object image dataset. Appropriate with its name, the dataset that belongs to this category contains vehicle images only. This dataset commonly comes with some bounding box labels that give information about vehicle location and vehicle object parts that is very important for vehicle fine-grained classification. The first dataset from this category is Stanford Cars. Stanford Cars dataset aimed to lift two 2D object representations to 3D on local feature appearance and location [13]. The second one is the Comprehensive Cars (Comp Cars) that is specifically designed to support research related to fine-grained categorization and verification [15]. Overall there are 136,727 vehicle images with additional labels such as vehicle make, model, and year relation, car attributes, viewpoints, and car parts. Urban Traffic Surveillance (UTS) dataset [21] is the newest in this category and is devoted to studies that require urban traffic conditions. Images on the UTS dataset derived from six video sequences recorded by a surveillance camera. The last dataset is Laboratory for Intelligent and Safe Automobiles (LISA 2010) [19], which is formerly named LISA-Q [20]. The images in LISA 2010 dataset were collected using an in-car camera during three scheme conditions, i.e., sunny evening rush hour traffic, cloudy morning on urban roads, and sunny afternoon on highways. The sample image from this category can be seen in Figure 1.



(a) (b) (c)

FIGURE 1. (a) Stanford Cars dataset; (b) Comp Cars dataset; (c) UTS dataset

2.2. General object image dataset. Unlike all image vehicle datasets containing vehicle images, a general object image dataset contains vehicle and other objects that often appear "near" the vehicle. [37] indicates that involving non-vehicle objects in the training process yields a more accurate and robust system. The first dataset from this category is INRIA Cars dataset. This dataset was first used in [14] to model the automatic local feature selection on object class recognition. The next one is PASCAL VOC 2007 dataset. This dataset is mostly used in ITS researches, such as in [16-18]. Each image in PASCAL VOC 2007 dataset includes some additional information such as class, bounding box, view, truncated label, and difficulty label. KITTI dataset also belongs to this category. This dataset purposed to autonomous driving car development, such as shown in [14]. Besides bounding box information KITTI dataset also has other information such as 3D bounding box, geographic coordinates, acceleration, and angular rates [31]. Another commonly used general object dataset is Microsoft Common Objects in Context (MS COCO). This dataset was gathered from complex everyday scenes in their natural context [32]. MS COCO dataset consists of 328,000 images from 91 categories, including car and equipped with ground truth in mask form. The last one is ImageNet which is a largescale ontology image dataset, firstly introduced in 2009 [36]. ImageNet has around 3.2 million images, consisting of 12 categories obtained by retrieving from the Internet. It also has strength since it still involves humans in the verification stage to maintain a good quality label. It also has several labels other than bounding box and class labels such as color, pattern, shape, texture to SIFT features. Figure 2 shows some image samples from this category.



(a) (b) (c)

Figure 2. (a) PASCAL VOC 2007 dataset; (b) KITTI dataset; (c) MS COCO dataset

3. **Preprocessing Methods in Vehicle Annotation.** This section will describe popular preprocessing methods since it is a crucial stage, and it is needed in most studies related to image recognition [22]. The first preprocessing method is background subtraction as an approach to detect moving objects in the stationary background [23]. However, in urban traffic, the background can be complicated because of the slow-moving object and illumination change. Several studies were conducted to tackle this issue and produced a method known as adaptive background mixture models, which can handle slow lighting changes, periodical motions, slow-moving objects, long term scene changes, and camera noises [24]. The modified version of this method also has been done by [25] by adding a foreground analysis based on intensity and texture information. Some of the commonly used texture information methods include the Maximally Stable Extremal Region (MSER) [42] and the Adaptive Local Texture Feature Background Model (ALTF-BM) [43]. The median filter is also used as a preprocessing method on the urban traffic surveillance system, aiming to eliminate noise in the image, especially salt and pepper noise type [26].

4. **Vehicle Annotation Method.** The vehicle annotation research field aims to get more vehicle features more quickly and effectively. These features are essential when it is unable to obtain license plate information. This paper divides vehicle annotation studies into two approaches: the hand-crafted features approach and the deep learning approach. In the hand-crafted features approach, a researcher still needs to decide important features and a method to obtain it. Meanwhile, the deep learning approach will automatically obtain important features by using the deep learning method.

4.1. **Hand-crafted features approach.** The first study related to the hand-crafted features approach in the vehicle annotation study was Feris et al. [25]. The developed method can handle crowded environments and different environmental conditions, in which traditional background modeling methods fail. In the following year, Feris et al. improved their method by adding fine-grained attributes [27]. Fine-grained attributes used in this research are dominant color, vehicle dimensions, speed, travel direction, date/time, and location. The experimental results showed that average accuracy for color attribute reached 90.72% and 87% for a vehicle with more than 18ft (large car).

Another research also was done by Duan et al. [28], who developed a vehicle recognition method based on local attributes and viewpoints using the MI-SVM (Multiple Instance – Support Vector Machines). Experiments in this study involved Stanford Cars and INRIA vehicles and concluded that the most meaningful region size is 50×50 for the Stanford dataset and 70×70 for the INRIA dataset. Chen and Ellis [29] proposed a semi-automatic vehicle annotation method using K-Means clustering and linear Support Vector Machine (SVM). They used two features, namely Measurement-Based Feature (MBF) and Pyramid Histogram Oriented Gradient (PHOG). This method's main disadvantage is not good when handling vehicles with high similarity in shape and size. Fernandez et al. proposed the Kalman Filter (KF) with the Constant Velocity (CV) model to predict vehicle bounding box features for multiple vehicle objects in a video frame [38]. However, there is no comprehensive experiment to measure its performance.

4.2. **Deep learning approach.** The next research shows the trend changing in a method used to obtain vehicle annotation. Goyal and Kaur [26] research conducted in early 2016 has brought deep neural networks in the urban traffic environment. This study used Hybrid Deep Neural Network (HDNN) [30] to identify vehicle position and classify vehicle type on Oxford Circus square dataset. However, the average time required by the system reached 6 seconds to detect and 234 seconds to classify. Another study that also uses a deep learning method has been done by Zhou et al. [21]. They joined 2 Convolutional Neural Network (CNN), one for detecting vehicle-like objects and the other for determining its attributes such as pose, color, and type. The experimental result showed that the proposed method reached accuracy above 90% when obtaining.

In 2017, Yu et al. [40] proposed a novel method which can generate large annotated vehicle images dataset. This method obtained vehicle type, coordinate, and model name as attributes. By using Faster R-CNN and joint Bayesian network, this method gained 85% accuracy in vehicle detection and 89% accuracy in vehicle model recognition under urban traffic conditions. In the same year, two state-of-the-art object detection methods were found: YOLO [33] and DSSD [34]. YOLO uses ImageNet and MS COCO dataset in the training stage and PASCAL VOC 2007 dataset in the testing stage [35]. According to the evaluation, the YOLO method has a lower mAP accuracy but faster processing time than Faster R-CNN used by [40]. On the other side, Deconvolutional Single Shot Detection (DSSD) also gives imposing result in general object detection. DSSD uses PASCAL VOC 2007 and 2012 as training data and PASCAL VOC 2007 and MS COCO as testing data. The evaluation result shows that DSSD has a higher mAP value than YOLO (81.50%) but slower speed than YOLO (6.4 fps). Research that exploits YOLO for vehicle annotation was conducted by Feng et al. [39], which proposed semi-automatic moving object annotation. The experimental results show a promising result that can reach 88.03% mAP score for their dataset and 65.65% mAP score for the MS-COCO dataset. This experimental also revealed that this method is still struggling when dealing with small size object. The advantages and drawbacks of each method are highlighted and can be seen in Table 1.

5. **Result and Discussion.** From the previous section, it is known that current vehicle annotation methods still have some shortages. We divide the source of its shortages into two issues. The first issue comes from the change of light intensity caused by day and night shifts, streetlight, or even shadow. This issue can distort the vehicle color. For example, in evening urban traffic conditions, a white car may turn yellowish due to streetlight, or turn blackish due to lack of light intensity like in [21]. The lighting issue can also cause a problem with vehicle size. It occurs when the shadow of the vehicle makes the car looks longer than it is supposed to be like in [26,27,29]. This issue can be solved by utilizing a module that is aware of lighting changes to choose the best method based on lighting

Table 1. Summary for latest vehicle annotation methods

Ref.	Involved dataset	Obtained features	Pros	Cons
[25]	◦ Own dataset ◦ PASCAL VOC 2007	◦ Vehicle coordinate ◦ Vehicle viewpoint	◦ Good in handling unstructured and crowded environments. ◦ No manual labelling efforts. ◦ Low computation resource.	◦ Fail to handle occluded vehicle by 40% or more. ◦ Cannot detect small and big vehicle. ◦ Only detect vehicle in few viewpoints. ◦ Cannot handle vehicle occluded by road object.
[27]	◦ Own dataset ◦ PASCAL VOC 2007	◦ Date-Time ◦ Location ◦ Direction of travel ◦ Vehicle color ◦ Vehicle dimension ◦ Vehicle speed	◦ Able to detect small and big vehicle. ◦ Support large scale data indexing.	◦ Wrong bounding box estimation issue. ◦ Need manual labelling efforts.
[28]	◦ INRIA vehicle ◦ Stanford Cars	◦ Vehicle part ◦ Vehicle viewpoint	◦ Able to generate discriminative and semantic local attributes. ◦ Good estimation result in viewpoint attribute.	◦ Need manual labelling efforts. ◦ Need huge computation resource.
[29]	◦ Own dataset	◦ Vehicle size ◦ Shape ◦ Vehicle type	◦ Significantly reduce the time required to generate anannotated dataset.	◦ Hard to distinguish vehicles with high similarity appearance.
[38]	◦ Own dataset ◦ KITTI	◦ Vehicle coordinate	◦ Able to detect multiple vehicle in a frame.	◦ No performance measurement.
[26]	◦ Own dataset	◦ Vehicle type	◦ Good in handling urban traffic condition.	◦ Very time consuming. ◦ Limited to bus and car type.
[21]	◦ Comp Cars ◦ GSV images ◦ UTS ◦ PASCAL VOC 2007 ◦ LISA 2010	◦ Vehicle viewpoint ◦ Vehicle color ◦ Vehicle type	◦ Able to detect multiple vehicle in a frame. ◦ Highly accurate in vehicle annotation system.	◦ Need huge computation resource. ◦ Very time consuming.
[40]	◦ Own dataset	◦ Vehicle coordinat ◦ Vehicle type ◦ Vehicle model	◦ Significantly reduces the time required to generate anannotated dataset.	◦ Hard to distinguish vehicles with high similarity appearance.
[39]	◦ Own dataset ◦ MS COCO	◦ Vehicle coordinate ◦ Vehicle type	◦ Able to detect multiple vehicle in a frame. ◦ Good in handling different wether conditions.	◦ Cannot handle small object. ◦ Need manual labelling efforts.

conditions. This approach is suggested since there has not been an excellent method for handling both of these situations.

The second issue comes from another vehicle. The massive number of vehicles on urban traffic can cause a problem known as vehicle occlusion like happened in [25]. When vehicle occlusion occurs, essential features from a vehicle covered by other vehicles become very difficult to obtain. This issue can resolve using the image reconstruction method that can artificially reconstruct occluded vehicle areas. So we can get enough information for obtaining essential features in the vehicle annotation process. The development of this method and its impact on the urban traffic surveillance system still becomes an interesting topic to be studied in the future.

6. **Conclusions.** The urban traffic situation has given new challenges in ITS research fields. The main module of ITS, which usually relies on vehicle license plate recognition, can fail when faced with the urban traffic situation. Recent research showed that vehicle annotation could obtain important features besides the license plate more effectively and

quickly. There are two main approaches to the vehicle annotation method. The first one, called the hand-crafted features approach, does not need high computation resources but still needs human intervention. The second one, called the deep learning approach, lacks human intervention but costs high computation resources. Previous sections have given detail about the advantages and drawbacks of recent research and discussed it. There are two sources of problems from the discussion: intensity light changes and other vehicles that commonly occur in urban traffic situations. This paper suggested developing a light adaptive method and image reconstruction method to address these two problem sources and become a big chance for future work.

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