A review on Machine Learning techniques used to enhance Traffic and Road safety

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Abstract— Transportation is one of the essential parts of the livelihood of human beings. This research paper presents my analysis of the techniques used and our contribution to the improvement of the usual methods of safety and technologies used in various transportation systems. The contribution, based on machine learning models, also including artificial intelligence techniques has been realized by the development of several approaches and tools of modeling, safety and advancement of transport facilities. The paper adopts different machine learning methods form machine learning to develop multiclass classifiers that identify the transport mode, including driving car, riding a bike or bicycle, riding a bus, walking and running. Methods that are considered here include K-NN, SVMs, Bagging and tree-based models. For training and validating purposes, data were obtained from smartphone sensors, footages from CCTV cameras, including accelerometer, gyroscope, and rotation vector sensors. Several features were created from which a subset was identified through the minimum redundancy maximum relevance method. Data obtained from smartphone sensors and some footages were found to provide the important information to distinguish between transportation modes. Based on that information, various methods were evaluated and compared. Furthermore, we will try to develop a new additional feature based on algorithms and random forest methods also including combination of already existing features to improve road and traffic safety.

Keywords— Transport, Machine learning, Sensors, Cameras, Smartphones.

Index of terms--- Decision Tree, Bagging, Random Forest, Support Vector Machine, K-Nearest Neighbor.

I. INTRODUCTION

Machine learning models is used on the context of learned data to learn from data and to construct a predictive model. The idea of Artificial Intelligence is at the forefront of machine learning techniques. It describes the analysis, development and design of models, approaches and frameworks that have used previously acquired and stored data to understand [1]. We are applying machine learning to make prediction intelligent, providing techniques to make models intelligent. Based on input parameters, the desired learned models are added to the produced model for future predictions on uncertain results / test data. Machine learning methods are primarily used to achieve viable alternatives in the scenario. In certain cases, by other intelligent methods, we are unable to get a satisfactory solution or no solution [2]. So, machine learning is helpful in terms of automated analysis of the data derived from sensors of smartphones and footages from CCTV cameras to enhance the transportation system. Nowadays, smartphones are equipped with powerful sensors such as GPS, accelerometers, gyroscopes, light sensors, etc. Researchers have also been able to explore new study areas by having such powerful sensors all integrated in a compact unit carried in daily life activities. Ubiquity, the ability to transmit and retrieve data through different means (e.g. Wi-Fi / cellular network / Bluetooth) and data storage / processing are the benefits of these mobile devices [3]. In ubiquitous computing systems, both identifying human activity and knowing the mobility of a user from sensor data are essential problems. As a type of user activity, the types of travel that a user takes, such as walking, cycling, etc., will enrich the versatility of the user with insightful experience and give more qualitative information to omnipresent computer systems [4].

The study shows how many machine learning techniques can be applied, including: K-Nearest Neighbor (KNN), Support Vector Machines (SVMs), and tree-based models consisting of a single Decision Tree (DT), and Random Forest (RF) methods to classify modes of transport using smartphone sensor data [8].

Due to its importance in realistic applications and particularly in smart video surveillance solutions, object tracking has attracted considerable interest in the research community. Object monitoring techniques are not stable enough for real-world content from CCTV cameras, considering the improvements achieved in recent years [5]. Most of the existing methods of tracking are focused on building a robust model of object appearance, functioning on handcrafted representation of attributes and building of classification models. Most of these classifiers, however, are constrained by their shallow constructs, whereas variations in object appearance are complex and time-varying [6].

Recent technology in machine learning have resulted in a new generation of methodologies for object detection and localization that outperform traditional methods. They rely on learning discriminatory characteristics automatically through a multi-layer CNNs, thus alleviating the need for handcrafted characteristics. Each layer consists of numerous neuron types that include fully convolutional operations, non-linear filtering and spatial pooling. In order to understand hierarchical and object-specific function representations automatically, end-to - end training is used [7].

In this paper, we will discuss all the machine learning and deep learning techniques and methods used in the transportation. To streamline the detector efficiency, a variety of techniques are investigated to improve the training data. In addition, a methodology is suggested to dynamically monitor the setup of the detector by using smartphone's GPS and calculating the camera's intrinsic parameters.

II. RELATED WORKS

In this part of the proposed structure, we review similar work in this section. Next, it discusses previous approaches to blurred object detection. Then, some standard standardized models of appearance are described. Subsequently, how the smartphone's detection models were generated is shown. Finally, it addresses mapping, identification, understanding, and data.

The images can be split into small patches to identify global blurs to eliminate the noise by averaging the approximate blurs. However, when identifying and recognizing local motion blurs, the condition is more complex, because some areas of the picture are non-blurred zones, so we do not simply apply the averaging scheme. A major challenge here, however, is to decide whether or not a small image patch is blurry in motion [9].

In [14], in the sparse representation framework, a blur-driven tracker is developed to tackle the blur problem. The motion blur is detected by Fourier analysis in [15], and then tracking is carried out according to the detection outcome in the subspace-based setting. All these algorithms above, though, are generative and do not learn from the context. In addition, to assist monitoring, they require motion blur estimation. However, in actual images, dynamic motion blur is very difficult to estimate. Thus, incorrect motion blur estimation could affect the tracking efficiency. The detection by recognition architecture follows our algorithm, which can learn from backgrounds. In order to separate a blurred target and backgrounds, the appearance model is therefore more discriminative. In fact, in tracking, we do not need to predict motion blur, which makes the algorithm quick and fast to apply [16].

Extensive research work on single-image blind deconvolution has been performed in the past. Blind de-blurring normally uses a single image and takes a previous parametric shape in early works. Through calculating only a few parameters, these parametric motion-blur kernel models can be obtained, but they are also overly simplistic for realistic motion blurring. Some probabilistic priors on natural images' edge distributions have been suggested to eliminate more general motion blurring from images [10] [11] [12] [13].

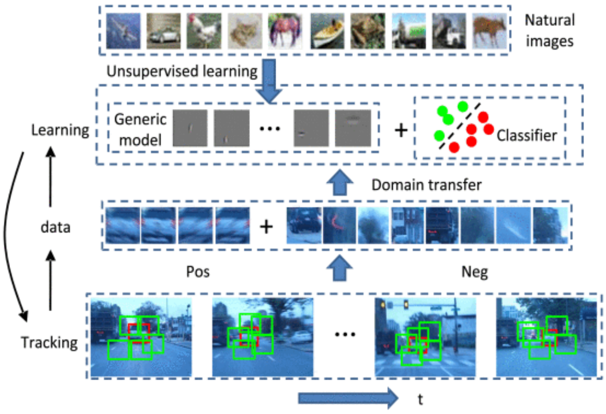

Figure 1.

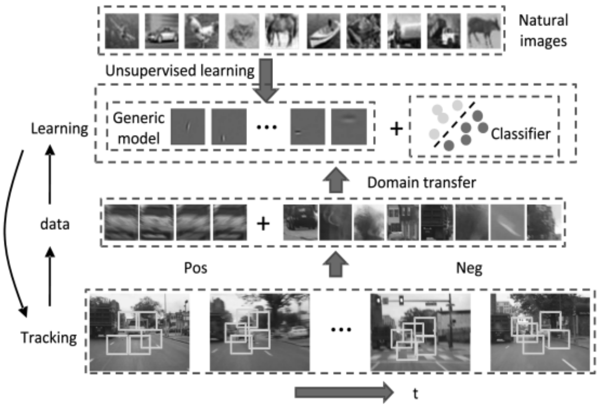

Figure 1 & Figure 2. Generic appearance model is learned from a large set of unlabeled samples before tracking. It is transferred to the appearance model of the target during tracking by incremental learning from the tracking results and scenes [16].

The standard detection method typically adopts hand-crafted characteristics such as Haar, local binary pattern, histogram of directed gradients, and their variants and combinations, followed by an online classifier such as AdaBoost or random forests. Then the object is detected by sub windows that are densely or stochastically sampled. Such methods require manual creation of features and prior experience. As motion blur is very complex in real videos, we cannot develop a new feature that is invariant with motion blur and works well in other complicated scenes as well [16].

Our detection algorithm is built on the concept of the particle filter, which can deal with nonlinear / non-Gaussian movements. In this context, object tracking in a Markov model with hidden state variables is conceived as an inference activity [17]

The raw data can be collected from sensors placed on vehicles by using a Vehicle Tracking System, analyzed and formatted to draw more tracking-related conclusions. The original type of data collected from the GPS system for the account of a customer who is involved in monitoring using the Vehicle Tracking System based on LBS is shown in figure 4. This type of data cannot be analyzed to provide the operator of the Vehicle Tracking System with information. To extract useful information, this data is translated into a workable format (such as exl) [18].

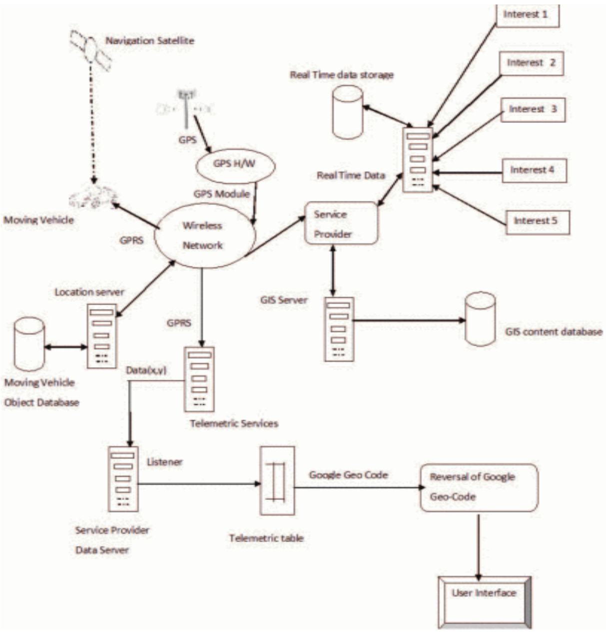

Figure 3. Scenario of data extraction from GPS devices [18]

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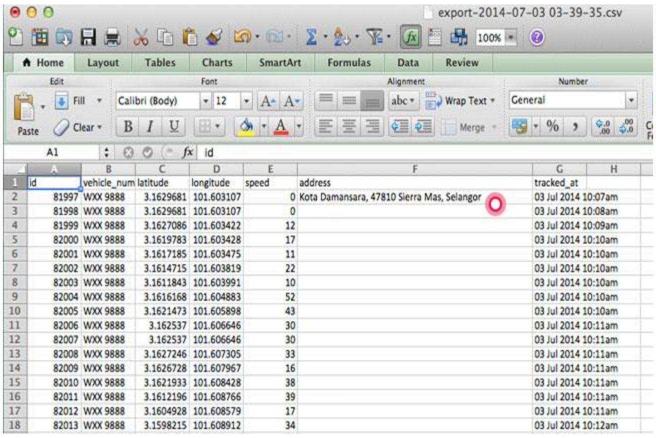
:ude/s,deviceId/s
3-11e7-a3d5-d763fb931811,13.5142313,43.6185601
7-11e7-8831-d7b8f038bfd0,13.520276428044,43.62
L1e7-b00c-61c250d2c4c3,13.5167188085862,43.622
1-11e7-984b-c17818544db1,13.5180683992929,43.6
a-11e7-84c8-a7c2a27aa153,13.5160460361504,43.6
>-11e7-bd71-f505232393dd,13.5211515309617,43.6
9-11e7-8d0f-8532eec2945b,13.521309519433,43.62
:-11e7-b2c5-0fdb232087b2,13.5192824923094,43.6
)-11e7-a03d-6fdd2a8be6f3,13.51825711,43.619965
>-11e7-b03c-35308739afed,13.51771602,43.622959
9a3a853da,13.5142313,43.6176758,8b5079fd-f8f0-
3-11e7-84a7-7984c7d9173d,13.5170221395199,43.6
>-11e7-9540-9dc289246497,13.5178798625896,43.6
a-11e7-8e3e-11c84b410d07,13.3870616,43.5831614
L-11e7-9457-77ffbd150dc2,13.5168155008503,43.6
5-11e7-b59c-896737b4d5c0,13.5188183333333,43.6
f-11e7-b9e4-e5ae88453b69,13.5205483982323,43.6
10028921f,13.5136269,43.62328257,8668bc0c-de02
5-11e7-8de6-addaad7e5814,13.5178791049325,43.6
```

Figure 4. Form of data extraction from the GPS devices



id	vehicle_num	latitude	longitude	speed	address	tracked_at
81997	WXX 9888	3.1629681	101.603107	0	Kota Damansara, 47810 Sierra Mas, Selangor	03 Jul 2014 10:07am
81998	WXX 9888	3.1629681	101.603107	0		03 Jul 2014 10:08am
81999	WXX 9888	3.1627086	101.603422	12		03 Jul 2014 10:09am
82000	WXX 9888	3.1619783	101.603428	17		03 Jul 2014 10:10am
82001	WXX 9888	3.1617185	101.603475	11		03 Jul 2014 10:10am
82002	WXX 9888	3.1614715	101.603819	22		03 Jul 2014 10:10am
82003	WXX 9888	3.1611843	101.603991	10		03 Jul 2014 10:10am
82004	WXX 9888	3.1616168	101.604883	52		03 Jul 2014 10:10am
82005	WXX 9888	3.1621473	101.605898	43		03 Jul 2014 10:10am
82006	WXX 9888	3.162537	101.606646	30		03 Jul 2014 10:11am
82007	WXX 9888	3.162537	101.606646	30		03 Jul 2014 10:11am
82008	WXX 9888	3.1627246	101.607305	33		03 Jul 2014 10:11am
82009	WXX 9888	3.1626728	101.607967	16		03 Jul 2014 10:11am
82010	WXX 9888	3.1621933	101.608428	38		03 Jul 2014 10:11am
82011	WXX 9888	3.1612196	101.608766	39		03 Jul 2014 10:11am
82012	WXX 9888	3.1604928	101.608579	17		03 Jul 2014 10:11am
82013	WXX 9888	3.1598215	101.608912	34		03 Jul 2014 10:12am

Figure 5. GPS data format in excel sheet for training

The GPS plays a significant role in the retrieval of relevant information in the Vehicle Tracking Device using Pounds for wireless contact. This knowledge is accessed by the GPS system and the original raw data format is updated according to the demand and need of the customer. Researchers obtained the actual data from the working software systems used for vehicle tracking and compiled the study report by using SPSS for vehicle location and movement over time [18].

III. BACKGROUND TECHNOLOGIES

In this section we will discuss about all the machine learning methodologies used in this research paper. To build the detection models, three methods were considered. In most of the literature, Support Vector Machine (SVM) and Decision Tree have been used to define transport modes, and several papers find the better way to be the Decision Tree.

A. Support Vector Machine

An efficient statistical learning algorithm is a Support Vector Machine (SVM) [18]. For the application of the help vector machine technique in the design and creation of classification models for classification activities, statistical learning methodology was applied. The pre-condition for the implementation of the support vector machine is specified in terms of vector space linear separability. Kernel functions are used by the help vector machine algorithm to solve the classification problem. From a collection of marked training data for pattern recognition or data regression, it may acquire a non-linear discrimination function. Both regression and classification tasks are provided by SVM and can accommodate several continuous and categorical variables. This feature will minimize the error of training and, at the same time, guarantee the classifier's generalization potential by maximizing the gap between the so-called support vectors [2].

B. Decision Trees

Decision Trees were developed in the mid-80s for problems with classification and regression [19]. These methods have many advantages; they are simple to understand and describe, represent the human decision-making process, can be displayed graphically, and for qualitative predictors, there is no need to construct dummy variables.

C. Bagging

Introduced in 1996 [20], the process of bagging or Bootstrap aggregation takes advantage of aggregating effects from various models to reduce the variance. It is possible to average the detection / prediction outcomes of various models based on different training sets. In reality, though we normally have only one training package. Instead, by taking repetitive samples from a single training set [21], bootstrapped training data (Pseudo training sets) can be collected, and a tree model can be created for each.

D. Random Forest

In contrast to other classification algorithms, this classification technique is fine. The Random Forests algorithm is capable of classifying and predicting test data of enormous scale and generating modest and very satisfactory outcomes. For the available training data collection, this approach implements ensemble learning and the creation and production of models in terms of multiple decision trees. The Random Forest Method, as proposed in 2001 [22], is identical to the Bagging Method which produces an ensemble of trees and the result is achieved based on majority votes.

E. K- Nearest Neighbor

To classify transportation modes, a basic but efficient approach was introduced, namely the K-Nearest Neighbor (KNN), which has been applied to various classification and regression problems in different fields. This approach first defines the K closest train observations in the training data set to the test observation for each test observation that involves various attributes and stores them in a separate set. The test observation class is established by taking the majority vote of the classes for the nearest K points. In the case of classification (versus regression), determining the average is equivalent to taking the majority vote [23].

IV. Challenges

Above discussed machine learning techniques proved to be very beneficial, but they sometimes show different predictions which can create problems building an effective machine for enhancing the traffic and public safety on roads. If I talk about the decision tree, when the tree gets bigger, the data would over-fit and the test data set may show poor results.

The training examples are used after preprocessing to train the initial appearance model. The taught model of appearance is more resistant to the blur effects in this manner. The original appearance paradigm is less discriminatory in distinguishing the object from its context without using the distorted variants of the samples.

One difficulty relating to Bagging is that the trees can be very similar since each tree is constructed using all the features; thus, the trees can be strongly correlated. Random forests reduce the number of characteristics to resolve this issue by randomly choosing a subset of characteristics to expand each tree. The number of features to use and the number of trees is the criteria to be calculated. Interestingly, including more trees does not lead to over-fitting in Random Forest and even Bagging tactics, but not much advantage is achieved at any stage from introducing more trees [24].

Two problems are associated in the use of SVM: A.) To pick the optimum input function subset for SVM and B.) Adjustment of kernel parameters. It reduces the number of input characteristics to achieve greater classification precision due to function selection parameters. For the purpose of feature selection, the specification of parameters is important to improve the accuracy of classification in the SVM [25].

V. Conclusion

Machine learning methods applied to the transportation domain can support various public or private sector industry in finding the necessary solutions. Its implementation illustrates the design and development of intelligent traffic and safety agent.

This paper discusses the main problems of target recognition, motion blur, image blur, and vehicle location using GPS data to improve the transportation system. During the data collection, different implementations were established concerning tracking artifacts, minimizing blur, and using GPS data. This work in the field of monitoring has made a meaningful contribution. Using improved application of different machine learning models, this work can be tailored in the future to produce better outcomes to increase traffic safety and minimize accidents in a region.

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