Prevention of Road Accidents By Detecting Driver Distractions Using Machine Learning

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Abstract- *This paper presents a method that is aimed towards the detection and evaluation of driver distraction while performing secondary tasks and an appropriate hardware and a software environment is offered and studied.In the modern day world, road accidents have become very common. They not only cause damage to property, but also keep at risk the lives of people travelling. Reduction of driver distraction is an important challenge for the safety of intelligent transportation systems.A new machine learning algorithm defines driver performance in lane keeping and speed maintenance on a specific road segment. —There is accumulating evidence that driver distraction is a leading cause of vehicle crashes and incidents. The purpose of this paper is to show a method for the nonintrusive and real-time detection of visual distraction, using vehicle dynamics data and without using the eye-tracker data as inputs to classifiers. Specifically, we present and compare different models that are based on well-known machine learning (ML) methods*

Keywords- Accident prevention, artificial intelligence and machine learning (ML), driver distraction and inattention, intelligent supporting systems.

I. INTRODUCTION

Road accidents are a human tragedy. They involve high human suffering and monetary costs in terms of untimely deaths, injuries and loss of potential income. Although there have been plenty of initiatives undertaken and many road safety techniques have been implemented but still our overall situation is far from satisfactory. A Driver is the most important participant of a car control, including steering, throttling, braking, maneuvering, and other operations. These primary tasks must be accomplished safely for all traffic participants and their belongings. Nevertheless, drivers often dedicate time and attention to other activities, different from the driver's primary ones. All other tasks the drivers perform while driving are defined as secondary tasks.

Machine learning (ML) and data mining (DM) technologiesmaybeabletoprovidetherightalgorithmsforcoping withsuch a challenge. ML is the technique of searching large volumes of data for unknown patterns. It has been successfully applied in business, health care, and other domain.

It is a hard test of endurance for drivers to take long distance driving. It is very difficult for them to pay attention to driving on the entire trip unless they have very strong willpower, patience, and persistence. Thus, the driver fatigue problem has become an important factor of causing traffic accidents. Driver drowsiness is a significant factor in a large number of vehicle accidents.

"Driver distraction is the diversion of attention away from activities critical for safe driving toward a competing activity."

This has been extended by Regan et al., adding the concept of driver in attention, which means insufficient or no attention to critical activities for safe driving toward a competing activity. It is worth noting, that such a definition suffers from hindsight bias since it is really difficult to say if the driver is distracted until after something dangerous happens, and then it will be too late for the system to intervene (Regan et al. mentioned this fact in his article). Given that, Regan et al. pointed out that "how to develop taxonomy of driver in attention without the benefit of hindsight is an important theoretical and practical challenge beyond the scope of this paper;" therefore, this is still an open point in the literature (and this is definitely beyond the scope of this paper).

Although this statement is absolutely true, nevertheless, it would almost be impossible to use the concept of distraction without some preliminary assumptions, even if the situation does not lead to an accident in 100 instances but it does on the 101st instance. Although the behaviour is not different, these are potentially critical situations, and we want that our systems can prevent such risky conditions (because we do not know which conditions could lead to an accident). In fact, in these situations, drivers are not ready to react appropriately to any unexpected event; thus, the accidents are more likely.

II. DESCRIPTION

Presently, there are mainly two methods to cope with the detection of structured road: model-based and the feature-based method.
Existing techniques in study of lane detection technology have diversity analysis angle and variety of advantages, disadvantages.

Advantages of the proposed system:

- To implement a low cost alternative.
- Enabling the use of semi-structured data sets.
- Increasing prediction rate using SVM algorithm implementations.

Disadvantages of the existing system:

- The prevailing system is expensive to set up.
- The program uses only structured data sets.
- Prediction accuracy rate is low.

However, in the literature, there is no unique and commonly agreed upon definition of distraction. Several definitions very often overlapped and mixed with inattention or with other driver's states, such as drowsiness and workload.

Although existing data are inadequate and not representative of the driving population, it is estimated that drivers engage in potentially distracting secondary tasks approximately 30% of the time that their vehicles are in motion. (Having a conversation with passengers is the most frequent secondary task, followed by eating, smoking, manipulating controls, reaching inside the vehicle, and using cell phones). Thus, we have considered visual distraction as the diversion of visual attention away from the road.

Lane Detection:

The fundamental aspects of lane detection approaches are based on different features, including the road colour and texture features based detection, the road edge features based detection and template matching. The lane detection, mentioned in the paper, is efficient and conveniently applicable for any car system. This paper proposes an idea of Hough lane detection technique which can detect discontinuous lanes as well.

The lane boundaries near the camera always show themselves line-like in the image, while the parts far from the camera probably contain curve-like shapes. They thus divided the image in near field and far field region.

Fig. 1: The road, having the lane markings

III. MODELING DRIVER'S STATE

Given the current state of the art and with reference to our previous works, we have selected a widely used ML technique and some other methods not deeply investigated in the literature to model the driver's state. These include support vector machines (SVMs), static and dynamic neural networks (NNs) [feedforward NNs (FFNNs) and layer-recurrent NNs (LRNNs), respectively], and adaptive neuro-fuzzy inference systems (ANFISs).

A. Description of the SVM Method

In recent years, SVMs have been arguably one of the most important developments in supervised classification. First proposed by Vapnik in 1998, SVMs are based on a statistical learning technique, and can be used for pattern classification and inference of nonlinear relationships between variables. This method has been successfully applied to a wide variety of domains, such as image processing (e.g., face recognition), text and speech recognition, and bioinformatics (e.g., protein classification) .SVMs often achieve superior classification performance compared with other learning algorithms across most domains and tasks; they are fairly insensitive to the curse of dimensionality and are efficient enough to handle very large scale problems in both sample and variables. The "classical" application of SVMs concerns a binary classification task. The main idea behind SVMs is to map implicitly data to a higher dimensional space via a kernel function and then solve an optimization problem to identify the maximum-margin hyper plane that separates training instances. The hyper plane is based on a set of boundary training instance called support vectors. New instances are classified according to the side of the hyper plane that they fall into. The optimization problem is most often formulated in a way that allows for non-separable data by penalizing misclassifications.

B. Description of the FFNN Method

Artificial NNs (ANNs), or simply NNs, are an information processing system, which is inspired by the biological nervous system (the brain) and consist of a large number of highly interconnected processing elements, working together to solve specific problems. In an NN, signals are transmitted through connection links, characterized by an associated weight, which is multiplied by the incoming signal (the input of the net) for any typical neural net. The output signal of a unit is obtained by squashing the net input into an activation function. One of the most important types of NNs— used within this paper— are the FFNNs. FFNNs have a layered structure, where each layer consists of units receiving their input from units in a layer directly below them and sending their output to units in a layer directly above them. There are no connections within the units of the same layer. FFNNs are considered static networks since they have no feedback elements and contain no delays; the output is calculated directly from the input through feed forward connections.

C. Description of the LRNN Method

In addition to static NNs (FFNNs) (whose topology corresponds to acyclic directed graphs), there are also the dynamic (recurrent) NNs, where the output depends not only on the current input to the network but also on the previous inputs, outputs, or states of the network. LRNNs, which were introduced by Elman [29] in an earlier simplified version, are a specific type of dynamic networks. Overall, recurrent networks are ANNs that apply to time-series data and that use outputs of network units at time t as input to other units at time t + 1. Under this viewpoint, they support a form of directed cycles in the network.

D. Description of the FIS and ANFIS Method

The starting point for talking about Fuzzy Logic (FL) is the consideration of the relative importance of precision. Sometimes, logic is based only on two truth values, true and false, and can be inadequate when describing human reasoning. FL uses all values inside the interval [0, 1] (where 0 is regarded as false and 1 as true) to describe human reasoning; therefore, it is a fascinating area of research because it does a good job of trading off between significance and precision. This is something that humans have been managing for a very long time. In this sense, FL has the ability to mimic the human mind to effectively employ modes of reasoning that are approximate rather than exact.

IV. DESCRIPTION OF THE EXPERIMENTS

A. Subjects

Twenty participants with previous experience on the driving simulator have been selected and divided into two groups. There are ten drivers between 20 and 25 years of age and ten drivers between 30 and 45 years of age. A minimum amount of driver experience was required. This entailed possession of a driver's license for at least two years and 6000 km driven per year. The driver's gender was not an investigated variable. (There were three females and seven males in each group).

B. Experimental Setup

As mainly done in other works studying distracted driving, a driving experiment has been conducted on a driving simulator because of safety issues and better control of the environment, and logistic and economic reasons. In particular, a Scaner II (www.scaner2.com) car simulator has been used. It is a fixed based system that comprises a mock-up of a car with real driving controls (i.e., seat, steering wheel, pedals, gear, and handbrake), a digitally simulated dashboard displaying a traditional instrumental panel, and a frontal projection screen where the simulated environment is displayed to the driver (seeFig.1). Distraction has been induced by means of a secondary visual research task, called a surrogate visual research task (SURT), which is methodology developed by S. Mattes in the project ADAM, and here reproduced on an in-vehicle display system.

Fig. 1. SURT display on the right part of the driving simulator cockpit.

C. Procedure

Participants performed a practice drive in the driving simulator for 15min. Then, they were asked to drive for approximately 50 min on a simulated three lane highway. The driving task consisted of keeping the lane and driving at an average speed of 100 km/h at a safe distance from the vehicles encountered ahead. For the moment, we have considered a motorway scenario for a couple of reasons. First, it represents a more structured and controlled environment; and second, it is more suitable for the integration with the ADAS application under investigation, i.e., the adaptive cruise control.

D. Data Collection and Processing

Distraction data constitute the target set since we have adopted a supervised learning method. In this methodology using SURT, the eye position of the subjects has been extracted from videos with video processing laboratory software and transferred to a log file as Boolean values (1:eyes on the SURT; 0: eyes infront of the screen). Then, the change of SURTstatus, from 0 to 1 and from 1 to 0, has been considered as the key factor to understanding if the driver was distracted or not. In fact, in the literature, if the drivers look away from the road for an interval between 1 and 2 s, they can be regarded as distracted. The switches in SURT status identify the period where drivers were engaged with secondary task completion. The number of correct answers, together with drivers' reaction time on the SURT (i.e., the difference between the instant the task is presented and the touch of the driver) has been recorded.

V. DATA ANALYSIS AND RESULTS

To measure the performances of each classifier, we have considered the following indexes:

- Correct rate (CR), which is the number of instances correctly classified;
- Sensitivity(SENS),which is the correctly classified positive instances or true positive instances;
- Specificity (SPEC), which is the correctly classified negative instances or true negative instances.

In the following, the best model is the one with the highest CR value, a good model is a model with CR > 90%, and an acceptable model is a model with CR > 80%. (These values are inferred reading similar works in literature and based on our personal experience).

The idea of using ML techniques to detect driver distraction is not completely new. In particular, Woeller et al. and Zhang et al. suggested that there are basically three approaches to such a recognition problem:

- Monitoring driver's perception;
- Monitoring driver's steering and lane keeping behaviour; and
- Recognizing the driver's involvement in a given secondary task.

Despite the fact that different classification methods can be found in the literature to detect distraction or inattention while driving, nevertheless, since the mental state of the driver is not directly observable, no simple measure can weight distraction precisely; thereby, all traditional methods show some limits. In this context, the predominant approach is to use ML techniques, which seem to be much more appropriate for this type of a classification problem. From a more "philosophical" point of view, one of the most ambitious goals of automatic learning systems is to mimic the learning capability of humans, and the capability of humans to drive is widely based on experience, particularly on the possibility of learning from experience.

From a more technical point of view, data collected from vehicle dynamics and external environment are definitely nonlinear. From the literature, several studies have proven that, in such situations, ML approaches can outperform the traditional analytical methods. Moreover, a human's mental and physical driving behaviour is nondeterministic. On the other hand, vehicle dynamics data are user, road, and situation dependent; therefore, the classifiers, based on ML techniques, are strongly tailored to the conditions and situation that are selected for the training phase. In fact, we suggest building a specific model for each driver and for each situation. How to adapt and generalize such a model to other situations is still an open problem worth investigating.

In particular, the predominant approach is to use static classifiers such as SVMs. Liang et al. developed real-time methods for distraction classification using SVMs and Bayesian networks. Their results are comparable to ours since, in [46], they achieved the best performance of more than 95%, whereas in [47], modelling the dynamic of the driver's behaviour using a dynamic Bayesian network (DBN) led to accuracy of about 80.1% on average.

VI. CONCLUSION

This paper has presented an overview of different driver distraction classifiers based on ML techniques. We explored the performances of several models: SVM, FFNN, LRNN, and ANFIS. All have been proven to constitute a viable means of detecting driver inattention, whose cognitive and visual distractions are particular forms. In this paper, we have pointed out the personalization aspect, with one specific model for each subject. With reference to the results shown in Section V, the SVM outperformed all the other classifiers, for which we have obtained accuracy comparable that in the literature. Our major innovative aspect consists of not using information on eye movements or head movements as inputs for the classifier. The European co-funded Integrated Project

D3COS (http://www.d3cos.eu/), started in March 2011, allows us to investigate at least some of the future activities previously mentioned.

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