Drowsy Driver Detection Using Wavelets and Support Vector Machines

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Abstract. Driving behavior emerges from the intricate and complex interactions between the driver, the vehicle and the environment. The purpose of a behavioral model is to explain and to predict the human behavior. For the construction of this kind of models, mathematical and Artificial Intelligence techniques have been tested. Some constraints of the system are 1) the supervision and monitoring of the driver-vehicle-environment system is a complex problem due to particularities such as stochastic, personal and dynamic. 2) The solution must be based on a non-intrusive system and 3) able to diagnose and predict hypovigilance from peripheral on-board sensors. The proposed diagnosis system is based on intelligent signal processing algorithms and real time methodologies as the Wavelets analysis and the Support Vector Machines learning approach for density estimation. In this paper, we search to accomplish the requirement of a faster and robust algorithm, able to work in real time. Results are validated using driver's data in real conditions. The framework of this study is the European research project SENSATION.

1. Introduction

Human factors, as excessive fatigue, extended inattention or stress, have been the key cause of many industrial accidents. Most nuclear accidents (Chernobyl, Three-mile Island and several US islands), the Challenger explosion, 40% of road accidents and, according with the NASA, approximately 21% of the aviation incidents are fatigue related, [1].

Driving is a complex behavior influenced by a wide range of factors in space and time. Factors include goals, distraction, errors, expectancies, workload, attention, traffic, vehicle safety features, automation level, fatigue, memory, capabilities, training and experience. Driving behavior is conceptually considered as a complex system in which the environment, driver and vehicle are influencing factors. An emerging driving behavior could not necessary be linearly predicted. However, a context-aware system could assist the driver in augmenting the probability of undertaking a safe behavior. To detect drowsiness in a human being, physiological measures, such as brain activity, can

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be used. The main disadvantage of this kind of measures -despite their accuracy is the contact requirement with the driver. For automotive systems, unobtrusive techniques must be used. Further, the ideal system will detect the precursors to drowsiness at least several minutes before onset, giving the driver time to rest or take another action. In order to monitor both the driver and the road environment to detect hypovigilance in real-time, it is necessary to integrate multiple parameters. Information on the road environment, personalized driver characteristics and advanced detection techniques must be fused to create a robust system.

This paper is organized as follows: Section two gives an introduction to Wavelets, Support Vector Machines for density estimation and CUSUM. Section three shows the drowsy driver detection proposed methodology. In section four, obtained results on driver's data in real conditions are presented. Finally, section five gives some conclusions.

2. Background

2.1. Continuous Wavelets

Wavelets, [3], allow analyzing in time and frequency the behavior of a signal. They are able to analyze non-stationary signals, in complement of the Fourier analysis that loses the information of temporal localization. The Wavelets analysis is based on a convolution of a Wavelet mother ψ which one dilates (s) and translates (τ), see equation 1, to have an approximation and a decomposition of the original signal.

$$\psi_s^\tau(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

Wavelets are known to be efficient in representing piecewise smooth functions. Away from singularities, the inner product between a wavelet (with a number of zero moments) and a smooth function will be either zero or very small. At singular points, a finite number of wavelets concentrated around the discontinuity lead to non-zero inner products. This is in contrast with Fourier series where discontinuities lead to many larger coefficients. This ability of wavelets expansions to capture both smooth and singular parts of a signal has been used in many applications, including denoising and compression.

2.2. DiscreteWavelets

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. It turns out, rather remarkably, that if we choose scales and positions based on powers of two - so-called dyadic scales and positions - then this analysis is much more efficient and just as accurate. We obtain such an analysis from the discrete wavelet transform (DWT). An efficient way to implement this scheme using filters was developed in 1988 by Mallat, [3]. The Mallat algorithm is, in fact, a classical scheme known, in the signal processing community, as a two-channel subband coder. This very practical filtering algorithm yields a fast wavelet transform a box into which a signal passes, and out of which wavelet coefficients quickly emerge. The filter bank is read from left to right. The input is a vector; perhaps arising as samples of a continuous signal/function. This is a two-channel filter bank. In brief, its effect is to 1) Separate the input into frequency bands: filter and downsample and, 2) Reassemble: upsample and filter. The filters could each be applied several times. One applies the H_0 lowpass (average) filter repeatedly at higher and higher levels, each branch followed by one H_1 highpass (difference) filter. See Fig. 1.

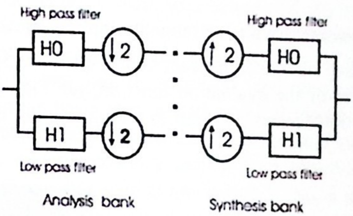

Fig. 1. Wavelet Filter Bank.

The left half of the filter bank is called the analysis bank, and its effect is to compute the wavelet coefficients of the signal vector. The right half of the filter bank is called the synthesis bank: it reconstructs the signal vector from the wavelet coefficients.

2.3. Support Vector Machines for Density Estimation

For Support Vector Machines (SVMs) in density estimation, [4], only one class have to be separated of the origin with an optimal hyperplane, Fig. 2. In order to build a SVM in the density estimation problem, with a nonlinear decision function, in a nonlinearly-separable case, one has to solve the following dual quadratic optimization (QP) problem:

$$\begin{aligned} &\underset{\alpha}{Maximize}\ L_D(\alpha) = -\frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j k(x_i, x_j) \\ &subject\ to:\ \sum_{i=1}^{l} \alpha_i = l, \\ &\qquad 0 \le \alpha_i \le \frac{1}{\nu} \quad i = 1, \ldots, l \end{aligned} \tag{2}$$

where k(,) is the kernel function, which makes a projection of the original space into a space (feature space) of a higher dimension. α are the Lagrange Multipliers introduced to transform the primal quadratic problem with linear constraints into the dual problem showed above. The parameter $\nu \in (0, 1)$ establishes an upper limit of the fraction of vectors remaining out of the learned distribution (outliers) and a lower limit of the fraction of support vectors. The evaluation function is defined as:

$$f(x) = \sum_{i=1}^{l} \alpha_i k(x_i, x_j) - \rho \tag{3}$$

The examples x_i associated with Lagrange multipliers greater than zero are called support vectors, since they have a significant contribution in (5). Geometrically, these vectors are on the border of the evaluation function, see Fig. 2. Large scale learning tasks, with more than 10000 instances, lead to a long training time and a large kernel matrix.

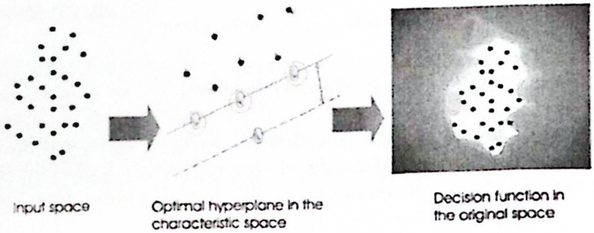

Fig. 2. Support Vector Machines for Density Estimation

Some solutions have been proposed in order to deal with this problem, [5], [6]. We have also proposed some heuristics, [13], [14], in order to reduce the training time.

2.4. Cumulative Sum (CUSUM)

CUSUM charts have shown to be efficient in detecting small shifts in the mean of a process. CUSUM works as follows: Let us collect k samples, each of size n, and compute the mean of each sample. Then the cumulative sum control chart is formed by plotting one of the following quantities:

$$S_m = \sum_{i=1}^{m} (x_i, \mu_0) \quad or \quad S'_m = \frac{1}{\sigma_x} \sum_{i=1}^{m} (x_i, \mu_0) \tag{4}$$

Against, the sample number m, where is the estimate of the in-control mean and is the known (or estimated) standard deviation of the sample means.

3. Methodology

Practically, a system can be diagnosed by two principal ways depending on the available information. The first one, when a mathematical or structural model is known, diagnosis can rely on estimation, analytic redundancy and expert systems. In the second case the model is not known, so a behavioral model has to be constructed from available observations on the system. The use of statistics, pattern recognition, neural networks, and other methods is the principal way of parameterization of the model. The diagnosis system has to supervise and diagnose the driver-vehicle-environment system. As we have seen, a mathematical model of this system is quite impossible to be constructed due to the number of factors and variables to be taken into account. In this work, one constructs a model from observations: x in n, each observation represents the system state at the instant t. So, a number of observations belonging to normal driver behavior will create a cloud of points. The general approach is illustrated in Fig. 3. It features a Base Line Generation that computes the model parameters off-line. Then, for the Real Time Diagnosis these parameters are used to evaluate the driver's performance every 50 msec. The final diagnosis deals with the instantaneous one by statistical methods to provide a final diagnosis to the driver with a minimum of errors.

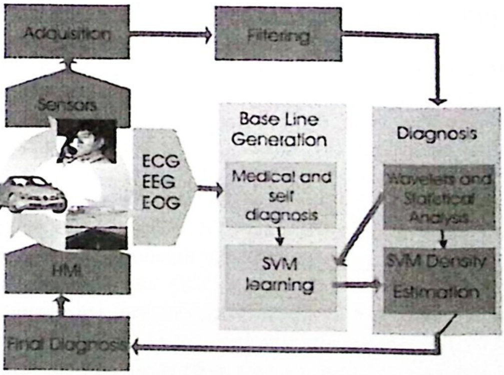

Fig. 3. General Diagnosis Methodology

A medical external expertise, based on EEG/EOG signals, is used as a target, in order to compare the resulting system. On-board measured variables are: lateral distance, steering-wheel angle and vehicle speed. The methodology is as follows:

1. **Singularities Detection.** On-board measured variables are used to compute a group of synthetic variables. By decomposing signals into elementary building blocks that are well localized both in time and frequency, the wavelet transform can characterize the local regularity of signals. This local regularity is measure from the
wavelet transform modulus maxima, [10]. First, our algorithm detects singularities (points where there are a change of the dynamics' signal) as temporal references for compute statistical artificial variables: average, standard deviation and the time traversed between singularities.

2. **Data fusion.** The cloud of computed artificial variables is used to create a normal class by means of the estimation of the probability density estimation function (PDF). However, there are multiple constraints for this kind of diagnosis. To represent as accurately as possible the normal behavior we need an exhaustive number of observations in different states.

3. **Final Decision.** The final result is provided by CUSUM.

4. Experiments and Results

Field experiments are being carried-out in the SENSATION. All the experimentation campaigns were performed using the CopiTech demonstrator vehicle. Two important results of these experiments are, on one hand, the driving behavior is personalized and could change in time, because two drivers have different driving characteristics in normal and abnormal modes. On the other hand, the pertinent parameters depend on the road situation. In fact we have to distinguish between different environments.

The experimentation protocol can be seen as follows: Drivers drove twice in a day, morning and afternoon; doing 184 km at 90 km/h each time. They have been instrumented with electrodes with the aim of record their brain (EEG) and ocular (EOC) activity. At the same time the medical expert asked to the driver his state of tiredness. In addition, all signals coming from on-board sensors were recorded and the scene in the cockpit and the environment of the vehicle were filmed and recorded on videocassette. Ulterior analysis of EEG and EOG allowed to known the physiological state of the drivers. There are seven variables: three physic variables (Wheel Angle WA, Lateral Position LP and Vehicle Speed VS) and four artificial ones (standard deviation and frequency of WA and LP) calculated into intervals between two singularities detected by the wavelets analysis.

4.1. Singularities Detection

The local frequency of the oscillations can be measured from the points where the modulus of the wavelet transform is local maximum, both along the scale and the spatial variable. As an example, we show the lateral position's signal analysis.

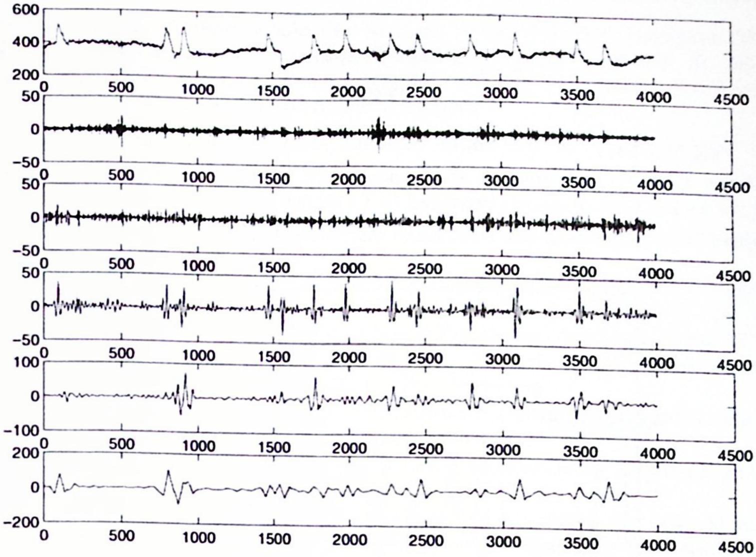

Fig. 4. Top: Analyzed signal. Bottom: Wavelet's detail coefficients at different levels.

To compute the wavelet transform, we use a complex Daubechies wavelet, due to the good capabilities of complex wavelets on detecting singularities, [11]. Both calculation of Wavelets and generation of artificial variables are done for the entire signal using fixed windows of 4046 samples, which make approximately 3.37 min for a sampling rate of 20 Hz. Different filter bank's output levels are shown in Fig. 4. Detail figures show the wavelets coefficients at different scales, higher level coefficient's modulus maxima shows where signal singularities take place.

4.2. SVM for density estimation and CUSUM for the final diagnosis

According to the process state, we can focus on problems in the driver's attention level. However, our interest is focused in the vigilant state. For one of the drivers, we have identified thanks to the medical expertise that the first 55 minutes belong to a vigilant (or normal) behavior and the rest to the hypovigilant one. For the learning process, we made use of the examples between 5 and 30 minutes of driving (30000 examples), obtaining 1399 support vectors for the learning parameter $\nu = 0.05$ and a Gaussian kernel with $\sigma = 0.35$. The results of the generalization procedure in the entire database are shown in figure 5. It shows at the top of the figure, the medical diagnosis given in ten levels. The level ten belongs to a high level of hypovigilance. In the middle, we show the output of the learned SVM PDF, normalized by the function:

$$f(x) = \frac{\max(-f(x,0))}{reg} \tag{5}$$

where $reg = f(x_i)$ of the entire database. This function provides a classical Probability Density Function for the hypovigilant behavior. The lower part of the figure shows the final diagnosis provided by CUSUM. A numerical performance is not computed since the medical and behavioral diagnoses don't arrive at the same time.

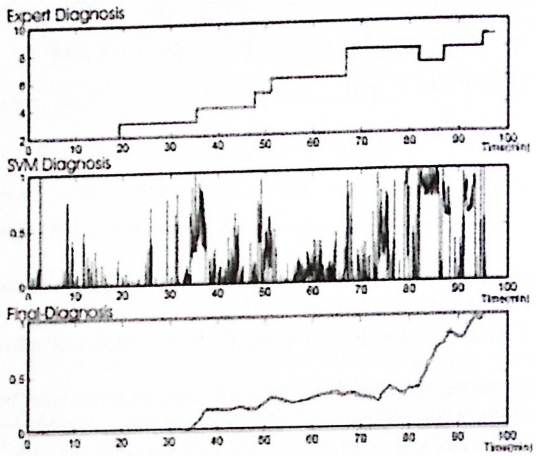

Fig. 3. High: External diagnosis expressed in ten levels. Middle: Wavelets-SVM punctual diagnosis. Low: Final diagnosis by CUSUM

5. Conclusions

This paper shows an Advanced Driver Assistance Systems (ADAS) focused in the diagnosis of a very complex problem: the driver's vigilance state. Several efforts are been or have been made by several teams all over the work to propose a reliable on-board and real time system. In this paper we have proposed a diagnosis system in order to perform the diagnosis of a vehicle driver in real time. The use of wavelets as an extraction methodology gives a more accurate description of the original physical variables and then the evolution over time. Wavelets joined to the Support Vector Machines shows its pertinence.

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