MODEL-BASED FEATURE EXTRACTION FOR ASSESSMENT OF DRIVER-RELATED FATIGUE

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Abstract: One of the most major causes of road crashes is the fatigue. In this paper it is shown a methodology for Driver Fatigue assessment based on computer vision (CV). CV is used to characterize different visual responses of the driver while driving and suffering from fatigue. Some of the visual responses are the eyelid and lips movements. The proposed Methodology uses an active appereance model (AAM) to adjust the facial model *Candide3* from images sequences where spatial measures can be computed. These measures include the eye closeness and the mouth openness. Results show that with the measures computed it's possible efficiently extract some discriminant parameters related to driver fatigue state. For example, the PERCLOS, the AECS, and the YawnFrec. Finally, an experimental framework is designed in order to compare the performance of the proposed method with psychological signal-based methods.

1 INTRODUCTION

Driving for long periods of time can decrease alert and performance of the driver who could start to suffer from fatigue (Ting et al., 2008). Fatigue and lack of sleep have been identified as the most frequent causes of traffic accidents in the road. For instance, the driver who is under these conditions is risking not only his/her own life but also other people lives. In order to prevent these kind of accidents, in the last decades a huge effort has been made to develop of monitoring systems that detects the fatigue in the driver and warned him/her by using different techniques. However, an efficiently system for fatigue assessment is still being an important issue to solve.

2 THEORETICAL BACKGROUND

Fatigue. Is the state of alteration in both the awareness level and the perception level of the person, this state affects psychomotor processes, such as speed of reaction, attention level, and making decisions that are crucial for the safe development of an activity. Fatigue is not the same as sleep, but induction of sleep could occur with fatigue. Fatigue can be caused by physical effort, emotional stress, lack of sleep, or an unspecified disorder.

Driver Fatigue. Is a state of reduced mental alertness, which impairs performance of a range of cognitive and psychomotor tasks, including driving (Saroj and Lal, 2001). The driver fatigue can be sub-divided into two groups: related to sleep and related to tasks. The first one, is caused by lack of sleep (this is the category select in this work), while the second one is caused by distracting tasks while driving.

Candide Model. It is a parameterized facial mask, that has been specifically developed for model-based coding of human faces. Different versions of this mask has been developed, the most current version is the third, which has been implemented mainly to simplify the animation of MPEG-4 facial animation parameters (Ahlberg, 2001).

2.1 Psychological Test for Attention Measurement

Works that deal with the assessment of driver-related fatigue require experimental frameworks where the methodology can be contrasted and validated. For ex-

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ample, attention test (such as interviews or computer based test), which are basically monitoring task that required psychomotor reactions. One test of attention most commonly used in drivers is the test of attention variables TOVA. It's considered the gold standard within this kind of tests. It consists in 22-minutes of psychomotor tasks where a subject needs to hold the attention and respond to a random stimulus. Another example, is the PVT test (psychomotor vigilance test), that measures the visual reaction time (RT) by mean of portable devices. This test is another common tool of measuring the fatigue in performance and lack of sleep studies. The PVT is a 10 minutes length test, like the TOVA test requires responding to a stimulus as fast as possible.

Anothers examples of tests that can be used in these kind of studies are those tests that aim to evaluate the ability to focus the attention. One example of such test is the Stroop task. In general any test that measures the RT is useful in these studies, because the sleep restriction and deprivation can be the main cause of an increase in the RT.

2.2 Classification of Driver Monitoring Systems

In order to reduce road crashes, enormous efforts have been done to develop driver monitoring systems. These systems can be classify in three classes (Vural et al., 2007). 1) Studies that analyze measures of the driver's performance. In this kind of systems the car is equipped with measurement devices that indicate if the person is driving as usual or not. These systems has the drawback that cannot be adapted to the driver habits. 2) Work that are related to the measurement of physiological signals. These methods provide good indicators of fatigue. However, these are invasive methods that could interfere with the driving task. 3) Works focus on detection of visual responses that present the driver based on CV. The CV based methods can be successful in order to assess fatigue states. However, so far just one visual response has been used and that could be the main drawback in the CV based methods (Zhu et al., 2004).

Measurement of fatigue indicators is a significant problem due to the absence of direct measures, which are not directly relate to the fatigue but to the effects of fatigue. The only direct measure is the self report. However there are problems related with its use because the emotional influence in the person (Wang et al., 2006). In the literature there are different studies related with the measurement of performance, physiological, of perception, among others. Although the technologies applied to fatigue assessment have evolve, the search for a fiable fatigue indicator still ahead (Saroj and Lal, 2001).

2.3 Visual Responses and Fatigue-Related Parameters

In order to detect driver fatigue it is required to measure different visual responses. Simultaneous measures will provide a less ambiguous scenary that just one measure. Some of the visual responses are: the eyelids, the head pose, and the facial expressions. From these visual responses fatigue-related parameters are computed. For example, head-position-dependent parameters and head-position-independent parameters. the last will be used in this work, more specifically are computed: the percentage of eye closening in time (PERCLOS), the eye closening average speed (AECS), and the yawning frequency in time (YawnFrec) (Zhu et al., 2004).

PERCLOS and AECS. These measures are characteristic of the eyelid movement. The PERCLOS has been already validated and it has been found that is the most appropriated parameters to assess the driver-related fatigue (Dinges et al., 1998). The AECS is a good indicator of fatigue. This parameter is defined as the time taken to completely close the eyes. The eye openess is characterized by pupil's shape. It can be measure by taking the ellipse axis relationship. This feature over the time is used to computed the PERCLOS (Zhu et al., 2004). In (Ji and Yang, 2002), it has been shown that the AECS in a tired person is definitely different from a rested person.

YawnFrec. A tired person is characterized by expressing less facial expressions because there is minimal activity of facial muscles, but it also show more open mouth. The mouth openness can be measure by detecting the lips movements whether the features around it deviate from its closed configuration. The mouth openess is characterized by the proportion between the height and width to computed the YawnFreq (Zhu et al., 2004).

3 FATIGUE ASSESSMENT BASED ON COMPUTER VISION

People in a state of fatigue show some visual responses that are easily observable from changes in their facial features like eyes and mouth. CV has different non-invasive techniques for monitoring of drivers (Wang et al., 2006). As Zhang (Zhang and Zhang, 2006) reported, the CV-based systems for monitoring drivers are the most promising commercial application for assessment of driver-related fatigue (Zhang and Zhang, 2006), (Dong and Wu, 2005), (Saeed et al., 2007), (Zhu et al., 2004), (Ji and Yang, 2002). However, CV is a challenging research area due to the different factors such as: facial expressions complexity, fast eye and head movements, and changes in illumination conditions, etc. These factors difficult the development of robust and real time implementations of these kind of systems.

Basic Requiremets for A CV-Based System. According to (Dong and Wu, 2005), and (Smith et al., 2003) a monitoring system to detect fatigue should fulfill the following requirements: 1) fully automatic. 2) to be based on only quantitative features, such as, the eye openness and closeness rate. 3) to work under changing illumination conditions. 4) to work under occlusion conditions that are frequent when head is moved from the reference point. 5) real-time. 6) non-invasive, without physical contact of the driver. 7) before an accident it should detect and warn the early occurrence of sleep.

Steps in A Visual System for Detection of Fatigue. First, near infrared image sequences were acquired. Second, mathematical morphology is used to improve the images quality and the success rate in the following steps. Third, the Haar algorithm is used to detect the face and then the Gabor algorithm is used to detect the person's eyes. Then the distance between the eyes is used reference to adjust the Candide model to the person's face. Fourth the AAM technique is used to track the movements of the face. Finally the feature extraction stage is performed using a model.

4 CHARACTERIZATION OF FACE MOVEMENTS

The most important points to characterize a face depend on the application and the facial model. In this work the movements of the eyes and mouth are considered. In these sense, a whole face model is used instead of a partial model of the eyes, as used in (Saeed et al., 2007).

In order to get a quite realistic fitting of model and detect the driver fatigue it's need to define the adjustable vertices of the model Candide. These vertices belong to the eyes and mouth ROIs where the parameters PERCLOS, AECS, and YawnFrec are computed. Additionally it is desirable that the movements of selected vertices are controlled by facial action units, these movements are part of the list of changes that are presented when there is a movement of the ROI encoded in terms of AUVs (Ahlberg, 2001).

Facial Motion Tracking. Previous to the computation of the parameters of fatigue the AAM models are used to adjust the face model to different subject faces. The AAM models are adjusted by machine learning algorithms from available features (Cootes et al., 1995). Then an alignment process is run to adjust the AAM model (vertices update) to the input images. To train the AMM an graphical user interface (GUI) was developed, were the following steps are done. 1) Scaling of the model to the face based on the inter-eye distance, 2) Rotations in axes X, Y, and Z to locate the model in the subject position, 3) Shape changes of the model regions are evaluated (control by shaped units) or movements in regions of the model (with vector control units of action, focusing on the mouth openness AUV11 and eye closeness AUV6) are evaluated too. 4) Points in the boundary of the face and eyes and mouth are reviewed and relocated. 5) The positions of the vertices of the fitted model are stored for each image in the sequence. Once the training algorithm is completed, a fitting algorithm is used to adjust the AAM to minimize the fitting error. For example, the decreasing gradient optimization can be used as described in Eq. 1, with the model A_0 and the input image $I(x)$. Once the model is adjusted the extraction of fatigue features can start.

$$FittingError = \sum^{x} [I(x) - A_0(x)]^2 \tag{1}$$

Eyelid and Lips Movements Characterization. To compute the PERCLOS and AECS in (Ji and Yang, 2002) is proposed to continually track the pupil and measure the eye closeness cumulatively over time, using the ratio of the vertices of the pupil ellipse. A single eye closure is defined as the difference between two periods of time in which the pupil size is 20% or less of the normal size. The closing eye speed is defined as the time period in which the pupil size is between 80% and 20% of the nominal size of the pupil.

In order to computed these two parameters more accurately, an average time is used of all measurements taken on a defined range (Ji and Yang, 2002).

To make these measures it is apply the methodology described in (Ji and Yang, 2002), but different from this, eye closeness is computed using the eye vertices which are defined in the model Candide 3. Specifically, we used some vertices of the eyelids. Thus, the eye closeness is calculated as:

$$c_{re} = \frac{d\,(v_{98} - v_{100}) + d\,(v_{54} - v_{55}) + d\,(v_{106} - v_{108})}{3} \tag{2}$$

$$c_{le} = \frac{d\,(v_{105} - v_{107}) + d\,(v_{21} - v_{22}) + d\,(v_{97} - v_{99})}{3} \tag{3}$$

From Eq. 2 and 3, when the eye closeness is less than or equal to 20% of the maximum distance between eyelids is considered that the eyes are closed. According to the work developed in (Dong and Wu, 2005) if the eyes are closed for 5 consecutive frames it can be considered that the driver is falling asleep.

In order to compute the rate of mouth opening, it is necessary to know the degree of the mouth openness, which is represented by the relation between the mouth's height and width. The graphical representation of the mouth openness in a period of time is know as YawnFrec. To compute the mouth openness the vertices (right, left, upper, lower), of the mouth in the model Candide 3 are used. In this sense, the mouth openness is computed as follows:

$$OpenMouth = \frac{d\left(v_7 - v_8\right)}{d\left(v_{64} - v_{31}\right)} \tag{4}$$

5 EXPERIMENTAL FRAMEWORK

Two different videos were acquired with 320x340 resolution. The subjects were instructed to blink and yawn in different head positions range from $45° y - 45°$. The subject 1 blinked 35 times and yawned 5 times. The subject 2 blinked 24 and yawned 4 times. The system was able to identified the total numbers of yawns and blinks for each subject. This means a 100% accuracy in detection of eye closeness and mouth openness. Indeed the parameters PERCLOS, AECS, and Yawnfrec could be determined every time. In order to validate the presented methodology, an experimental framework is proposed. First, a commercial driving simulator is going to be used and three diferent physiological test will be set up (the PVT test, the Stroop test, and the RT test). These tests are embedded in the software PEBL (Open source Psychology Software), available at "http://pebl.sf.net". From these tests some basic measures will be made, in similar ambiental and physical conditions to those presented in the computer-vision-based methodology in order to compare results and validate the parameters.

6 CONCLUSIONS

In this paper was proposed a characterization methodology based on models to assess fatigue. Two variables are measured by means of computer vision. The eye closening range and the mouth opening range. These measures are the base to calculate the parameters PERCLOS, AECS y YawnFrec. It has been found that the proposed methodology is practical and reliable whithin the previously described conditions. Also an experimental framework based on psychological measures was defined in order to validate the proposed methodology. As future work, it is proposed to complement the above methodology with estimation of head's position in order to compute additional parameters. This will provide more information to the assessment of the driver fatigue.

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