Deep Bio-Sensing Embedded System for a Robust Car-Driving Safety Assessment

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Abstract—Recent statistics confirmed that the car driver drowsiness monitoring reduces drastically the road accidents. In scientific literature, several advanced approaches have been proposed to monitor the driver’s level of attention, providing a real-time warning to increase driving safety. With this aim, we propose an innovative method which consists of ad-hoc designed bio-sensing system to assess the car driver’s physiological state. The designed bio-sensing system includes a probe which detects a physiological signal of the subject i.e. the PhotoPlethysmoGraphy (PPG). The physio-probe device has been embedded on several points of the car’s steering wheel in order to sample the PPG signal from the driver’s hand. Furthermore, ad-hoc motion magnification algorithm was developed to reconstruct PPG from visual car driver face motions when physical PPG signal is unavailable. An innovative deep learning system completes the proposed pipeline in order to classify the driver drowsiness from the so collected PPG signal. The drowsiness detection performance (average accuracy of around 90%) confirmed the effectiveness of the proposed approach.

Index Terms—ADAS. Deep learning, Bio-signals

I. INTRODUCTION

In the last few years, various techniques have been implemented to measure the car driver drowsiness. The Drowsiness status denotes a physiological state that leads to a reduction of the level of awareness and a tendency to fall asleep [1]. This fact motivates the need to develop an effective solution to detect drowsiness in the early stages. Specifically, there is an increasing growth of studies that focus on analyzing correlation between car driver drowsiness and such electrical bio-signals of the subject i.e. EEG (Electroencephalography) or ECG (Electrocardiography). However, the mentioned techniques are impracticals, since they require that the driver wears a range of bio-sensors. Nevertheless, driver monitoring based on physiological signals has been used in various applications spanning cardiology to the automotive field [1]. In order to overcome the mentioned limitations, PhotoPlethysmoGraphic (PPG) signal has been used to assess a subject’s physiological status [1], [2]. Researchers have become increasingly interested in the PPG signal because it does not require the driver to wear any sensors and it is very simple to sample. [1]. The PPG signal formation is regulated by the subject’s bloodstream directly connected to cardiac activity which in turn is regulated by Autonomic Nervous System (ANS) that characterizes the subject’s awareness level [3]. Furthermore, several studies confirmed the correlation between blood pressure estimation and physiological attention, becoming an important aspect of determining the drowsiness state [4], [5]. Despite being an effective tool, the PPG signal is very susceptible to Motion Artifacts (MA) generated by body movements, and it also requires the use of specific sensing devices with ad-hoc post-processing pipeline [1], [6]. Therefore, developing a robust and non-invasive system to monitor the PPG signal alongside assessing the subject’s blood pressure could represent an advance in automotive monitoring systems. The authors propose an innovative pipeline to assess the driver’s drowsiness level by extracting features of the PPG signal without requiring invasive devices. The remainder of the paper is structured as follows. In Section II, we introduce the PPG signal specifying the underlying physical principle that characterizes its formation. In Section III, the main scientific contributions reported in literature are discussed. In Section IV the authors reported the proposed pipeline. In Section V, the experiments and validation results are analyzed. Finally, in Section VI, conclusions and future developments are analyzed.

II. THE PPG: UNDERLYING PHYSICAL PHENOMENA

Photoplethysmography (PPG) is a non-invasive estimation of blood volume changes in tissue by measuring characteristics of light either absorbed or reflected from tissue [1]. More specifically, PPG is a physiological signal generally acquired using an optical sensing system which monitors the blood flow dynamic related to the cardiac phases [1], [2], [7]. We collect the PPG signal by illuminating the region of interest
of the subject’s skin using a Light Emitting Diode (LED). By coupling the LED with a photo-sensing device, we are able to sample the part of back-scattered light (photons), which is not absorbed by the blood flow (Back-Scattered signal) of the subject on which the optical sensing system is placed [8]. An electrical transduction circuit of the optical signal completes the PPG signal sampling pipeline. As reported, ANS regulates the heart rate of the subject, generating an impact in the arterial blood flow. The so collected data will be properly processed.

A. The PPG Sensing System

Recently, several hardware architectures have been proposed to acquire the PPG signal [8], [9]. In this section, we describe the proposed hardware pipeline based on the use of a photo-multiplier silicon device, called Silicon PhotoMultiplier (SiPM) [10]–[12]. Our proposed sensing device is therefore composed of two OSRAM LED emitters (SMD package) emitting at 850 nm and used as optical light sources with a SiPM detector. The total area of the proposed SiPM device is 4.0 × 4.5 mm². Furthermore, the detector consists of 4871 square microcells with 60 µm of the pitch, a geometrical fill factor of 67.4%. It is also packaged in a surface mount housing (SMD) having a 5.1 × 5.1 mm² total area. In [8]–[10], we reported further details about the proposed hardware system. In Fig. 1, we reported the implemented PPG sensing device. The designed hardware board includes an SPC5 32-bit Chorus microcontroller device employed to sample the PPG optical signal (through the embedded 12-bit Analogic to Digital Converter (ADC)) and perform the required signal filtering and stabilization [11]–[13]. The sampling PPG signal introduces various types of noise (e.g., motion artifacts, micro-breathing movements, etc.) [11], which compromises the robustness. This issue requires the usage of such filtering layer of the raw PPG. To this aim, we implemented a raw PPG signal filtering pipeline using a Butterworth band-pass filter in the 0.5 - 8 Hz range. In particular, we proposed an innovative, robust, and de-noising pipeline signal, called PPG-PRS [13]–[15]. The resulting signal contains PPG standard compliant waveforms [11], [12]. In Fig. 2, we reported a detail of the compliant filtered PPG waveform.

III. RELATED WORKS

In this section, we summarize previous approaches on evaluating car-driver status using physiological signals. Generally, existing approaches propose invasive and computationally expensive solutions [16] alongside using high-performance systems to ensure high levels of safety while driving [14], [16]. In this context, the PPG signal is the easiest to sample among all the physiological signals [16]. On this basis, promising approaches on drowsiness detection are listed, followed by the latest approaches using deep learning. In the automotive field, the use of PPG signals is preferred to monitor drowsiness instead of acquiring other electronic signals, such as the ECG. Indeed, the ECG requires contact with at least three points of the car driver (Einthoven triangle) [14], reducing comfort and robustness. In addition to detect physiological signals, researchers have adopted such visual information (i.e., facial expressions, eye blinks, etc.) to analyze the driver’s level of attention [17]. Several studies have pointed out the correlation between a subject’s attention level and the dynamic of related Heart Rate Variability (HRV) [18]. In this context, many efforts have been made to design and implement efficient, reliable, and sustainable solutions for fatigue and drowsiness monitoring based on usage of physiological data. In [18], the authors used three types of recurrence plots (RPs) derived from the R-R intervals of the heartbeats to feed a Convolutional Neural Network for the classification of drowsy/awake status. Specifically, the authors investigated the pattern of Heart Rate Variability (HRV) to monitor the car driver’s drowsiness [18]. In this work, the HRV is collected by using ECG and PPG sensors, which inevitably introduce some artifacts. Over the last years, researchers have investigated the use of blood pressure to determine the level of attention, alongside analyzing physiological signals. For example, Monte-Moreno et al. [19] proposed a non-invasive approach to estimate the systolic and diastolic blood pressure by acquiring PPG signal. In order to estimate the blood glucose level (BGL), systolic (SBP), and diastolic (DBP) blood pressure, in [19] a signal processing module is designed to extract features from the PPG waveform to be used as input data for a different machine learning algorithms. In [13], the authors described an innovative approach to estimate BP from PPG signal. The experimental results confirmed the effectiveness of the proposed approach.

IV. METHODS AND MATERIALS

This section presents the overall pipeline. The Visio2PPG pipeline architecture is described first. Afterwards, we introduced a Deep Long Short-Term Memory (D-LSTM) frame-
Moreover, a pipeline to estimate blood pressure is described. Finally, we provide details about our implemented ad-hoc Deep Convolutional Neural Network (D-CNN).

### A. The proposed Visio2PPG Reconstruction Pipeline

In this section, we describe the Visio2PPG architecture that comprises a PPG sensing device for preliminary system calibration coupled with a Computer Vision camera module to sample subject’s face from whom extracting facial descriptors.

A Machine Learning algorithm that correlates the aforementioned subject’s face descriptors with the corresponding PPG waveforms, completes the proposed pipeline. In the training-calibration stage, the proposed pipeline correlates the time-dynamic (in all sampled video frames) of the selected face descriptors with the corresponding PPG features to evaluate the car driver’s drowsiness and the corresponding blood pressure level. During the calibration phase, the PPG signal is collected using the previously described coupled LED-SIPM sensing device, embedded in the vehicle steering wheel [12], [13]. After acquiring the PPG signal, the PPG-PRS algorithm produces a compliant PPG time-series [13], [14], filtering the raw PPG signal. Therefore, we stabilize the PPG time-series by removing motion and noise artifacts. In addition, the PPG-PRS algorithm provides a study of the first and second derivatives of the filtered PPG signal to detect the minimum and maximum extreme points of each selected compliant PPG waveform. When collecting the PPG signal, we recorded a video sequence of the subject’s frontal face with a camera device having a low framerate, under high light condition. Recently, a significant amount of works focused on the correlation between facial micro-movements and the cardiac pumping activity [20], confirming that these micro-movements are strongly correlated to the PPG signal. In order to amplify these micro-movements, some authors have formulated several approaches based on Motion Magnification. This process is particularly hardware-demanding requiring high frame-rate acquisition devices (on average, framerate ranging from 10 Kfps up) [21]. Inspired by the work of Wu et al. [22], where the authors used Video Magnification to reveal the bloodstream, we proposed an approach to elaborate video sequences of the car driver’s face. The purpose is to preliminarily identify significant landmarks or descriptors on the driver’s face. To detect the mentioned landmarks, we used the approach proposed by Kazemi and Sullivan in [23]. It estimates the location of 68 coordinates that map the facial structures or structure-landmarks (i.e., eyes, noise, mouth, etc.) on a subject’s face image. We analytically formalize the reconstruction of landmark dynamics by using Kazemi and Sullivan algorithm \( \psi_{KS}(\cdot) \). Formally, let be \( I_t(x,y) \) the captured \( M \) gray-level (or luminance channel in case of color camera device) driver face video frames at the instant \( t \), the \( i-th \) landmark dynamic time-serie \( l_i(t_k,x_t,y_t) \) is reconstructed using the following equation:

\[
\ell_i(t_k,x_t,y_t) = \psi_{KS}(I_k(x,y)); k = 1..N_f; i = 1..N_L
\]

where \( \ell_i(t_k,x_t,y_t) \) represents the pixel intensity dynamic of the \( i-th \) landmark identified at the frame position \( (x_t,y_t) \) while \( N_f \) represents the number of captured frames and \( N_L \) represents the number of 68 identified landmarks (Eq. 1). Once detecting landmarks dynamics, we analyzed the descriptors time-series \( \ell_i(t_k,x_t,y_t) \) in order to correlate their temporal intensity with the underlying cardiac activity. The main advantage of the proposed method consists in not requiring the use of high-frame rate camera devices.

### B. The Deep LSTM architecture

As introduced, we propose ad-hoc Deep Long Short-Term Memory (D-LSTM) framework to correlate the driver’s facial landmarks and the corresponding cardiac activity. In particular, our D-LSTM network is based on Vanilla architecture initially proposed by Hochreiter and Schmidhuber in [24]. In this contribution, we significantly improved the approach previously described in [25] based on employing a D-LSTM architecture to reconstruct some features of the PPG signal to characterize the driver’s drowsiness level. The proposed D-LSTM architecture is composed of 1 input layer, 2 hidden layers, and 1 output layer. Specifically, we designed the input layer with 64 units and the two hidden layers with 64 and 128 cells, respectively. The output layer comprises 1 cell providing the predicted PPG sample. Each LSTM layer is followed by a batch normalization and a dropout layer appointed to boost the overall performance. We trained our model with an initial learning rate of \( 10^{-3} \). We also set the batch size to 512, and the maximum number of training epochs to 200. In training-calibration phase, the proposed Deep LSTM learns the correlation between the selected facial landmark time-series \( \ell_i(t_k,x_t,y_t) \) with the corresponding sampled PPG signal, for each subject. The output of the so designed Deep LSTM pipeline represents predicted extreme points of PPG signal. We carried out several tests that reported acceptable performances related to reconstruction of the features of the PPG signal. Our findings suggest that it is not required to use all the landmark time-series but thanks to the D-LSTM architecture, the computing of a composite signal as a function of all the sampled landmarks signals is enough for the designed application. Specifically, we perform the following computation:

\[
\mu(t_k) = \frac{1}{N_L} \sum_{j=1}^{N_L} \ell_j(t_k,x_t,y_t)
\]

Using Eq. 2, the so computed signal \( \mu(t_k) \) will be fed as input of the D-LSTM. The deep architecture will be trained to correlate the input signal \( \mu(t_k) \) with such features of the corresponding PPG signal of the analyzed subject i.e. with the extreme points \( m1,m2,m3,m4 \) as reported in Fig.2. Once collecting PPG signal, the extreme points \( m1,m2,m3,m4 \) are computed by the PPG-PRS algorithm through first and second derivative-based approach [13]. Otherwise, when the Vision2PPG reconstruction system takes over the pipeline (in the absence of real PPG signal because the driver does not have the hand in contact with the sensor in the steering wheel), the
extreme points are predicted by D-LSTM previously trained on the sampled PPG signal. After the Deep LSTM framework has learned the correlation between the driver’s facial landmarks and the extreme points of the corresponding PPG signal, the training-calibration phase will be dropped. The calibration phase requires 15/20 seconds of PPG signal (our sensing device performs acquisition at 1 kHz) and corresponding visual frames (at 40 fps). Finally, the underlying trained model provides a feed-forward estimation of the PPG extreme points as per Fig. 2. An HRV block closes the pipeline providing a corresponding attention measurement based on classical frequency analysis of the so determined extreme points of PPG.

C. The Blood pressure estimation pipeline

In this section, we describe the pipeline used to monitor the driver blood pressure since it is strongly correlated to the driving safety. We propose a novel solution to measure blood pressure level of the subject by simply acquiring the corresponding facial video frames and then processing it with the proposed Vision2PPG reconstruction pipeline. As described, we retrieved the extremal points of the subject’s PPG signal. These points are fed as input of a properly configured Shallow Neural Network that classifies the normal-blood pressure subjects from those who report pressure values beyond the norm. Once collecting the set of extremal points of the PPG waveforms, we characterized the subject’s cardiac activity depending on the blood pressure. Formally, for each pair of PPG waveforms $PPG^j$, $PPG^{j+1}$, we define the following indicators:

$$\varphi = \left[ m_1^j, m_2^j, m_3^j, m_4^j, dx_j^i, dy_j^i, mAI_j^i \right]$$  \hspace{1cm} (3)

$$m_i^j = (x_i^m, y_i^m)$$  \hspace{1cm} (4)

$$dx_j^i = x_{m_i}^{j+1} - x_{m_i}^j$$  \hspace{1cm} (5)

$$dy_j^i = y_{m_i}^{j+1} - y_{m_i}^j$$  \hspace{1cm} (6)

$$mAI_j^i = (y_{m_i}^j - y_{m_i}^1 - y_{m_i}^j - y_{m_i}^1) / (y_{m_i}^j - y_{m_i}^1)$$  \hspace{1cm} (7)

$\forall j = 1, \ldots, \left(N_{PPG} - 1 \right), i = 1, 2, 3, 4$, where $mAI_j^i$ is a modified version of the so-called Augmentation Index, usually computed for measuring the arterial stiffness while $N_{PPG}$ represents the number of estimated extremal points (Eq. 7). The other indicators reported in the Eqs. (3)-(6) characterize cardiac cycles and, therefore, the corresponding blood pressure level. The elements of the vector $\varphi$ represent the input of the aforementioned Shallow Neural Network (SNN) designed to learn the correlation between the computed input of elements and the corresponding value of the systolic and diastolic blood pressure. The designed SNN (with an hidden layer of 500 neurons) is trained with the Scaled Conjugate Gradient backpropagation (SCG) algorithm [14]. The output of the SNN framework is a binary value which is a discriminating flag denoting if the subject shows normal pressure values (0) or not (1). The set 120/80 indicates 120 mmHg for systolic pressure and 80 mmHg for diastolic pressure. Under the supervision of a team of physiologists, we setup 120/80 mmHg as acceptable blood pressure whereas higher/lower values are considered anomalous.

D. The Deep CNN Pipeline

To assess the level of car driver drowsiness, the authors propose an innovative pipeline based on ad-hoc Deep Convolutional Neural Network (D-CNN). The proposed D-CNN network is composed of three convolutional layers. Except for the last convolutional layer, each layer is followed by a ReLU activation layer (with batch-normalization) and $2 \times 2$ max-pooling layers. The first convolutional layer performs 32 operations with $3 \times 3$ kernel filters, where the second and the third ones show $64 \times 64$ and $128 \times 128$ kernel filters of $3 \times 3$, respectively. A Softmax layer completes the D-CNN pipeline performing binary classification of the visual input data i.e., drowsy/wakeful state of the analyzed driver. We performed fine-tuning for 100 epochs using Adam optimizer and cross-entropy as the loss function. To conduct our experiments, we also set the learning rate to 0.001 and the batch size to 32. The input visual frame of the D-CNN is a segmented car driver eye ($77 \times 77$ resolution) obtained through Haarcascade classifier [26]. We designed the proposed D-CNN in order to be hosted in the STA1295 Accordo5 embedded automotive-grade platform, which includes a 3D-GFX accelerator cell 1.

E. The driving safety monitoring

In this work, we proposed a pipeline that combines the driver’s physiological and visual data, sampled by specific sensors placed in the car. On this basis, we implemented a pipeline which reconstructs the features of the driver’s PPG signal from visual information when the steering embedded sensors will do not provide real PPG data. The extracted features allow us to reconstruct the driver’s level of attention through the analysis of HRV and evaluating the blood pressure dynamics providing a robust measure of the driving safety level. We increased the robustness of the proposed approach by processing the video frames of the driver’s face through a D-CNN model, performing a further classification of the driver’s attention level. In Fig.3, the overall scheme of the proposed driving safety estimation architecture is shown. We have implemented a block called Driving Safety Decision System (DSDS) to analyze the outputs produced by the previous pipelines (i.e., HRV analysis from PPG or Visual landmarks based reconstructed signal, SNN output related to blood pressure estimation from PPG or Visual reconstructed PPG, D-CNN classification of the facial expression of the driver). In detail, DSDS generates an acoustic signal, whether at least one safety control block estimates a significant level of risk. The acoustic signal is managed by the STA1295 Accordo5 system, which hosts the DSDS software implementation. To sum up, the Vision2PPG pipeline reconstructs
the extreme points of the PPG signal of a monitored car-
driver. Therefore, the distribution in the frequency domain
of the reconstructed PPG extreme points \((m_1, m_2, m_3, m_4)\)
from the proposed pipeline is robust and allows to obtain a
frequency spectrum (FFT) very close with the real one (i.e.,
determined by the driver’s real PPG signal). Through this
reconstructed PPG data, we obtained a robust HFT suitable
to characterize the driver’s drowsiness level [17]. Moreover,
a PPG based blood pressure analysis will be performed by
SNN sub-system which is correlated to driver drowsiness.
A further DCNN architecture works simultaneously with the
Deep LSTM framework, providing a further assessment of the
driver’s attention level based on the analysis of facial features
as illustrated in [25]. The system provides a measure of the
overall driver’s attention level by analyzing the rankings of the
three mentioned sub-systems.

V. EXPERIMENTAL RESULTS

In this section, we describe the experimental setup. Seventy
both healthy (45 subjects having a blood pressure less or equal
to 120/80 mmHg), and hypertensive (25 subjects having a
blood pressure higher than 120/80 mmHg) took part in the
data collection. The minimum age of the subjects was 20
years, while the maximum age was 75 years. After signing
the consent form\(^2\), subjects were recorded (frontal face) using
a color camera device having a max resolution of 2.3 Mpx and
40 fps as framerate. The collected dataset includes systolic and
diastolic pressure and PPG signal measurements, plus video
sequences of the subject’s face. Moreover, subjects performed
different drowsiness states under the supervision of a team
of physiologists. Simultaneously, we collected the EEG signal
from subjects determining the real level of attention. Each
measurement session is around 10 minutes long, 5 of which
in a state of full attention and 5 in a state of low attention.
The PPG was acquired by using the described sensing device
with sampling frequency at 1 kHz. In order to collect the
blood pressure measurements, we used a classic certified
sphygmomanometer. In the collected dataset, the minimum
pressure value is around 105/70, while the maximum pressure
value is 160/95. The collected dataset was split into 70% for training, 15% for validation and 15% for testing. In our
experiments, a NVIDIA GeForce RTX 2080 GPU as used
for training and testing. Moreover, MATLAB full toolboxes
rel. 2019b environment for Deep Learning framework were
employed. We compare our proposed method with another
similar pipelines [2]. Table I shows the accuracy benchmark
comparisons both regarding to the early recognition of the low-
attention driver (Drowsy Driver) and to the early detection
of the high-attention driver (Wakeful Driver). A measure
of the average performances is reported (overall accuracy).
This comparison highlights the effectiveness of the proposed
method, showing a 2% increase in accuracy with respect to
[2]. We also validated the performance of SNN network used
to estimate the blood pressure level by comparing our method
with other approaches in literature [27]. Table II shows the BP
values measured both to normal-pressure subjects (Class 1)
and to those with an abnormal BP (Class 2). As confirmed by
the metrics in Table II, the margin of error for the implemented
pipeline is also considerably low. The results for SSN network
suggest that our model provides reliable classification results
as confirmed by the overall accuracy of 88.73%.

\(^2\)Ethical Committee CT1 (authorization n.113 / 2018 / PO)
VI. CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a multi-modal approach that combines visual and physiological data to evaluate the driver’s drowsiness. The obtained results confirmed the robustness of the proposed approach. Future work aims to collect more data to further improve the performance of the safety monitoring [27]–[30].

ACKNOWLEDGMENT

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REFERENCES


TABLE I

| Method | Drowsiness Estimation |   
|--------|----------------------|-------|
|        | Overall Accuracy     | Drowsy Driver | Wakeful Driver |
| Proposed | 95.07%               | 95.77%      | 94.36%         |

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TABLE I

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall Blood Pressure (BP) Estimation</th>
<th>Class 1 Normal BP</th>
<th>Class 2 Abnormal BP</th>
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<td>Proposed</td>
<td>88.73%</td>
<td>88.88%</td>
<td>92.30%</td>
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