

Advanced Deep Learning in Automotive-grade Driving Assistance Systems

Francesco Rundo¹, Sebastiano Battiato², Sabrina Conoci³

¹STMicroelectronics, ADG Power and Discretes R&D, ²University of Catania, ³University of Messina
Francesco.rundo@st.com , battiato@dmi.unict.it, sabrina.conoci@unime.it

Abstract

Next generation cars embed intelligent assessment of car driving safety through innovative solutions often based on usage of artificial intelligence. The safety driving monitoring can be carried out using several methodologies widely treated in scientific literature. In the context of the national funded research project “ADAS+”, the involved partners designed and implemented an innovative approach that uses ad-hoc designed bio-sensing system suitable to reconstruct the physiobased attentional status of the car driver. To reconstruct the car driver physiological status, the authors implemented a bio-sensing probe consisting of a coupled LEDs at Near infra-Red (NiR) spectrum with a (Silicon Photo-Multiplier) photo-detector SiPM, delivered by STMicroelectronics, coordinator partner of the ADAS+ project. This probe allows to detect a physiological signal called PhotoPlethysmoGraphy (PPG). The PPG signal formation is regulated by the concentrations of oxygenated and non-oxygenated hemoglobin in the subject's bloodstream which will be directly connected to cardiac activity in turn regulated by the Autonomic Nervous System (ANS) that characterizes the subject's states of attention. This so designed car driver drowsiness monitoring will be combined with further driving safety assessment based on correlated intelligent driving scenario understanding.

1 Introduction

Physiological signals represent a relevant data source to be employed for the development of promising applications from cardiology to industrial and automotive fields [Tomohiko et al, 2015]. The increasing proliferation of non-invasive devices for collecting physiological parameters has led to explore various approaches to analyze physiological signals taking advantage of these new technologies instead of using obtrusive or even invasive tools. In this context, PhotoPlethysmoGraphic (PPG) signal has been proposed as a valid solution to analyze a subject's physiological status [Tomohiko et al, 2015]-[Vicente et al, 2011]. PPG is a convenient and simple physiological signal that provides infor-

mation about the cardiac/neuro-physio activity of a subject [Rundo et al, 2018]. In the automotive industry, the increasing improvements in safety awareness systems have led to the development of ADAS (Advanced Driving Assistance Systems) architectures based on continuous monitoring of the driver's drowsiness by using physiological signals. Drowsiness refers to a physiological state characterized by the reduction of the level of consciousness and difficulty in maintaining the wakeful state [Rundo et al, 2018; Vinciguerra et al, 2019]. Cardiac activity (specifically the heart rate) is regulated by the Autonomic Nervous System (ANS) through the action of the sympathetic/ parasympathetic sub-systems [Rundo et al, 2018]. The action of the respective ANS sub-systems is related to the attentional state of the subject, which is reflected in the cardiac activity and, therefore, in the physiological signals such as the PPG signal. Based on these assumptions, the study of cardiac activity and, therefore, of the correlated physiological signals, represents a great tool for monitoring drowsiness status of a subject as well as pathologies which may indirectly have an impact on the subject's guidance [Rundo et al, 2018, Vinciguerra et al, 2019]. Specifically, we focused on the use of the PPG signal for monitoring the subject's blood pressure and drowsiness level. Several studies have confirmed that a system for monitoring the risk of driving in an automotive environment can be obtained by monitoring the so-called "driver fatigue condition" which in turn is connected to a careful measurement of the level of physiological attention combined with the pressure level [Tomohiko et al, 2015; Rundo et al, 2018; Vicente et al, 2011; Vinciguerra et al, 2019]. The PPG based car driver drowsiness monitoring will be combined with further driving safety assessment systems. We propose one of the delivered use-case: Detection and tracking of salient pedestrians embedded in the driving scenario.

2 The intelligent physio-based car driver drowsiness monitoring system

As introduced, the main usefulness of the PPG signal consists in having a non-invasive car driver data sampling approach for monitoring the drowsiness of the subject. The pulsatile 'AC' component of the PPG signal is formed by a physiological impulse regulated by synchronized pulsing of

the heartbeat. The remaining slowly changing component ('DC') contains information about the respiratory act, the thermoregulation activity and so on. With each contraction the heart exerts an adequate force for the right distension of arterioles and capillaries. If we have a device with a light emitter and detector embedded to the subject's skin, the pressure on the capillaries caused by the heartbeat can be detected at each pressure peak. More in detail, the heart pump activity causes in the subcutaneous capillary a pressure gradient that stretches the small vessel. In this physiological phase, if the arteries will be hit by a certain light source, some of this will be reflected (back-scattered) and then can be acquired by ad-hoc closed detector [Rundo et al, 2018, Conoci et al, 2018]. In this way the back-scattered light information will be transduced into an electrical signal (the final PPG signal) which can be easily processed by the downstream system. Further details in [Rundo et al, 2018, Conoci et al, 2018]. In Fig 1 we report an instance of the PPG signal formation process we have outlined in the previous description.

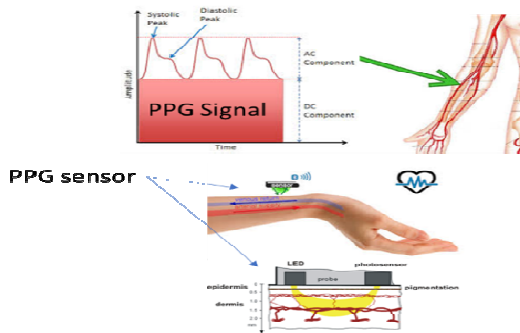


Figure 1. The PPG signal formation process with a detail of the sampling system

The proposed pipeline is equipped with a PPG sensing probe which samples data through a coupled LEDs - Silicon PhotoMultiplier (SiPM) device delivered by STMicroelectronics [Rundo et al, 2018; Conoci et al, 2018; Mazzillo et al, 2018]. The proposed PPG probes comprises an array device, called Silicon Photomultipliers (SiPMs) [Mazzillo et al, 2018], characterized by a total area of $4.0 \times 4.5 \text{ mm}^2$ and 4871 square microcells with $60 \mu\text{m}$ pitch. The device present a geometrical fill factor of 67.4% and are packaged in a surface mount housing (SMD) with about $5.1 \times 5.1 \text{ mm}^2$ total area. We propose a Pixelteq dichroic bandpass filter with a pass-band centered at about 540 nm with a Full Width at Half Maximum (FWHM) of 70 nm and an optical transmission higher than 90–95% in the pass-band range was glued on the SMD package by using a Loctite 352TM adhesive. The SiPM has a maximum detection efficiency of about 30% at 565 nm and a Photo-Detection Efficiency (PDE) of about 27.5% at 540nm (central wavelength in the filter pass-band). As anticipated, the

PPG detector consists of a light emitter with a detector based on technology. The OSRAM LT M673 LEDs combines together a SMD package and InGan technology [5,6]. The used LEDs devices cover an area of $2.3 \times 1.5 \text{ mm}^2$ with a 120° angle view. In addition to a spectral bandwidth of 33 nm, the LEDs have of a lower power emission (mW) in the standard range. We designed a printed circuit board (PCB) that incorporates a user-interface based on NI (*National Instruments*) instrumentation to optimize the use of PPG probe. In order to sample the car driver PPG signal, we placed such PPG sensor probes on the car steering wheel. To proper collect the physiological signal, the driver has to maintain only one hand on top of the embedded PPG sensor probes, to trigger the signal. Ad-hoc pre-processing pipeline has been designed to properly filter and process the collected raw PPG samples. To this end, a SPCx MCU with STA1295 Accordo5 microcontroller hosting artificial intelligence algorithms has been delivered [Mazzillo et al, 2018; Rundo et al, 2019b]. A schematic overview of the designed PPG-based drowsiness monitoring system is reported in Fig. 2.

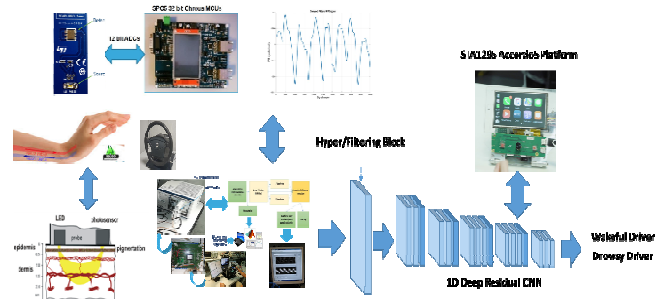


Figure 2. The PPG sampling hardware system

The so collected driver PPG waveforms (raw data) of the car driver will be collected in the STA1295 MCU as per scheme reported in figure 2. Furthermore, considering the real scenario relating to driving on the road, it is plausible to hypothesize the presence of several type of noises due to the movement of the driver's hands or road-driven vibrations. To this end, both in terms of frequency filtering and signal stabilization, the authors have proposed a bio-inspired pipeline that allows to obtain excellent results as widely documented in the work reported in [Trenta et al, 2019a; Rundo et al, 2019b; Rundo et al, 2021]. The PPG frequency range is in the range 1-10 Hz.

To perform an effective filtering between 1-10 Hz, a further bio-inspired algorithm described in [6] has been implemented to perform intelligent stabilization of the PPG signal. This algorithm has been named "Hyper-filtering Filter System" and it was inspired to classical hyper-spectral approach [Trenta et al, 2019a; Rundo et al, 2019b; Rundo et al, 2021]. The hyper-spectral processing usually applied to 2D imaging is able to process visual data leveraging features from the filtering of the image across to the whole electro-

magnetic spectrum. With aims to apply the hyper-spectral theory to 1D signal, the authors discovered the hyper-filtering approach [Trenta *et al*, 2019a; Rundo *et al*, 2019b; Rundo *et al*, 2021]. The information derived from hyper-filtering at different frequency ranges of the source PPG signal was analyzed to try to obtain information characterizing the "frequency spectrum of each signal sample" to be used to assess the driver's attention level (Drowsiness monitoring). Consequently, each layer of Hyper filtering has been divided into 11 sub-bands. Once the number of sub-bands has been established, a deep Reinforcement Learning [Trenta *et al*, 2019a; Rundo *et al*, 2019b; Rundo *et al*, 2021] algorithm described has been applied in order to retrieve the right frequency configuration of each hyper-filtering layers. Finally, for each set of the so-processed hyper-filtered PPG-derived signals, we can compute for each waveform's sample $s(t_k)$ a pattern-signal composed by the intensity-dynamic of that sample in each hyper-filtered signals. We will thus obtain a fairly large dataset of so built pattern-signals. The so collected dataset of hyper-filtered pattern-signals will be classified by ad-hoc designed temporal-residual downstream deep classifier described in the next section.

2.2 The proposed 1D Deep Classifier

In Fig. 2 we have showed an overview of the proposed pipeline scheme including the designed Deep 1D Temporal Dilated Convolutional Neural Network (1D-CNN) suitable to classify the hyper-filtered signal patterns [Rundo *et al*, 2019b]. A temporal convolutional residual network embeds a dilated causal convolution layer capable of acting on the temporal stages of each set of wave sequence [Rundo *et al*, 2021; Rundo *et al*, 2019d] has been implemented. The proposed 1D-CNN is composed of 12 residual blocks with a dilated convolution (3x3 kernel filters) followed by normalization, ReLU activations blocks and spatial dropout. The deep backbone includes a final softmax stage for data classification. For each of the blocks there is a progressive increase in the dilation starting from 2 and increases with a power of 2 till to 16. The output of the 1D-CNN is a binary assessment (0-0.5: Drowsy Driver ; 0.51-1: Wakeful Driver) of the driver's drowsiness level associated to the PPG signal of the monitored car driver. The described Deep Learning framework proved to be effective in assessing the driver's level of drowsiness as shown by the results reported in the following table.

Method	Driver Attention Level Detection	
	Drowsy Driver	Wakeful Driver
Proposed	98.71 %	99.03 %
Shallow Network [Rundo et al, 2019b]	96,50 %	98,40 %
MLP	92,22 %	91,98 %
SVM	90,11 %	88,76 %

Tabella 1: PPG-based Driver Drowsiness Monitoring Performance As showed in Table 1, the implemented system outperformed similar approach based on classical machine learning methods such Support-Vector Machine (SVM), Multi-layer Perceptron (MLP), shallow-neural [Rundo *et al*, 2021; Rundo *et al*, 2019d]. As introduced, the proposed car driver drowsiness monitoring has been combined with an intelligent driving scenario safety assessment based on pedestrians detection and tracking.

3. The Criss-Cross enhanced Mask-R-CNN for intelligent pedestrian tracking system

The following figure shows the proposed combined approach embedding the introduced intelligent PPG-based drowsiness monitoring system with enhanced Mask-R-CNN used for pedestrians segmentation and tracking of the driving scenario.

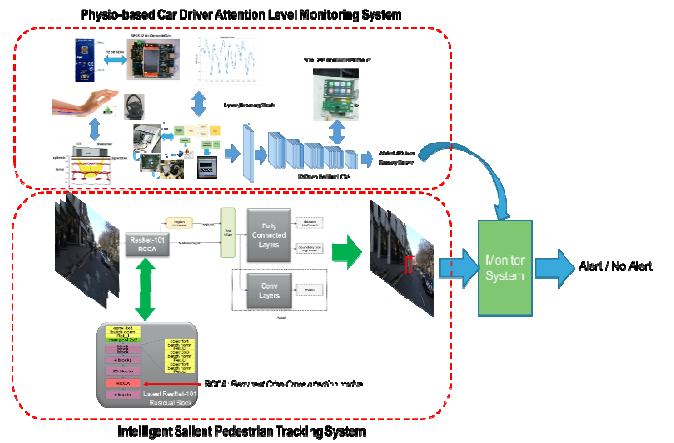


Figure 3: Overall scheme of the proposed pedestrians tracking pipeline

As schematized in Fig. 3, an enhanced Mask-R-CNN architecture [sequence [Rundo *et al*, 2021] embedding Self Attention is proposed. Mask-R-CNN is widely used in the automotive field [pp6]. The target of the implemented enhanced Mask-R-CNN regards the ability to perform a pixel-based segmentation of the input image representing the driving scene frame. Moreover, with this solution we are able to generate the corresponding bounding-box that characterizes the Region of Interest (ROI) on which to perform post-processing. The features generator backbone is based on classical DenseNet-201 [Rundo *et al*, 2021]. This deep classifier embeds a Recurrent Criss-Cross Attention (RCCA) layer [Rundo *et al*, 2021; Rundo *et al*, 2019d]. The attention mechanism based on Criss-Cross algorithm was firstly proposed in scientific literature [Rundo *et al*, 2021; Rundo *et al*, 2019d] showing very promising performance in several tasks including semantic segmentation. Specifically, the proposed Criss-Cross attention module is able to compute an innovative pixel-based contextual processing of the input image-frame.

As introduced, the so enhanced Mask-R-CNN allows us to obtain the bounding-box of the pedestrian which we will need to determine the distance from the driver's car. Quite simply, the height and width of the segmentation bounding box of each segmented pedestrian will be determined. Only bounding-boxes that have at least one of the two dimensions greater than two heuristically fixed thresholds (L_1 and L_2 respectively for length and width) will be considered *salient pedestrians*. Some instances in the next figures.



Figure 4: Some instances of the driving scene frames overlaid with segmented salient pedestrian in different configurations (on foot, by bicycle, etc ..). In red, the predicted bounding boxes segmentation.

As reported in the following, Table 2, the proposed deep system shows very interesting performance in CamVid dataset [Rundo *et al*, 2021].

Method	Pedestrian Tracking System
	<i>mIoU</i>
Proposed	69,70 %
Faster-R-CNN (ResNet-50 backbone)	53,95 %
Classical Fully Convolutional Network (ResNet-101 backbone)	63,96 %

Tabella 1: Experimental Results of the Pedestrian Tracking System

4. Acknowledgment - Funded Research project

The authors thank the physiologists belonging to the Department of Biomedical and Biotechnological Sciences (BIOMETEC) of the University of Catania, who collaborat-

ed in this work in the context of the clinical study Ethical Committee CT1 authorization n.113 / 2018 / PO. This research was funded by the National Funded Program 2014-2020 under grant agreement n. 1733, (ADAS + Project). The reported information is covered by the following registered patents: IT Patent Nr. 102017000120714, 24 October 2017. IT Patent Nr. 102019000005868, 16 April 2018; IT Patent Nr. 102019000000133, 07 January 2019.

References

- [1] [Tomokiko *et al*, 2015] Tomohiko Igasaki ; Kazuki Nagasawa ; Nobuki Murayama ; Zhencheng Hu. Drowsiness estimation under driving environment by heart rate variability and/or breathing rate variability with logistic regression analysis. In IEEE Proceedings of the International Conference on Biomedical Engineering and Informatics (BMEI), 2015;
- [2] [Vicente *et al*, 2011] José Vicente ; Pablo Laguna ; Ariadna Bartra ; Raquel Bailón, Detection of driver's drowsiness by means of HRV analysis, in IEEE Proceedings of Computing in Cardiology, 2011;
- [3] [Rundo *et al*, 2018] Rundo, F.; Conoci, S.; Ortis, A.; Battiato, S. An Advanced Bio-Inspired PhotoPlethysmoGraphy (PPG) and ECG Pattern Recognition System for Medical Assessment. Sensors 2018, 18, 405;
- [4] [Vinciguerra *et al*, 2019] Vinciguerra, V., Ambra, E., Maddiona, L., Romeo, M., Mazzillo, M., Rundo, F., Fallica, G., di Pompeo, F., Chiarelli, A.M., Zappasodi, F., Merla, A., Busacca, A., Guarino, S., Parisi, A., Pernice, R., PPG/ECG multisite combo system based on SiPM technology, Lecture Notes in Electrical Engineering, 2019, Vol 539, pag. 105-109;
- [5] [Mazzillo *et al*, 2018] Mazzillo, M., Maddiona, L., Rundo, F., Sciuto, A., Libertino, S., Lombardo, S., Fallica, G., Characterization of sigms with nir long-pass interferential and plastic filters, IEEE Photonics Journal, 2018, Vol. 10, Issue 3;
- [6] [Conoci *et al*, 2018] Sabrina Conoci , Francesco Rundo , Giorgio Fallica , Davide Lena , Irene Buraioli , Danilo Demarchi, Live Demonstration of Portable Systems based on Silicon Sensors for the monitoring of Physiological Parameters of Driver Drowsiness and Pulse Wave Velocity, in IEEE Proceedings of Biomedical Circuits and Systems Conference (BioCAS), 2018;
- [7] [Trenta *et al*, 2019a] F. Trenta, S. Conoci, F. Rundo and S. Battiato, "Advanced Motion-Tracking System with Multi-Layers Deep Learning Framework for Innovative Car-Driver Drowsiness Monitoring," 2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019), Lille, France, 2019, pp. 1-5, doi: 10.1109/FG.2019.8756566.
- [8] [Rundo *et al*, 2019b] Rundo, F.; Spampinato, C.; Conoci, S. Ad-Hoc Shallow Neural Network to Learn Hyper Filtered PhotoPlethysmoGraphic (PPG) Signal for Efficient Car-Driver Drowsiness Monitoring. *Electronics* **2019**, 8, 890.
- [9] [Rundo *et al*, 2021] Rundo F, Conoci S, Spampinato C, Leotta R, Trenta F and Battiato S (2021) Deep Neuro-Vision Embedded Architecture for Safety Assessment in Perceptive Advanced Driver Assistance Systems: The Pedestrian Tracking System Use-Case. *Front. Neuroinform.* 15:667008. doi: 10.3389/fninf.2021.667008
- [10] [Rundo *et al*, 2019c] Rundo, F.; Rinella, S.; Massimino, S.; Coco, M.; Fallica, G.; Parenti, R.; Conoci, S.; Perciavalle, V. An Innovative Deep Learning Algorithm for Drowsiness Detection from EEG Signal. *Computation* 2019, 7, 13.
- [11] [Rundo *et al*, 2019d] Rundo, F., Petralia, S., Fallica, G., Conoci, S., A nonlinear pattern recognition pipeline for PPG/ECG medical assessments, Lecture Notes in Electrical Engineering, 2019, Vol 539, pag. 473-480;