A survey of biometric techniques for intelligent vehicle systems

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ABSTRACT

The current research in the avenues of fatigue, distraction, stress, and drowsiness use various bio-signals in their assessment of identifying the driver's well-being such as ECG (electrocardiogram), EEG (electroencephalography) and EMG (electromyography). These methods have been studied to prevent vehicular accidents that could occur during a duration of driving. The early detection mechanisms could prevent harm to the driver and others that share the same road. The number of accidents that happen on the road as explained by other studies are at an all-time high, and the need for a reduction of these situations is required. Hence, this work explores and analyzes various biometrics-based techniques for intelligent vehicle systems.

KEYWORDS

ECG, EEG, EMG, Biometrics, Bio-signal, Intelligent vehicle

1 INTRODUCTION

The state of automobile technology is evolving rapidly; there are many security-related concerns in the field where devices that compliment these systems are failing to identify the driver or protect the driver from being the victim of theft through the use of falsified fingerprints. Currently, there is one considered to be the best approach to identifying the driver which is the non-contact and non-intrusive method: the method would abstract away the tools that collect information about the driver. The goal of such an action is to be less intrusive to the individual maneuvering the vehicle as to mimic natural and real driving which otherwise would not be the case with intrusive methods. There needs to be also many considerations taken when it comes to assessing the driver i.e. fatigue, heart rate, stress etc. which are discussed in the sections, and new technology including algorithms that are used to improve the process.

2 BIO-INFORMATION BASED RECOGNITION TECHNIQUES

Currently, the recognition technology requires many parameters to be accurate in its assessment of the driver's state, be fatigue or stress—having a few parameters creates a less accurate portrayal of the driver's well-being.

2.1 ECG-based Techniques

ECG (electrocardiogram), is useful in many ways, and these technological advancements highlight its usefulness in different aspects of this research area. There are many studies that have used ECG recognition technology to their advantage: Singh et al. [1] developed a basic framework for a simple real-time heart-rate monitoring system using non-contact capacitive ECG where the system uses an electrode structure which can be integrated into a steering wheel. After testing, they found that the system gives good quality ECG signal and good accuracy of HR estimates. Fratini et al. [2] found that there was a lot of literature regarding the individual identification via ECG analysis: however, there was no agreement on an appropriate method. They proposed a unifying framework to appreciate previous student efforts and to guide future research. The technology can also be improved: Silva et al. [3]'s goal was to improve the current signal acquisition methods for ECG. They made a circuit using virtual ground to enhance usability: the results of their experiment validate the potential for their paper's method. There also exists a cost-effective method for the online acquisition and processing of ECG signals concerning person authentication. Belgacem et al. [4] found that the result of this research is promising for individual authentication.

Choi et al. [5] saw existing security issues and driver-specific issues using a multi-dimensional feature extraction with ECG signal method, such as a low identification accuracy, and the learning time is delayed because of a complex network structure, High Time Complexity (HTC). However, this does not address remnant issues or accuracy concerns since the resolution was adjusted without the consideration of ECG's P, QRS Complexes, and T wave features in the analysis of time-frequency regarding multidimensional features. They propose a way to address this issue where a driver identification system using a 2D spectrogram is considered: the system identifies the optimally adjusted section using a spectrogram. Rettore et al. [6] notice that current methods for authenticating users allows an attacking driver to use them, to remedy this issue they developed a virtual sensor which determines the driver's identity. The resulting precision of their new device after using embedded sensor data is above 98% in precision. Choi et al. [7] observed that ECG signal acquired in environments where driver's motion artifact is included need to be normalized because of how intense the noise is which is called distortion. They propose an adaptive threshold filter-based driver identification system to fix the distortion of ECG's morphological features such as P, QRS Complexes and T waves as well as the driver's motion artifact that impacts performance in the environment. They found that after applying the algorithm: there was impactful improvement in the average and identification performance compared to the original results that were not normalized.

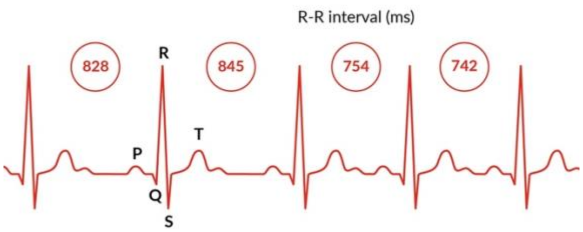

Figure 1: Heart Rate Variability [8]

[9,10] found that using ECG signals is beneficial at detecting driver stress levels in terms of Heart Rate Variability (HRV) as shown in Figure 1; ECG is considered effective, reliable, and nonintrusive. It is difficult to consider ECG as nonintrusive since it requires twelve to sixteen leads to be attached to the participant; but the creative methods mentioned before in [11]'s implementation of ECG into the steering wheel does decrease the number of leads required to be placed on the participant. Moreover, a different study [12] was able to use only one lead ECG setup without gel and a recurring Ag/AgC1 electrodes which resulted in a 94.3% recognition rate by using only the participant's fingers. For the driver fatigue system, [13, 14] agree on the complexity of fatigue. Wang et al. [13] found that drivers fall under serious fatigue when the landscape of the environment is a monotonous region while Shiwu et al. [14] found recognition accuracy of fatigue is increased if it is in terms of four states i.e. alert, mild fatigue, deep fatigue, and drowsiness.

2.2 EEG-based Techniques

EEG (Electroencephalography) signals could become a useful metric in this assessment where Kar et al. [16] discover that higher order entropy measures of these signals in the wavelet are a much more precise indicator of fatigue compared to past proposed methods. In that same vein, Jap et al. [17] used four EEG activities delta, theta, alpha and beta as pictured in Figure 2; additionally, fifty-two subjects were used in their particular method of detecting fatigue where all four of these algorithms showed an increase in the ratio of slow wave to fast waves in EEG activities. Yang et al. [18] proposed a driver recognition model that is based on Bayesian network, information fusion, and physiological features. Their results show that there is an importance of having more features, more features help infer driver's fatigue accurately and reliably and that ECG and EEG are very important features for fatigue recognition.

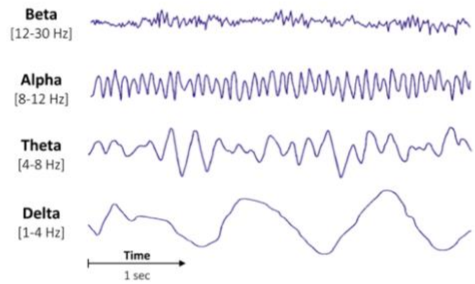

Figure 2: Band power of EEG signals. [15]

2.3 EMG-based Techniques

Electromyography signals are useful for recording the electrical activity in a muscle and has an ability to distinguish between skeletal muscle disorders from muscle wasting and weakness that surface from the nervous system. It can also detect muscle abnormalities; EMG is a skilled interpreter of muscle activity appearance, and the sound of the activity can be transmitted through a loudspeaker. Consequently, EMG can be inconvenient as it requires attaching sensors to an arm or a shoulder where there is more muscle mass, many issues can arise from the attachment and detachment of these sensors in daily life. EMG's use of wet type sensors has the benefit of measuring these signals noiselessly, but at an additional cost for disposable electrodes preventing the spread of EMG from permeating the daily lives of average people. The EMG signals also have an extensive list of properties: nonstationary, nonlinear, complexity, and large variation which can lead to difficulty in the analyzation of these signals.

Atzori et al. [19] observed that the current literature is promising but the results are not applicable to real-life scenarios: the advances in rehabilitation for robotics still has an issue about the usage of non-invasive technique for myoelectric prosthetics that give an unnatural limited control capability and must be learned through long training sessions. Their goals are to narrow or close the gap by creating a database: the database would be targeted for studies concerning relationship between surface EMG, and hand kinematics and hand surfaces. It would aide in the development of non-invasive naturally controlled robotic hand prostheses. However, Zhai et al. [20] stated that they have obtained a higher overall accuracy than the best results using the same dataset but with a combination of four different sets of features compared to Atzori et al. [19]. They showed that EMG spectrograms are an effective feature for discriminating multiple classes of hand gestures when it is forced to be undergone by principal component analysis for dimensionality reduction. The authors consider Surface Electromyographic (sEMG) which is easily usable and non-invasive on the surface, but has some sensitivity to factors such as electrode placement and recording environment. EMG's success is dependent on the experimental design, the number of electrodes, the type of electrodes, and the number of movements. Hand movements are particularly dynamic processes, a more natural movement is needed to produce real life scenarios and systems that can provide continuous recognition of those desired movements. Their suggested method uses spectrograms then principal component analysis (PCA): they hypothesize that projection of EMG spectrogram onto subsets of principle components could improve information representation and reduce computational load in sEMG. Their results demonstrated an improved classification accuracy by an estimated 10% over pure time domain features for 50 different hand movements with the inclusion of small finger movements and the different levels of forced exertion.

3 CONCLUSION

There are many methods for the analyzation of the driver's state: the state of the driver in terms of stress, fatigue, heart rate, skin conductance and other parameters. All these factors can create an accurate picture of the driver's well-being. The current technological approaches consider the use of algorithms and devices to aid in gaining more information about the driver. The research discussed in this paper shows promising results from different areas where inefficiency and issues with driver identification is replaced with more efficient, non-intrusive, and better performing algorithms or devices. The use of putting ECG sensors inside the seat belt and the seat or only using a finger to identify the driver are interesting methods for attaining driver information.

Ref.	Type	Bio-signal	Parameters	Method
[9, 10]	Stress	ECG, HRV, Physiological Sensors	Physical Activity	Machine Learning
[5]	Stress	ECG, HRV, Physiological Sensors	Physical Activity	Modeling
[13, 14, 18]	Fatigue	EEG, ECG, HRV	Multiple Physiological Features, R-R Intervals	Arrhythmia Recognition, Neural Networks, Information Fusion and Dynamic Bayesian Network
[19, 20]	-	EMG Signals	Wrist, Muscle	Wet Electrodes, Dry Electrodes

Table 1: Different approaches for assessing a driver's state.

This paper looked at how research in this field is using innovative methods to bridge the gap between evolving automobile technology and devices that exist with it and, it considered the usefulness of ECG, EEG, EMG, and HRV in support of garnering precise results. Table 1 shows the current approaches, methods, and parameters used to assess different types of issues a driver can face while on the road i.e. stress, fatigue, distraction, drowsiness, and emotion.

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