A Case-Based Classification for Drivers' Alcohol Detection Using Physiological Signals

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Abstract. This paper presents a case-based classification system for alcohol detection using physiological parameters. Here, four physiological parameters e.g. Heart Rate Variability (HRV), Respiration Rate (RR), Finger Temperature (FT), and Skin Conductance (SC) are used in a Case-based reasoning (CBR) system to detect alcoholic state. In this study, the participants are classified into two groups as *drunk* or *sober*. The experimental work shows that using the CBR classification approach the obtained accuracy for individual physiological parameters e.g., HRV is 85%, RR is 81%, FT is 95% and SC is 86%. On the other hand, the achieved accuracy is 88% while combining the four parameters i.e., HRV, RR, FT and SC using the CBR system. So, the evaluation illustrates that the CBR system based on physiological sensor signal can classify alcohol state accurately when a person is under influence of at least 0.2 g/l of alcohol.

Keywords: Physiological signals · Alcoholic detection · Case-based reasoning

1 Introduction

In the year 2012 in Sweden, 24% of car drivers were killed in crashes, under the influence of alcohol. Again 19% of road fatalities were due to intoxicated driver, rider, pedestrian, or cyclist. By the year 2020, Swedish government has a target that 99.9% of traffic should consist of drivers under the legal Blood Alcohol Content (BAC) limit of 0.2 g/l. [1]. Therefore, detection of alcoholic state of driver has been of great interest for car companies for many years.

A real time monitoring and detection of alcohol has been implemented using microwave sensor technology by Wendling et al. as described in [2]. Authors in [3] presented breathalyzer which is a device for estimating blood alcohol content (BAC) from breath sample. Also, Kiyomi et al. developed a new breath-suction type alcohol detector which does not require a long and hard blowing to the detector through a mouthpiece [4]. Another highly efficient system has been proposed with the aim at early detection and warning of dangerous vehicle maneuvers typically related to drunk driving [5]. Tunable Diode Laser Absorption Spectroscopy (TDLAS) based method for remote detection of alcohol concentration in vehicle has been suggested in [6].

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Kumar et al. proposed a real time non-intrusive drunk driver detection method using ECG sensors attaching under the driver seat [7]. A major limitation of the ECG sensor on the driver's seatback is very sensitive to impedance changes and disturbance resulted from environmentalnoise. K. Swathi et al. have compared and showed changes in the ECG features: heart rate, P wave, PR interval, QRS duration, QTC interval, ST segment, T wave, TP interval and frontal axis between non-alcoholics and alcoholics [8]. Kumar et al. have proposed a real time non-intrusive drunk driver detection method using ECG sensors attaching under the driver seat [9]. According to our knowledge, the research on drivers' alcoholic state classification based on physiological signals is very limited. However, future vehicles with embedded sensors in vehicles will get benefit from such systems.

In this paper, the proposed approach has considered 4 physiological parameters i.e., Heart Rate Variability (HRV), Respiration Rate (RR), Finger Temperature (FT), and Skin Conductance (SC). The Case-Based Reasoning (CBR) approach has been applied successfully in classification of physiological sensor signals [10–13].In addition, in some similar domains CBR has been achieved higher accuracy in classification compare to the other classification methods, such as Neural Network (NN) and Support Vector Machine (SVM) [14]. Here, the CBR approach is used as an artificial intelligence method to classify the alcoholic state of the driver. A number of features are extracted and selected to formulate a new query case, which is further entered into a case-library. The new case is matched with all previous cases and calculated a similarity value for each previous case. Based on the similarity value, most similar case together with its' class (i.e *drunk* or *sober*) is used for the final classification. An experiment work has been conducted, where the classification accuracy is observed considering both each individual parameters and as well as combination of them.

The rest of the paper is organized as follows: Sect. 2 describes materials and methods, and Sect. 3 presents results and evaluation. Finally, Sect. 4 summarizes the work.

2 Materials and Methods

2.1 Data Collection

The data have been collected from 12healthyparticipants (10 male, 12 female), age between 22 and 32 years. A total of five different sessions consisting 12 experiments were conducted where 3 sessions (6 tests) were taken place in normal lab environment in sitting position, one session (3 tests) was carried out using driving simulator, Häslö, Västerås[1] and another session (3 tests) was conducted in Mälardalen University robotics lab using Volvo construction equipment simulator called Volvo articulated hauler machine. Each participant has signed a letter of consent in order to participate in the study. The participants were informed about the study and the data acquisition sessions. In each session, two measurements were taken, without drinking alcohol i.e. the person is sober and when the test person is intoxicated with 37.5% of alcohol i.e.

[1] http://www.htop.se/start.asp?lang=1.

drunk. Each test subject was in a seated position and the physiological sensors data were collected with cStress[2] system attached to the subject's body. In order to detect how physiological parameters changes with blood alcohol concentration the alcohol level is acquired in every two minutes using Sesame alcohol measurement device[3] when the person has been intoxicated. Here, using the cStress system, in each session, five physiological parameters i.e., RR, IBI, FT, and SC were collected for each test person.

2.2 Approach

The overview of the proposed classification system is presented as a step diagram in Fig. 1. The 4 physiological signals that are obtained from each participant during data collection phase are inputted into the CBR system. Duration of recording for each participant is around 10 min. In order to get a homogeneous dataset, during the pre-processing step, the first and last one minute recording from each data set have been discarded, then 8 min recording have been considered for further processing. These 8 min signals are then segmented into 2 min data for the feature extraction. Before feature extraction from these segmented signals, noise and artifacts are handled for each individual signal. A k-nearest neighbor (K-NN) based interpolation algorithm has been applied to handle artifacts in IBI signals [15]; and Infinite impulse response (IIR) filter and smoothing running average method available in cStress system have been used to handle artifacts in FT, SC and RR signals. Thereafter, features are extracted from the segmented signals for all input signals. Then, using the extracted features, case formulation is performed and a case library is built for the CBR classification.

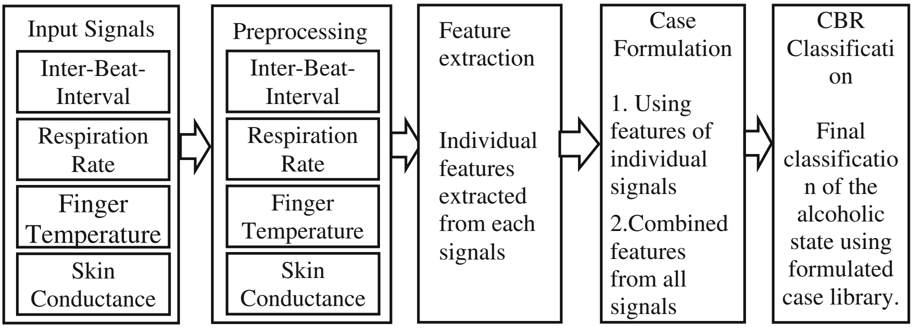

Fig. 1. Step diagram of the proposed CBR classification scheme.

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2 http://stressmedicin.se/neuro-psykofysilogiska-matsystem/cstress-matsystem/.

3 Hök instruments, sesame. [Online]. Available: http://hokinstrument.se/technology/product/.

2.2.1 Feature Extraction

Feature extraction is one of the important tasks to solve any classification problem using a classifier. A number of features for each parameter have been extracted. Here, both the time domain and frequency domain features of HRV have been extracted from the IBI signals. In time domain, statistical methods are applied on the Inter-beat-interval (IBI) signals to extract standard deviation of RR intervals (SDNN), root mean square of the all successive RR interval difference (RMSSD), number of pairs of adjacent NN intervals differing by more than 50 ms (NN50) features, percentage of NN50 count (pNN50), and standard deviation of differences between adjacent NN intervals (SDSD). To extract frequency domain features of HRV, power spectral density (PSD) has been estimated from the IBI Signal. Low frequency power (LF) (0.04–0.15 Hz), high frequency power (HF) (0.15–0.4 Hz), total power, LF peak (0.04–0.15 Hz), HF peak (0.15–0.4 Hz), and total peak are extracted from the PSD of IBI signal. Moreover, power at ultra-low frequency range (ULF) ($\leq$ 0.003 Hz) power, very low frequency range (VLF) (0.003–0.04 Hz), normalized LF power (LF/(Total power − VLF)*100), and normalized HF power (HF/(Total power − VLF)*100) are estimated from the PSD. From the RR signal, arithmetic mean and standard deviation are calculated as features in time domain. Another feature called dominant respiration frequency (DRF) is estimated from the PSD of RR signal. DRF is the maximum energy frequency which lies between the frequency range 0.1 Hz and 1.5 Hz [16]. From FT and SC signals a derivative of slope is used to extract the important features [17]. In addition, mean, standard deviation, max, and temperatures are calculated from FT and SC as features. Different weight values in the range between 1 and 10 have been used to achieve optimal accuracy. The extracted and selected features from the 4 physiological signals and their optimal weight values for the CBR classification are presented in Table 2.

2.2.2 Case Formulation

In developing a CBR system, the first task is the case formulation, which represents the instance of things or a part of a situation that is experienced. A case library or case base has been constructed from the formulated cases where each case comprises unique features extracted from the 4 physiological sensor signals to describe a problem. In this study, here, each case is labeled as '*Sober*' or '*Drunk*' based on the recording events. Hence, CBR classification classifies each subjects as *Sober* or *Drunk* state. Moreover, during the case formulation two approaches were taken into consideration; 1st create a case base using the features extracted from each individual physiological parameters only i.e., HRV, RR, SC and FT only; 2nd, a case is formulated based on combination of features extracted from the individual physiological parameters.

2.2.3 CBR Classification

In CBR, the term 'case' represents an experience that is achieved from a previously solved problem; the term 'based' means in CBR cases are the source for reasoning; and the term 'reasoning' means the approach of problem solving i.e., the intension of CBR is to solve a problem by drawing conclusion using previously solved cases [18]. Aamodt and Plaza [19] have described the CBR cycle, which contains four steps that are *Retrieve, Reuse, Revise and Retain*. Here, in the proposed CBR classification system the first 3 phases are implemented.

In this study, previous solved cases are retrieved for a current query case using the similarity function presented in Eq. 1.

$$Similarity(T,S) = \sum_{i=1}^{n} W_i \times f(T_i, S_i) \tag{1}$$

Where T is the target or new case, S is retrieved cases stored in the case library, and f is the similarity function, and $W_i = \frac{lw}{\sum_{i=0}^{n} lw_i}$ and lw_i is a local weight for each feature. The weight for each features are gathered by the help of expert of the domain and presented in Table 1 (see Sect. 2.2.1 (Feature Extraction)). Euclidean distance function is used to calculate the similarity f of each feature by normalizing the absolute difference between two features for the current and retrieved cases and dividing that by the difference of the maximum and minimum distance. The similarity then gets by subtracts the result from 1, represented in Eq. 2. The similarity value '1' means 100% similar between two cases and the value '0' means dissimilar between the cases.

$$(T_i, S_i) = 1 - \frac{abs(T_i, S_i)}{max(T_i, S_i) - \min(T_i, S_i)} \tag{2}$$

For the classification of combined features, additional weights are considered for each type of signals based on the classification accuracy of each signals. Hence, Eq. 1 is updated by multiplying the weights value for each signal, which is shown in Eq. 3.

$$Similarity(T,S) = \sum_{i=1}^{n} W_i \times f(T_i, S_i) \times S_w \tag{3}$$

Here, S_w is the weight value for each signal based on their individual classification.

3 Results and Evaluation

The proposed approach is evaluated in two fold. First, an evaluation is performed for the cases considering features obtained from individual signals. Secondly, building cases by combining features from all four signals. In the combined approach, additional weight values are multiplied with the similarity function. The weight values are considered based on the evaluation result obtained in the first phase i.e., considering individual signals. For CBR classification, a number of different weight values ranges from 0 to 10 have been assigned to achieve maximum accuracy for each parameter and also for combined features.

Table 1 shows the accuracy for K1 considering the top most similar retrieved case; and for K2 considering the top 2 most similar cases are retrieved, where one of them matches with the target case. It can be seen form Table 1 that the highest accuracy considering K1 for HRV, FT, SC and RR is 67%, 89%, 67% and 59% and considering

K2 is 85%, 95%, 86% and 81% respectively. However, the accuracy for combination of all four features for K1 and K2 are 83% and 88% respectively.

Table 2 shows the summary of the evaluation. In total, 103 are cases labeled with either *Sober* or *Drunk* in combined. However, for individual HRV has 148, RR has 164, FT and SC have 119 cases for consideration. It can be seen from Table 3 that the sensitivity of the system is 81% for HRV, 78% for RR, 97% for FT, and 89% for SC. The specificity is 80% for HRV, 76% for RR, 82% for FT, and 81% for SC. Thus, the overall accuracy for HRV is 85%, RR is 81%, FT is 95% and SC is 86% respectively. Furthermore, for the cases while combining all the four parameters the obtained sensitivity is 83%, specificity is 92% and accuracy is 88%.

Table 1. A list of accuracy for individual and combined feature based classification for K1 and K2

	HRV		**FT**		**SC**		**RR**		**Combination (HRV+FT+SC+RR)**	
	K1	**K2**	**K1**	**K2**	**K1**	**K2**	**0.56**	**0.81**	**K1**	**K2**
Accuracy1	0.62	0.85	0.88	0.93	0.63	0.83	0.57	0.79	0.74	0.85
Accuracy2	0.60	0.84	0.89	0.94	0.67	0.86	0.57	0.79	0.74	0.84
Accuracy3	0.63	0.79	0.88	0.95	0.65	0.86	0.58	0.8	0.73	0.84
Accuracy4	0.59	0.79	0.88	0.95	0.63	0.86	0.58	0.81	0.74	0.83
Accuracy5	0.66	0.84	0.89	0.95	0.65	0.86	0.59	0.81	0.67	0.83
Accuracy6	0.65	0.84	0.88	0.94	0.67	0.85	0.58	0.81	0.65	0.83
Accuracy7	0.67	0.85			0.65	0.86	0.57	0.8	0.73	0.84
Accuracy8	0.63	0.85			0.65	0.87	0.55	0.74	0.75	0.85
Accuracy9	0.63	0.85			0.65	0.86	0.57	0.71	0.77	0.86
Accuracy10	0.63	0.82			0.64	0.83			0.80	0.85
Accuracy11									0.80	0.88
Accuracy12									0.80	0.87
Accuracy13									0.72	0.85
Accuracy14									0.79	0.87
Accuracy15									0.82	0.87
Accuracy16									0.83	0.88
Accuracy17									0.81	0.87
Accuracy18									0.83	0.87

Table 2. Classification of individual and combined features for K2

Feature	HRV	RR	FT	SC	Combined
Total case	148	164	119	119	103
P (Drunk Cases)	74	82	62	62	54
N (Sober Cases)	74	82	57	57	49
TP	60	64	60	55	45
FP	15	20	10	11	4
TN	59	62	47	46	45
FN	14	18	2	7	9
Sensitivity TP/(TP + FN)	0.81	0.78	0.97	0.89	0.83
Specificity TN/(FP + TN)	0.80	0.76	0.82	0.81	0.92
Accuracy (TP + TN)/(P + N)	0.85	0.81	0.95	0.86	0.88

4 Discussion and Summary

In this paper, a CBR classification system for driver's alcoholic state detection based on multiple physiological parameters (HRV, RR, FT and SC) and CBR has been proposed. Both the individual and combined signals have been classified using the CBR system and presented in Table 1. Here, FT has the highest sensitivity, Specificity and overall accuracy while RR has the lowest accuracy. Though FT has highest accuracy for individual signal classification but it could be biased by external factors. Therefore, combined classification has been conducted to achieve a more reliable result. It has been observed while combining the 4 physiological parameters, an acceptable accuracy has been achieved considering the sensitivity, Specificity and overall accuracy. Thus, the proposed approach for driver's alcoholic state classification shows one of the alternative of the Breathalyzer and it has significant potential for advancing many real time applications such as driver monitoring.

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