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Mental State Monitoring System for the Professional Drivers Based on Heart Rate Variability Analysis and Case-based Reasoning

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Abstract—**The consequences of tiredness, drowsiness, stress and lack of concentration caused by a variety of different factors such as illness, sleep depletion, drugs and alcohol is a serious problem in traffic and when operating industrial equipment. A system that recognizes the state of the driver and e.g. suggests breaks when stress level is too high or driver is too tired would enable large savings and reduces accident. So, the aim of the project is to develop an intelligent system that can monitor drivers' stress depending on psychological and behavioral conditions/status using Heart Rate Variability (HRV). Here, we have proposed a solution using Case-Based Reasoning (CBR) to diagnose individual driver's level of stress. The system also considers feedback from the driver's on how well the test was performed. The validation of the approach is based on close collaboration with experts and measurements from 18 drivers from Volvo Construction Equipment (Volvo CE) are used as reference.**

I. Introduction

LACK of concentration due to illness, drugs, sleepiness, drowsiness, fatigue and stress is the most common risk factors for vehicle crash-related accidents. According to the European commission's estimation, car accident related cost in Europe is around 160 billion Euros on which 60-80% can be estimated due to the psychophysical condition of the drivers [1]. Study shows that around 10-20% of all accidents are caused by driver's lack of attention [2]. Stress is one of the factors that causes inattention and could be caused by several features including job, family-related matters, workload and disease. Long time driving, traffic or driving in a bad weather could also cause stress while driving a vehicle. Professional/commercial drivers use their vehicles long hours every day in different situations: at night, daylight, or in dusk or fog. So for heavy commercial vehicle drivers there is a risk for inattention and the heavy workload causes stress and fatigue and as a consequence causes performance degradation. Thus, stress can cause problems in judging distances, lack of concentration, fatigue, restlessness, tiredness while driving a vehicle. Therefore, it is important to monitor drivers' signs of stress while driving which could save many lives and costs.

Several physiological sensor signals such as, Electrocardiogram i.e. ECG (heart rate variability), Elektro-okulogram i.e. EOG (percentage of eyelid closure, tracking of gaze), Electroencephalogram i.e. EEG (brain activity), Pulse Oximeter (Oxygen saturation measurements) can provide psychological and behavioral state of a driver. However, identification of driver's state and generating alarm due to stress is difficult while driving and is a challenging issue. So, it would be valuable both for passenger cars and heavy commercial and industrial vehicles to develop a system that can diagnose this risk factor automatically while driving. Moreover, it will be helpful if the system can alert the driver in a suitable way and if necessary, generate audible alarm or activate light when the driver is inattentive. In a serious situation where the driver seems overwhelmed by stress, it can deactivate some controls and activate some predefined tasks or components to further support in the control of the vehicle or to alert a nearby motor station or police station.

This paper has proposed an intelligent stress monitoring system to identify driver's state. The system will support the professional drivers to reduce risk of accidents while driving/operating a vehicle. The proposed system applied artificial intelligence (AI) and signal processing techniques. Sensor signal processing methods for example, Fast Fourier Transformation (FFT) is used to extract features from the ECG signal. AI method i.e., CBR [4] is applied for accurate diagnosis and classification.

The paper is organized as follows; related work is outlined in section II. Section III gives an overview of our system being proposed together with relevant background knowledge. Then in section IV we describe the study design. Section V explains the preprocessing of the ECG signal and feature extraction process to formulate cases. Section VI presents matching functions for retrieving and ranking similar cases followed by an evaluation in section VII. Finally, the paper is concluded by section 8 with summary and discussions.

II. Related Work

In recent years, the intelligent monitoring system based on physiological sensor signals for drivers has emerged and become a popular topic among the researchers. Driver's concentration monitoring is one of the important issues for improved road safety that comes in literature in different ways. The authors in this paper [5] present a driver condition recognition strategy based on HRV parameter. Here, feature selection is performed based on searching and selection. Searching is performed adopting the best individual N (BIN) and selection is done by kernel-based class seperability (KBCS). The k-nearest neighbour algorithm is used for the classification. In 2011, Lin et al. [6] have developed a driver's monitoring system using a wearable photoplethysmography (PPG) on a smartphone. It detects only one physiological parameter i.e., heart rate (HR) and warns the driver in abnormal situations. Fördős et al. in [7] have implemented a sensor net to improve the traffic safety by identifying tired, indisposed, or bad state-of-minded drivers. The research work has been done at the Budapest University of Technology and Economics. Drowsiness or tiredness diagnosis systems based on vision-based or physiological techniques is discussed in [8]. The vision -based approach is depended on the eye movement to determine level of tiredness. Image processing techniques are also applied in determining drowsiness or inattention [9]. Blinding duration and its frequency are measured using Fuzzy logic to determine level of inattention. Driver's mouth state is monitored in [10] where the system generates alert while the driver is dozing or talking with others. Rigas et al. [11] proposed a car driver's stress determination system using Bayesian Network. Healey et al. detect driver's stress level using real time electrocardiogram, electromyogram, respiration and skin conductance sensors data [12]. In our previous work [13] [14][30], a stress diagnosing system using CBR has been designed based only on the variation of the finger temperature measurements. In the earlier research [13] [15], we have further demonstrated systems for classifying and diagnosing stress levels exploiting the psychophysiological sensor signals and other features. These systems are developed on CBR as well as on fuzzy sets theory. Also our system discussed in [16] has been tested in a small pilot study[12] through a marine simulator with the aim of safety navigation. The objective of this study is to detect any differences in individual task loads and stress levels on mariners using radar and nautical chart displays in north-up and head-up modes. An experienced clinician and three trainee clinicians are involved within this study. The evaluation shows a promising result for the mariner in diagnosing stress while they are driving in a marine simulator. Moreover, some of the recent medical CBR systems are studied (based on literature review) along with a survey (e-mail questionnaire to the corresponding authors) between the year 2004 and 2009 in [29].

In this paper, we have proposed a monitoring system in particular for the professional drivers using HRV. The initial work is outlined in a workshop paper [3]. However, this current paper also includes the study design to show how the data is collected and an evaluation with the clinical expert to investigate the system's performance using HRV.

III. Background and System Overview

When our brain appraises stress, the sympathetic nervous system (SNS) activates and releases stress significant hormones. However, during relaxation, the parasympathetic nervous system (PSNS) performs the reverse action and returns the body to it's normal state. HRV [17] reflects the activities of autonomous nervous system (ANS) and is a well-known parameter to analyze balance between the SNS and PSNS activities. As a result, analysis of HRV becomes popular to diagnose stress-related disorders [18, 19, 20, 21, 22, 23].

It represents the variations in beat-to-beat alteration in the heart rate. Each heartbeat initiated with the firing of the Sinoatrial (SA) node i.e., the dominant peacemaker of the heart. When a person is stressed the SNS increases the SA firing rate and thereby reduces the inter-beat interval [24].

The trace of each heartbeat consists of the three complexes i.e. P, R, and T. The ECG signal reflects the electrical activity in the heart during the ventricular contraction using the QRS complex. The time period between consecutive beats (or RR intervals) can be detected from the QRS complex and it helps to determine the measurement of the HRV analysis. Each R wave appears after a certain amount of time and the time difference between two R waves is the rate of the RR interval or inter-beat interval (IBI). Intervals between normal (sinus) beats are usually called NN intervals.

The proposed system supports in quantifying stress levels using HRV measurements. An overview of the case-based classification system is shown in Fig. 1. It works in several steps. In the first step, during the calibration phase, the system takes the ECG signal. Then, from the signal, it identifies essential features and formulates a new problem case with the extracted features. The new problem case is then fed into the CBR cycle. The CBR cycle commonly works in 4 steps: Retrieve, Reuse, Revise and Retain. The retrieval phase is one of the major phases in a CBR cycle where the matching between features of two cases plays a vital role. In CBR, the new problem case is matched against all the cases in the case library to retrieve the most similar cases. The k-Nearest Neighbour (kNN) algorithm is applied for the retrieval of similar cases. The new problem case is matched using fuzzy similarity matching algorithm [13]. The most similar cases are then displayed in a sorted list depending on their similarity values.

IV. Study Design

In this paper, a wheel loader was chosen as the object of the study. Typical of these working machines is bucket loading of granular material (for instance gravel) on an adjacent dump truck (or other load receiver, mobile or stationary) within a time frame of 25-35 seconds, depending on working place setup and how aggressively the operator uses the machine. It takes a certain amount of training to be able to use a wheel loader efficiently. Even for professionals, operating a working machine for several hours is certainly exhaustive, as it involves both physical and mental workload. Even though the operator sits still and the controls do not demand a large amount of power he/she has to keep balance and be prepared. Mentally the operator has to maintain attention and respond appropriately all the time [25].

[1] http://www.sspa.se/research/projects/baltic-sea-safety-surship-project-bassy
[2] http://www.surship.eu/project/bassy/overview

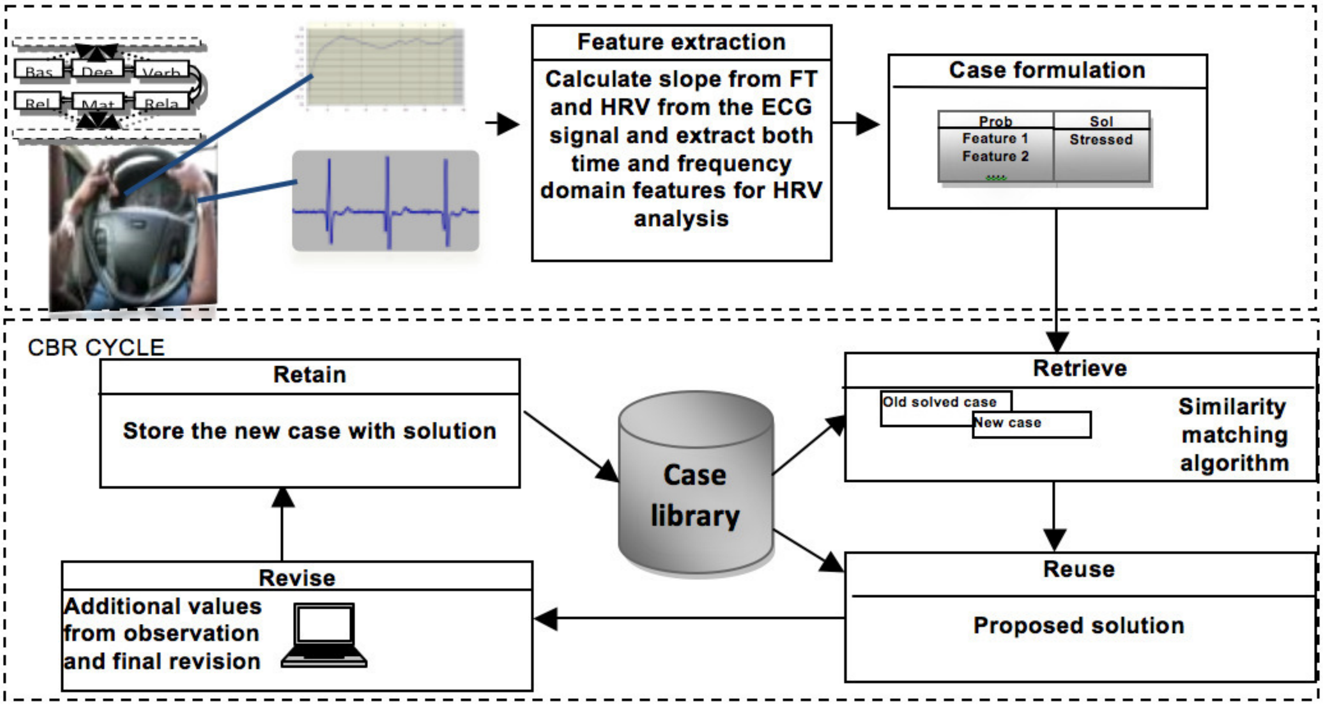

Fig 1. Steps of the proposed driver's state monitoring system

Our focus in the study presented in this paper has been specifically on bucket filling. In all, eighteen people have been asked to participate as test operators in this study – not only professionals, but also less experienced operators [26]. The psychophysiological measurements were conducted using the cStress software from PBM Stressmedicine Systems, acquiring, among other signals, heart rate using a C2 physiological monitoring system from J&J Engineering. The ECG sensors were placed on both wrists (see Fig. 2).Since every human being has an individual response to workload, some sort of reference or calibration is needed in order to be able to correctly evaluate the results of psychophysiological measurements.

While not common procedure in the research community, establishing a Psychophysiological Stress Profile (PSP) has proven to be valuable in clinical work with patients with stress-related dysfunctions. The PSP shown in Table I is essentially taken from [13][31] and has been implemented in the cStress software. It contains 15 minutes of data recording, guiding the patient (or in our case the wheel loader operator) through six steps.

Each operator was given an exclusive 2.5 hours session, starting with the Psychophysiological Stress Profile (PSP) described above. Afterwards, testing of the machine in three different traction force settings was performed, with ten minutes' self-training prior to each live session. Then the operator was asked to perform a self-evaluation of, among other things, the tested machine version's ease of bucket filling and his own stress level on a visual analogue scale.

TABLE I.
PSYCHOPHYSIOLOGICAL STRESS PROFILE (PSP)

Designation	Observation time	Description
R01: Base line	3 min	Relaxed silent reading of a neutral text
R02: Deep breathing	2 min	Deep breathing under guidance, approx. 6 bpm
R03: Nonverbal stress	2+2 min	Two periods of thinking about a stressful situation, feedback and guidance in between
R04: Relaxing	2 min	Relaxing with closed eyes, normal breathing
R05: Math stress	2 min	Counting aloud backwards from 2500 in steps of 7
R06: Relaxing	2 min	Relaxing with closed eyes, normal breathing

During all sessions various machine data were also recorded off the wheel loader's CAN bus, enhanced by additional data, either calculated or acquired from externally mounted sensors. All tests were also recorded on video using an externally placed digital video camera and later synchronised with the acquired data from the CAN bus and cStress.

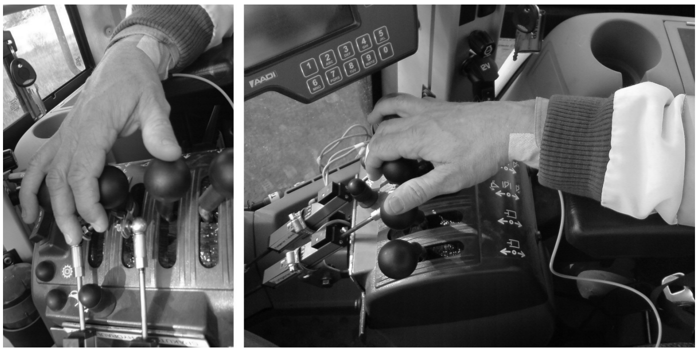

Fig. 2 Right hand controls and sensor placement on right wrist

V. Signal Processing and HRV Feature Calculation

To calculate the HRV features from the IBI signal (Fig. 3) we need to preprocess the signal since subjective random artifact (which could cause due to movement, connection problem etc.) in the IBI signal could influence the corresponding feature values. The normal range of the IBI signal is 0.4 to 1.1 second. However, some IBI values can be higher than the range because of these artifacts. Therefore, to handle the artifact problem, first the artifacts are detected and then the signal is re-sampled.

Artifact detection: For the detection, first the signal is divided horizontally into a number of windows (winH) in every 30 seconds. Again, each horizontal window is divided vertically into a number of windows (winV).

-Now, for each window (winV) the frequency and mean are calculated.

-Then the mean of the lowest frequency window (winV) is compared with the normal range (0.4 to 1.1 sec).

-If the mean value doesn't fall within this range then all the sample data are considered as artifacts.

These steps are continued until the program reaches the last window (winH) and determines all the artifacts. The program also identifies length of the artifacts for each window (winH) and has marked the entire original sample in that length as artifact.

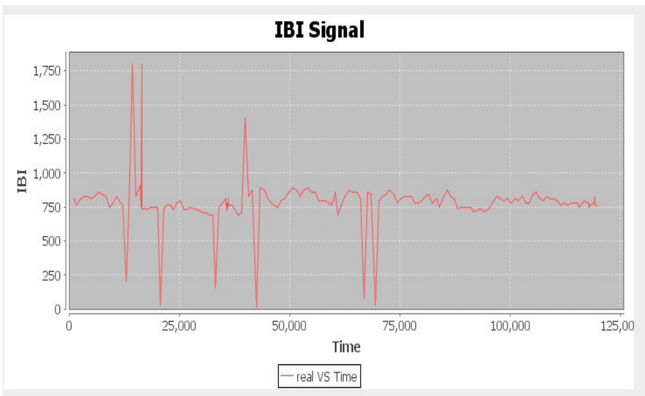

Fig. 3. Inter-beat interval (IBI) sample measurement

Signal Re-sampling: This length of sample is then replaced by the same length of usual data received just before or after the artifact. The usual data are defined by the highest frequency window (winV). Thus, for each subject, the artifact data are re-sampled. A detail description about handling artifacts in IBI signal is available in [27].

In the system, both time and frequency domain features are considered for the HRV analysis. First, the IBI values obtained after the preprocessing step (handling the artifacts) are represented in the time domain. The time domain features analyze the beat-to-beat variations. Here, statistical methods are applied to get the time domain features i.e., Mean value of the RR interval (*Mean NN*), Standard deviation of RR intervals (*SDNN*), Root mean square of the all successive RR interval difference (*RMSSD*) and Percentage of NN 50 in total number of beats (*pNN 50*).

The IBI values are then transferred into the frequency domain. The frequency domain analysis is performed based on the spectral analysis of HRV. The Spectral analysis of HRV can be used for assessing levels of parasympathetic and sympathetic activities in the ANS.

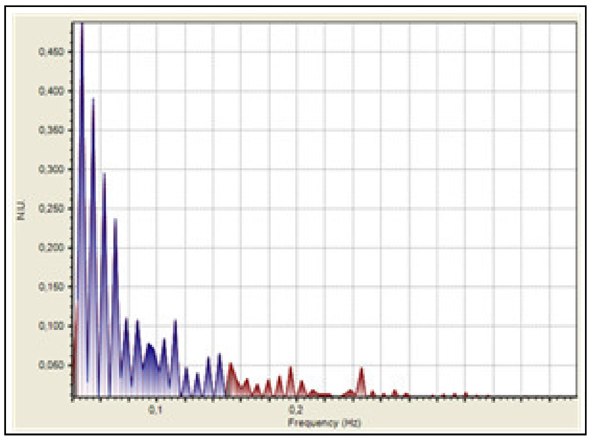

Fig. 4. The normalized unit of power spectral density

Thus, the pre-processed IBI signal is transferred into the frequency domain using FFT. FFT calculates the power spectral density (PSD) of HRV. PSD shows energy variations in different frequencies. Unit of PSD is energy (watts) per frequency (hertz). Fig. 4 illustrates an example PSD of an IBI signal. To extract the frequency domain features the PSD is divided into different locations of frequency bands (range of the location may vary depending on the problem domain). Here, the HRV spectrum is divided into Ultra Low Frequency (*ULF* < = 0.003 Hz), Very Low Frequency (*VLF* 0.003–0.04 Hz) that reflects the parasympathetic influences on Heart rate (HR). High frequency (*HF* 0.15 - 0.4 Hz) is generally considered to be an index of cardiac vagal control [4]. Low frequency (*LF* 0.04–0.15 Hz) appears due to both the vagus and cardiac sympathetic nerves. The *ratio of LF and HF* spectra can be proposed as an index of cardiac sympathovagal balance [28].

TABLE II.
THE TIME AND FREQUENCY DOMAIN HRV FEATURES AND THEIR WEIGHT VALUES

Domains	Features	Weight
Frequency domain	LF	10
	HF	10
	LF HF ratio	9
	VLF	8
	TP	3
	LF Norm	7
	HF Norm	7
	ULF	1
Time domain	Mean NN	10
	pNN50	9
	SDNN	10
	RMSSD	10

Total Power (*TP* 0 - 0.4 Hz) reflects total variance in HR pattern over a length of recording, Normalized Low Frequency (*LF norm* LF / (Total power – VLF) X 100) presents the proportion of total HRV that occurs in the low frequency band and Normalized High Frequency (*HF norm* HF / (Total power – VLF) X 100) shows the proportion of total HRV that occurs in the high frequency band [40]. Weight reflects the relative importance of a feature. The weight values (Table II) of the features are defined based on a survey [15]. The survey, for the frequency domain HRV analysis, presents the frequency of appearance of these features in the literature. The feature with maximum appearance gets the maximum weight value i.e. 10.
Except the baseline, features are calculated for the R02 to R06 (i.e., deep breath, nonverbal stress, relax, math stress and relax) of the Calibration phase (Table I). So, finally eight frequency domain features and four time domain features are calculated for each step. Then, a new problem case for the proposed CBR system is formulated based on these time and frequency domain features.

VI. CASE-BASED CLASSIFICATION

The objective of the proposed system is the diagnosis of an individual's driver's status where the main functionality lies in solving a new problem case by using solution of past-solved cases.

$$\text{Similarity}\ (C,S) = \sum_{f=1}^{n} w_f * \text{sim}(C_f, S_f) \qquad (1)$$

To retrieve the past solved cases for a current problem case the general similarity function applied in the system is shown in Equation 1. Similarity is given in a value between 0 and 1 where 0 means no similarity and 1 means 100% similarity. Here, Similarity(C, S) is the global similarity function for a new case C and stored case S and sim(C_f,S_f) is the local similarity function. Weights are defined for each feature of the system. Where, $w_f = \frac{lw_f}{\sum_{f=1}^{n} lw_f}$ and lw_f is the local weight for each feature.

In the proposed system, the local similarity sim(C_f,S_f) is calculated using *modified Euclidean distance function* and *fuzzy similarity matching algorithm*.

For Euclidean distance the similarity for each feature i.e. $\text{sim}(C_f, S_f)$ is calculated by normalizing the absolute difference between the two features for these two cases and dividing it by the difference of the maximum and minimum distance. To get the similarity values it is then subtracted from 1. Equation 2 represents this calculation.

$$\text{sim}(C_f, S_f) = 1 - \frac{\text{abs}(C_f - S_f)}{\text{Max}(C_f, S_f) - \text{Min}(C_f, S_f)} \qquad (2)$$

Different weights are also defined for the steps of the calibration phase and the final similarity is calculated using equation 3.

$$total\_similarity, S_{total} = w_t * \sum_{i=02}^{06} similarity\_for\_R_i \qquad (3)$$

Here, i denote the steps from R02 to R06 and $w_t = \frac{lw_s}{\sum_{f=2}^{6} lw_s}$ where lw_s is the local weight of a particular step i.e. from R02 to R06.

Another similarity matching algorithm i.e., fuzzy similarity is applied to the system where the crisp values are converted into fuzzy values by using a triangular member function. If *m1*, *m2* and *om* are the elements of the converted fuzzy set then the similarity between current case and the old cases is calculated using Equation 4.

$$sim(c_f, s_f) = s_f(m_1, m_2) = \max(om/m_1, om/m_2) \qquad (4)$$

Where, $s_f(m_1, m_2)$ calculates the local similarity on feature f between the new and old cases. m_1 and m_2 are the two triangular fuzzy sets and om is the overlapping area between them. When the overlapping area (*om*) is bigger than the similarity values of the feature is higher. Thus, for two identical fuzzy sets the similarity will reach unity.

Hence, the system retrieve similar past cases for a new case where the local similarity $sim(c_f, s_f)$ can be calculated using *modified Euclidean distance function* or *fuzzy similarity matching algorithm*.

However, solution of a past case often requires adaptation to find a suitable solution for a new case. In that case, in the system a user can adapt the solution manually for example this adaptation could be a combination of two solutions from the list of retrieved and ranked cases in order to provide a solution to the current problem case. Afterwards, the case is sent to the revision step where the solution is verified manually for the correctness and presented as a confirmed solution to the new problem case. In the retention step, if necessary, this new case with its verified solution is added to the case library as a new knowledge.

VII. Evaluation

In the project, the measurements were collected using more than one parameter (Finger temperature, skin conductance, respiration rate, CO2/ETCO2) together with the ECG signal. All these parameters are considered while doing manual classification for this evaluation. However, the system performs the classification based only on the HRV parameters. An expert who is working in the psychophysiological stress domain both as a researcher and as a clinician is involved in the manual classification. The main goal of the evaluation is to compare the system's performance with the expert's classification.

Table III.
Sensitivity and specificity analysis using the time and frequency domain features *(library 1: 46 cases)*

Criteria/ Indices	Using Only Frequency Domain Features (100%)	Using Only Time Domain Features (100%)	50% Time and 50% Frequency Domain Features	30% Time and 70% Frequency Domain Features	20% Time and 80% Frequency Domain Features	40% Time and 60% Frequency Domain Features
True positive (TP):	9	7	8	9	10	8
False positive (FP):	2	3	3	1	1	3
True negative (TN):	5	4	4	6	6	4
False negative (FN):	2	4	3	2	1	3
Sensitivity = TP / (TP + FN)	0.82	0.63	0.73	0.82	0.91	0.72
Specificity = TN / (FP + TN)	0.71	0.57	0.57	0.86	0.86	0.57
Accuracy = (TP+TN)/ (P+N)	0.76	0.61	0.67	0.83	0.89	0.67

For the evaluation purpose, the sensitivity and specificity test was carried out within the collected 18 driver cases. We have only considered the individual profile data for this evaluation. In the evaluation, two case libraries were used: *library 1:* this is from our previous study with 46 reference cases where data is collected from normal persons in different test conditions and *library 2:* this library consists of these 18 driver's cases. These 18 driver cases are matched with old cases exists in *library 1* and *library 2*. The Leave-one-out method was applied where one case was taken out at a time from the case library and then the case was matched against the rest of the cases in the case library. Here, in order to retrieve similar cases, kNN (k=1) i.e., the top most similar case is considered.

Table IV.
Sensitivity and specificity Analysis using time and frequency domain features *(library 2: 18 cases)*

Criteria/Indices	(100%)Using Only Frequency Domain Features	Using Only Time Domain Features (100%)	50% Time and 50% Frequency Domain Features	Features30% Time and 70% Frequency Domain	Features20% Time and 80% Frequency Domain	Features40% Time and 60% Frequency Domain
True positive (TP):	10	7	8	10	10	10
False positive (FP):	3	6	3	2	5	3
True negative (TN):	4	1	4	5	2	4
False negative (FN):	1	4	3	1	1	1
Sensitivity = TP / (TP + FN)	0.91	0.64	0.73	0.91	0.90	0.91
Specificity = TN / (FP + TN)	0.57	0.14	0.57	0.71	0.28	0.57
Accuracy = (TP+TN)/ (P+N)	0.78	0.44	0.67	0.83	0.67	0.78

The time-domain, frequency-domain and the combination of time-frequency domain features are considered for the evaluation. Here, the goal is to investigate the features that provide us more accurate result or if we could improve the performance by adjusting the combination of the features. A weighted average method was applied in order to combine the features. When the features from only one domain was taken into consideration then the weight of that domain is assigned to 100% and the weight values for all the other domain features were assigned to zero. When considering the combination of the domains, weights were assigned in such a way that the total weight value is 100% e.g., 30% time and 70% frequency domain features.

Evaluation with library 1: In Table III, the single and multi-domain features are assigned different percentages to emphasize the importance of the features. Among the 18 cases, 7 cases are classified as *healthy* and 11 cases are classified as *stressed*. It can be seen lowest achievement (i.e., 63% sensitivity is achieved and the obtained specificity and accuracy are only 57% and 61%) shows when using only the time domain features. Whereas, when considering a combination (i.e., **80% of frequency and 20% of time domain**) of features the sensitivity, specificity and accuracy achieved as highest as 91%, 86%, and 89%. On the other hand, in another combination of the features the sensitivity, specificity and accuracy achieved as 82%, 86%, 83% which presents the 2nd highest value.

Evaluation with library 2: Likewise from Table IV, it can be seen that the lowest value is obtained here when using only the time domain features. Whereas, when considering the combination of features i.e., 80% of frequency and 20% of time domain features the sensitivity, specificity and accuracy is achieved as the 2nd highest as 90%, 28%, and 67%. On the other hand, another combination (considering **70% of frequency and 30% of time domain features**) gives the sensitivity, specificity and accuracy as highest as 91%, 71%, 83% respectively.

TABLE V.
Classification accuracy while K=1, K=2 and K=3 *(using library 1)*

Case Id	Expert Classification	Systems Classification		
		K=1	K=2	K=3
1	stressed	stressed	stressed	stressed
2	healthy	Healthy	healthy	healthy
3	stressed	stressed	stressed	stressed
4	healthy	healthy	healthy	healthy
5	stressed	stressed	stressed	stressed
6	healthy	healthy	healthy	healthy
7	stressed	stressed	stressed	stressed
8	stressed	stressed	stressed	stressed
9	healthy	stressed 92.65%	stressed 92.12%	healthy 92%
10	stressed	healthy 91.55%	healthy 91%	healthy 90.5%
11	stressed	stressed	stressed	stressed
12	stressed	stressed	stressed	stressed
13	healthy	healthy	healthy	healthy
14	stressed	stressed	stressed	stressed
15	healthy	healthy	healthy	healthy
16	stressed	stressed	stressed	stressed
17	healthy	healthy	healthy	healthy
18	stressed	stressed	stressed	stressed

TABLE VI.
Classification accuracy while K=1, K=2 and K=3 *(using library 2)*

Case Id	Expert Classification	Systems Classification		
		K=1	K=2	K=3
2	healthy	stressed 91.78%	stressed 91.21%	healthy 91%
3	stressed	stressed	stressed	stressed
4	healthy	healthy	healthy	stressed
5	stressed	stressed	stressed	stressed
6	healthy	stressed 90.5%	healthy 90.2%	stressed 89%
7	stressed	stressed	stressed	stressed
8	stressed	healthy 92.45%	healthy 92.2%	stress 91.6%
9	healthy	healthy	healthy	healthy
10	stressed	stressed	stressed	stressed
11	stressed	stressed	healthy	stressed
12	stressed	stressed	stressed	stressed
13	healthy	healthy	healthy	stressed
14	stressed	stressed	stressed	stressed
15	healthy	healthy	healthy	healthy
16	stressed	stressed	stressed	stressed
17	healthy	healthy	healthy	healthy
18	Stressed	stressed	stressed	stressed

Since, we have used kNN (k=1) i.e., the top most similar case for the previous comparison. However, the overall accuracy could be increased if we consider K=2 and K=3. The similarity values are presented in percentage in Table V and Table VI (brown colored rows). For example, in Table VI, case 2, 6 and 8 provide us inaccurate result when K = 1. However, it can be seen that the similarity values are very close to K=1 even when we consider K=2 and K=3. So if we consider the value for K=3 the accuracy will be increase i.e., both the expert and system will classify the case as 'healthy'. This divergence in the accuracy can be due to the fact that experts sometimes consider contextual information. Thus, if the system presents a list of cases not only with K=1 but also considering K=2 and K=3 there is a better chance that the user can select more accurate result by analyzing the similarity values and contextual information.

VIII. CONCLUSIONS

The paper presents a stress monitoring system in particular for the professional drivers using HRV analysis. The classification is mainly based on the case-based reasoning. The result shows a performance close to the expert in monitoring stress for the drivers. It also presents that a combination of time and frequency i.e., the multi-domain features performs better in terms of sensitivity, specificity and accuracy rather than the single domain features i.e., using only time or frequency domain features. Many systems that have applied HRV analysis for diagnosing psychological state are using either frequency or time domain features or both of them. However, CBR system has the potentiality of using weighted combination of he features which allows tuning of the feature values for better performance. In future, the system could be extended to combine other physiological parameters in driving situation.

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