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Mental Stress Detection using Heart Rate Variability and Morphologic Variability of ECG Signals

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Abstract—**Mental stress is one of the major risk factors for many diseases such as hypertension, coronary artery disease, heart attack, stroke, even sudden death. Conventionally, interviews, questionnaires or behavior observation are used to detect mental stress in an individual. In our study, we have investigated objective characteristics, like various short term heart rate variability (HRV) measures and morphologic variability (MV) of ECG signals for detecting mental stress. A number of HRV measures were investigated, both in time domain and frequency domain. Experiments involved 16 recordings of ECG signals during mental stress state and normal state, included in a multi-parameter data base on physionet.org portal. Results revealed that the HRV measures named mHR, mRR, normalized VLF/LF/HF, difference between normalized LF and normalized HF, and SVI are effective metrics for mental stress detection. Better results were obtained by using MV analysis and a decision-support module based on both methods, HRV and MV.**

Keywords: mental stress detection; heart rate variability; morphologic variability; decision-support system.

I. INTRODUCTION

Stress typically describes a negative concept and is perceived as a subjective experience that can have an impact on one's mental and physical well-being. In biology, factors causing an organism's condition to waver away from homeostasis can be interpreted as stressors. On the other hand, an organism's effortful attempt at restoring conditions back to or near homeostasis, oftentimes consuming energy and natural resources, can also be interpreted as stress. More generally, stress may be defined as the non-specific response of the body to any demand placed upon it. A recent definition asserts that stress should be restricted to conditions where an environmental demand exceeds the natural regulatory capacity of an organism [1].

Some researchers make a distinction between "eustress" and "distress" where the first is a good stress, such as joy, or a stress leading to an eventual state which is more beneficial to the organism. In this paper we will refer to stress only as distress, stress with a negative bias, particularly distress caused by an increase in driver workload [2].

Most stressors are intellectual, emotional and perceptual and yield a kind of feeling that is created in our minds when we feel threatened and tensed due to various situations. Nowadays stress is one of the most common problems in daily life, marked by certain crises. It can make us feel depressed, rejected, disgusted, angry, and finally may bring us some chronic diseases such as hypertension or cardiovascular diseases. For instance, mental stress has been reported to provoke myocardial ischaemia in patients with coronary artery disease [3], [4] and is a risk factor for hypertension [5], atherosclerosis [6], [7], even for sudden death [8]. Neurovascular responses to mental stress may be of prime importance to elucidating the mechanistic link between mental stress and vascular injury, but both neural and vascular responses during and after mental stress remain equivocal and controversial.

In this respect it is important to objectively recognize whether we are under stress and if we can detect stress warning signs early it is possible to prevent its impact on our life. There are a number of stress detection methods, for example, interviewing, questionnaire, behavior observation, and analysis of physiologic signals such as EEG, ECG, etc. In this work, we have used a signal derived from the ECG biosignal and called *RR interval signal*. The analysis of RR interval time series in terms of Heart Rate Variability (HRV) has been widely used for monitoring Autonomic Nervous System [9]. Heart rate variability refers to the regulation of the sinoatrial node that is the natural pacemaker of the heart by the sympathetic and parasympathetic branches of the ANS. HRV refers to certain variations between consecutive heartbeats, and it is used to describe the balance in sympathetic and parasympathetic activities. A number of research works showed that mental stress affects the HRV (e.g. [1], [3], [10], [11]). There are various HRV measures that can be adopted for different pathologic state detection, including mental stress

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state. This paper presents a study in which we have investigated both different HRV and morphologic variability (MV) indices that can act as effective measures for mental stress detection. The paper is organized as follows: Section 2 describes the using of HRV for stress evaluation, Section 3 presents the concept of morphologic variability and its use for ECG analysis, Section 4 describes experimental results, and finally Section 5 draws some conclusions of our research.

II. HEART RATE VARIABILITY AND MENTAL STRESS

In our study short term analysis of ECG data is performed, by means of the following processing stages.

A. Pre-processing

In order to determine ECG cycles by means of R peaks detection in the ECG, a preprocessing stage is necessary. This way, false or missed peaks that appear due to noise or artifacts are corrected. First, the base line wander of ECG traces is removed by using a band pass filter with cutoff frequencies of 0.5 and 40 Hz. Then, a median filter with length 8 filters ECG added noise.

The *dynamic time warping* (DTW), as normalization procedure, is used in order to align the current QRS complex to the previous two and the next two complexes.

Then R peaks and the length of QRS complex are automatically detected using the Pan-Tompkins algorithm based software (physionet.org). This type of algorithm is credited with an average error rate of about 1% and false detections occur mostly due to noise [12].

B. HRV Measures

One of the two standard methods for HRV analysis [13] uses time domain analysis of the RR interval signals directly. The other method refers to frequency domain analysis that extracts HRV measures from the power spectrum of the RR interval time series, computed by means of Fourier transform.

1) HRV Analysis in Time Domain

There are many HRV measures of the RR time series that can be defined on time domain, e.g. mean RR interval (*mRR*), mean heart rate (*mHR*), standard deviation of RR interval (*SDRR*), standard deviation of heart rate (*SDHR*), coefficient of variance of RR intervals (*CVRR*), root mean square successive difference (*RMSSD*), number of pairs of adjacent RR intervals differing by more than 20 ms to all RR intervals (*pRR20*), and number of pairs of adjacent RR intervals differing by more than 50 ms to all RR intervals (*pRR50*). In our study we have considered only the most useful and relevant measures ranked according to their discriminative power [14]. They are: *mean RR interval* (*mRR*) and *mean heart rate* (*mHR*). The formulae for calculating the chosen HRV measures in time domain are shown in Table I.

TABLE I. CONSIDERED HRV MEASURES FOR TIME DOMAIN

Measure	Unit	Formula
mean RR interval (*mRR*)	ms	$\frac{\sum_{i=1}^{N}(RR_i)}{N}$
mean heart rate (*mHR*)	bpm (beats per minute)	$\frac{\sum_{i=1}^{N}(60000/RR_i)}{N}$

2) HRV Analysis in Frequency Domain

Frequency domain method implies the computation of the power spectral density of the RR interval signal. The basic measures are power spectrum of very low frequency (*VLF*), of low frequency (*LF*), and of high frequency (*HF*), respectively. We have considered the best efficient measures (in terms of classification power) derived from the above basic measures, such as: normalized very low frequency spectrum (*nVLF*), normalized low frequency spectrum (*nLF*), normalized high frequency spectrum (*nHF*), difference of normalized low frequency spectrum and normalized high frequency spectrum (*dLFHF*), Symphatovagal balance index (*SVI*) [10], [14]. The formulae for the above frequency domain measures considered in our study are defined in Table 2. In the table below VLF, LF and HF represent the power spectrum from 0.003 to 0.04 Hz, 0.04 to 0.15 Hz, and 0.15 to 0.4 Hz respectively, for the RR signal. The spectral components of the RR time series are obtained by applying Fast Fourier Transform.

TABLE II. CONSIDERED HRV MEASURES FOR FREQUENCY DOMAIN

Measure	Unit	Formula
normalized very low frequency spectrum (*nVLF*)	%	$(VLF / VLF+LF+HF) \times 100$
normalized low frequency spectrum (*nLF*)	%	$(LF / VLF+LF+HF) \times 100$
normalized high frequency spectrum (*nHF*)	%	$(HF / VLF+LF+HF) \times 100$
difference of *nLF* and *nHF* spectrum (*dLFHF*)	%	$\mid nLF - nHF \mid$
Symphatovagal balance index (*SVI*)	–	LF / HF

We are faced with a 3-class classification problem, in order to distinguish low mental stress state, high mental stress and normal state of the individual subjects. Classification results in terms of accuracy are calculated and compared to evaluate performance of HRV measures. The classification experiments were performed by using each of HRV measures in time domain and frequency domain as a single feature by means of a minimum distance classifier. Finally, *the separability index* (*Q*) [15] as defined in Eq. (1) is calculated and used for HRV measure performance evaluation. The separability index *(Q)* values are in the range of [0, 1]. *Q* near zero indicates the best separability, while approaching to one indicates inseparability.

$$Q = V^2 / (V^2 + D^2), \quad (1)$$

where V^2 is the mean-squared within class distance and D^2 is the mean-squared between class distance.

III. MORPHOLOGIC VARIABILITY

Time-domain, frequency-domain and non-linear analyses are used to calculate HRV, but they only offer information about the RR interval. The information about the changes in the beat morphology is gathered by *morphologic variability* (*MV*), a complementary method that can be used to improve the results offered by the HRV metrics [16]. This method is based on the difference between the lengths of each consecutive QRS complex in order to obtain the *morphologic distance* (*MD*):

$$MD = |QRS_{i-2} - QRS_{i-1}| + |QRS_{i-1} - QRS_i| + |QRS_i - QRS_{i+1}| + |QRS_{i+1} - QRS_{i+2}| \quad (2)$$

The morphologic variability for an ECG record can be calculated from the MD time-series using metrics similar to those for HRV analysis. The metric we have used for time domain is *morphologic variability mean RR interval* (*MV-mRR*). Similarly, we have obtained the 5 metrics for frequency domain, by using *MV-VLF, MV-LF, MV-HF, MV-dLFHF*, and *MV-SVI*, defined in a similar manner as in Table II. The results from both HRV and MV analysis are further compared and combined in order to obtain the best automatic classification results for stress detection.

IV. EXPERIMENTAL RESULTS

Experiments were made on the 16 recordings of ECG signals during mental stress state and normal state, included in a multiparameter data base on physionet.org portal: http://www.physionet.org/physiobank/database/drivedb/ . This database contains a collection of multiparameter recordings from healthy volunteers, i.e. ECG, EMG, GSR (galvanic skin resistance, measured on the hand and foot), and respiration, taken while they were driving on a prescribed route including city streets and highways in and around Boston, USA. The objective of our study was to investigate the feasibility of automated recognition of stress on the basis of the recorded signals. The 16 records each contain a complete experiment, with durations of 65 to 93 minutes.

The driving protocol [2] consisted of a set path through over 20 miles of open roads in the greater Boston area and a set of instructions for drivers to follow. Although stressful events could not be specifically controlled on the open road, the route was planned to take the driver through situations where different levels of stress were likely to occur, specifically, the drive included periods of rest, highway and city driving that were assumed to produce low, medium and high levels of stress, respectively. Two fifteen-minute rest periods occurred at the beginning and end of the drive. The rest periods were used to gather baseline measurements and to create a low stress situation. After the first rest period, drivers exited the garage through a narrow, winding ramp and drove through side streets until they reached a busy main street in the city. This main street was included to provide a high stress situation where the drivers encountered stop and go traffic and had to contend with unexpected hazards such as cyclists and jaywalking pedestrians. The route then led drivers away from the city, over a bridge and onto a highway. Between a toll at the on-ramp and a toll preceding the specified off-ramp, drivers experienced uninterrupted highway driving. This driving was included to create a medium stress condition.

Our study was dedicated to the analysis of the lead II ECG signal, sampled at 500 Hz, and for the test phase we have used features from 5-min intervals of ECG data during those rest, highway, and city driving conditions that correspond to normal (no stress), low stress, and high stress, respectively.

1) RR Interval Time Series

RR interval time series signals during normal state (N) and mental (low and high) stress state from 16 subjects consisting of 32 segments of low stress, 32 segments of medium stress and 48 segments of high stress were used. The length of each segment is variable and details are shown in Table III.

TABLE III. RR INTERVAL TIME SERIES SIGNALS DURING NORMAL STATE AND MENTAL STRESS STATE

No.	Subject	Record duration (min)		
		Low stress (LS)	**Medium stress (MS)**	**High stress (HS)**
1.	S1	30	11	25
2.	S2	30	16	38
3.	S3	30	18	44
4.	S4	30	15	36
5.	S5	30	16	38
6.	S6	30	15	36
7.	S7	30	17	41
8.	S8	30	14	36
9.	S9	30	12	29
10.	S10	30	15	36
11.	S11	30	15	36
12.	S12	30	15	37
13.	S13	30	15	35
14.	S14	30	14	33
15.	S15	30	10	24
16.	S16	30	7	17

2) HRV Metrics Values

The HRV measures values in time and frequency domains, for each ECG recordings from ”drive stress” data base, are shown in Table IV. One can observe that there are certain differences between these values during quasi-normal (low stress), medium and the high stress states.

TABLE IV. HRV METRICS IN TIME AND FREQUENCY DOMAIN DURING LOW, MEDIUM AND HIGH STRESS STATES

Record	State	mRR(sec)	mHR(bpm)	nVLF(%)	nLF(%)	nHF(%)	dLFHF(%)	SVI
stress01	Low	1.078	57.301	19.932	27.531	52.537	0.274	0.524
	Medium	1.042	60.465	12.030	22.974	64.996	0.812	0.353
	High	1.053	58.623	15.292	27.886	56.822	0.289	0.491
stress02	Low	1.402	63.894	12.938	31.713	55.350	0.352	0.573
	Medium	1.366	64.363	24.911	18.114	56.975	0.256	0.318
	High	1.323	66.011	21.667	27.789	50.544	0.214	0.550
stress03	Low	1.260	68.359	18.193	29.831	51.977	0.202	0.574
	Medium	1.236	69.033	19.200	25.299	55.501	0.210	0.456
	High	1.228	69.342	31.626	31.965	36.409	0.017	0.878
stress04	Low	1.371	64.833	39.673	33.442	26.885	0.107	1.244
	Medium	1.162	72.664	55.394	26.252	18.354	0.043	1.430
	High	1.278	68.022	40.295	39.188	20.517	0.136	1.910
stress05	Low	1.430	62.409	42.813	27.989	29.198	0.010	0.959
	Medium	1.373	85.500	9.339	27.920	62.742	0.541	0.445
	High	1.169	76.151	33.907	46.817	19.276	0.915	2.429
stress06	Low	1.149	52.712	26.997	43.403	29.601	0.061	1.466
	Medium	1.010	60.317	43.200	36.232	20.568	0.054	1.762
	High	0.943	64.264	61.211	25.344	13.445	0.036	1.885
stress07	Low	1.277	67.459	48.647	29.137	22.216	0.037	1.312
	Medium	1.239	69.034	52.593	18.019	29.388	0.093	0.613
	High	1.239	68.809	41.700	27.308	30.992	0.019	0.881
stress08	Low	1.489	60.534	28.379	22.085	49.536	0.149	0.446
	Medium	1.464	61.197	38.099	34.982	26.919	0.032	1.299
	High	1.435	62.015	51.477	26.756	21.767	0.019	1.229
stress09	Low	1.414	62.974	46.840	15.725	37.435	0.180	0.420
	Medium	1.326	65.693	38.522	32.750	28.729	0.025	1.140
	High	1.344	65.020	48.535	24.453	27.011	0.013	0.905
stress10	Low	1.304	66.486	24.167	35.185	40.649	0.039	0.866
	Medium	1.145	73.804	47.548	18.530	33.922	0.150	0.546
	High	1.169	72.402	42.291	24.516	33.192	0.056	0.739
stress11	Low	1.533	59.649	21.826	28.855	49.319	0.241	0.585
	Medium	1.443	61.777	31.980	34.201	33.819	0.001	1.011
	High	1.392	63.491	42.364	22.283	35.353	0.082	0.630
stress12	Low	1.592	58.135	14.246	32.292	53.462	0.316	0.604
	Medium	1.556	58.944	21.366	35.777	42.857	0.080	0.835
	High	1.438	62.075	23.797	32.599	43.604	0.096	0.748
stress13	Low	1.134	53.256	14.093	69.780	16.127	0.151	4.327
	Medium	0.900	67.136	66.125	16.110	17.766	0.002	0.907
	High	0.845	72.092	32.314	29.755	37.931	0.017	0.784
stress14	Low	1.134	53.256	14.093	69.780	16.127	0.151	4.327
	Medium	0.900	67.136	66.125	16.110	17.766	0.002	0.907
	High	0.845	72.092	32.314	29.755	37.931	0.017	0.784
stress15	Low	1.490	60.569	37.476	14.165	48.360	0.196	0.293
	Medium	1.477	60.904	28.121	27.341	44.538	0.079	0.614
	High	1.422	62.411	46.004	30.682	23.313	0.025	1.316
stress16	Low	1.054	57.320	24.287	53.171	22.542	0.061	2.359
	Medium	0.877	70.641	15.919	23.652	60.429	0.260	0.391
	High	0.881	70.569	28.958	30.391	40.652	0.055	0.748

3) *Morphologic Variability Metrics Values*

We have mainly investigated the MV metric values in frequency domains, for the same ECG recordings from ”drivedb” data base, and they are shown in Table V. One can visually notice that low, medium and high stress states are more distinguishable, especially when considering MV - dLFHF and MV - SVI metrics.

TABLE V. MORPHOLOGIC VARIABILITY METRICS IN FREQUENCY DOMAIN DURING LOW, MEDIUM AND HIGH STRESS STATES

Record	State	MV-mRR(sec)	MV-SDANN	MV-nVLF(%)	MV-nLF(%)	MV-nHF(%)	MV-dLFHF(%)	MV- SVI
stress01	Low	0.073	0.185	22.166	44.728	33.107	11.621	1.351
	Medium	0.075	0.238	43.806	32.996	23.198	9.799	1.422
	High	0.076	0.250	41.941	31.832	26.227	5.605	1.214
stress02	Low	0.099	0.239	41.768	46.169	12.063	34.105	3.827
	Medium	0.099	0.179	58.861	23.784	17.355	6.430	1.371
	High	0.099	0.181	48.700	32.941	18.359	14.582	1.794
stress03	Low	0.106	0.212	28.547	35.201	36.252	1.051	0.971
	Medium	0.109	0.196	29.039	48.416	22.545	25.872	2.148
	High	0.109	0.198	18.088	47.772	34.141	13.631	1.399
stress04	Low	0.086	0.273	28.095	42.951	28.954	13.997	1.483
	Medium	0.099	0.316	76.595	16.224	7.181	9.044	2.259
	High	0.098	0.267	33.717	34.924	31.360	3.564	1.114
stress05	Low	0.086	0.138	25.123	46.339	28.538	17.801	1.624
	Medium	0.387	0.550	35.897	38.310	25.793	12.517	1.485
	High	0.090	0.224	51.301	36.413	12.286	24.128	2.964
stress06	Low	0.093	0.166	16.343	44.204	39.454	4.750	1.120
	Medium	0.103	0.259	29.412	43.140	27.449	15.691	1.572
	High	0.099	0.210	29.214	36.719	34.066	2.653	1.078
stress07	Low	0.092	0.105	19.735	45.963	34.302	11.661	1.340
	Medium	0.097	0.213	33.618	40.310	26.072	14.238	1.546
	High	0.097	0.221	18.356	48.926	32.718	16.208	1.495
stress08	Low	0.088	0.115	25.295	35.883	38.822	2.940	0.924
	Medium	0.090	0.161	61.313	20.593	18.094	2.500	1.138
	High	0.098	0.245	84.184	7.151	8.665	1.514	0.825
stress09	Low	0.090	0.140	20.914	53.144	25.942	27.202	2.049
	Medium	0.093	0.215	40.290	37.754	21.956	15.798	1.720
	High	0.093	0.214	43.481	31.595	24.924	6.671	1.268
stress10	Low	0.075	0.233	21.183	41.168	37.649	3.519	1.094
	Medium	0.087	0.303	66.452	23.110	10.439	12.671	2.214
	High	0.085	0.314	72.045	18.067	9.887	8.180	1.827
stress11	Low	0.091	0.193	20.288	48.119	31.593	16.526	1.523
	Medium	0.092	0.241	45.205	31.712	23.084	8.628	1.374
	High	0.095	0.262	50.825	26.448	22.727	3.721	1.164
stress12	Low	0.081	0.145	21.731	42.038	36.231	5.807	1.160
	Medium	0.082	0.141	60.394	20.769	18.837	1.932	1.103
	High	0.082	0.164	46.805	30.019	23.177	6.842	1.295
stress13	Low	0.076	0.141	19.438	48.492	32.070	16.422	1.512
	Medium	0.082	0.224	25.149	39.059	35.792	3.267	1.091
	High	0.082	0.231	44.102	30.791	25.107	5.684	1.226
stress14	Low	0.076	0.141	19.438	48.492	32.070	16.422	1.512
	Medium	0.082	0.231	25.149	39.059	35.792	3.267	1.091
	High	0.082	0.224	44.102	30.791	25.107	5.684	1.226
stress15	Low	0.091	0.200	26.286	40.624	33.090	7.535	1.228
	Medium	0.091	0.190	41.459	31.996	26.544	5.452	1.205
	High	0.095	0.202	61.668	25.356	12.976	12.379	1.954
stress16	Low	0.094	0.221	16.978	46.078	36.944	9.134	1.247
	Medium	0.102	0.318	63.034	17.189	19.776	2.587	0.869
	High	0.101	0.299	65.253	20.558	14.190	6.368	1.449

4) *Classification Results*

Classification results for individual subjects, considering input feature vectors containing all shown metrics, are expressed in terms of accuracy. The minimum distance classifier used half of recordings for training vectors and the other half of the recordings as test input data. Table VI presents results for HRV analysis, and Table VII shows obtained values for MV analysis in frequency domain.

TABLE VI. CLASSIFICATION RESULTS FOR LOW, MEDIUM AND HIGH STRESS STATES BY MEANS OF HRV METRICS IN TIME AND FREQUENCY DOMAIN

State	Accuracy (%)	
	HRV time domain metrics	HRV frequency domain metrics
Low Stress	75%	66.8%
Medium stress	82.3%	79%
High stress	86%	81.5%
Average	81.1%	75.76%

TABLE VII. CLASSIFICATION RESULTS FOR LOW, MEDIUM AND HIGH STRESS STATES BY MEANS OF MV METRICS IN THE FREQUENCY DOMAIN

State	Accuracy (%)
	MV Frequency domain metrics
Low Stress	89.2%
Medium stress	90.5%
High stress	88.4%
Average	89.36%

The top five best classification results for normal and stress states, both for HRV and MV analysis of RR intervals are shown in Table VIII.

TABLE VIII. TOP FIVE BEST LOW, MEDIUM AND HIGH STRESS STATES CLASSIFICATION BASED ON CLASS SEPARABILITY INDEX

Rank	HRV / MV metrics	Accuracy
1	MV frequency metrics	89.36%
2	MV time domain metrics	81.24%
3	HRV time domain metrics	81.1%
4	HRV frequency metrics	75.76%

V. CONCLUSIONS

In this study we highlighted two different methods for mental stress detection, one more commonly used – the HRV analysis – and a new method – morphologic variability, that approaches the changes in morphology of ECG beats. The results indicate a better precision of the morphologic variability method as compared to the traditional HRV analysis. The best obtained results indicate a high accuracy of stress detection, approximately 90%, so our method offers an objective and effective technique (that may be combined with subjective tools) for detecting and evaluating this special state of humans – the mental stress. Moreover, the developed algorithms may run in real time, which makes them suitable to generate useful alarms for certain applications.

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