Person-State Classification Systems using Wearable Smart Devices

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Abstract

High precision medical equipment are expensive & require professional medical intervention to lend meaningful assistance. There is a need for low cost and accurate solutions for integration in home environments for preventive healthcare. An efficient and non-invasive technique for continuous vitals monitoring using contact-based sensors integrated into wearable devices, namely, Samsung gear band, for person state classification is proposed. The gear band collects Photo Plethysmography (PPG) signals from integrated PPG sensors. PPG is an optical technique where in light (typically, of red or green wavelength) is used to non-invasively probe the surface of the skin to detect volumetric changes in the blood circulation. The PPG signals can be used to extract key heart rate & heart-rate variability measures which can then serve as vital biomarkers to understand the health of the person. Novel signal processing techniques are used to minimize the noise due to motion artefacts caused by movements/deviations. The impact of ambient noise, temperature and humidity is reduced through the use appropriate signal conditioning methods. Advanced machine learning techniques are employed for person state classification (fatigue/awake/drowsy/sleep) and health estimation through data-driven extraction of critical HRV indicators. A dataset of over 50 hours of data was collected from primarily 3 subjects under different states such as sedentary, sleep and mental fatigue. Five different machine learning techniques are employed showing promising results with 65-90% accuracy obtained for individual subject state classification and over 70% accuracy for cross-subject state classification.

Introduction

Fatigue and drowsiness are one of the key contributors to accidents be it on the roads or in industrial setups. Chronic stress/fatigue also leads to severe cardio vascular diseases which contributes to accidents. Hence, there is a dire need for driver and worker state monitoring and classification systems which are efficient, inexpensive and deployable in user environments. In this work a novel solution for the person state classification is devised. The technique employs a wearable smart device, namely, Samsung Gear S2, for collection of Photo Plethysmography (PPG) signals. The PPG signals are captured from different subjects under states such as sedentary, sleep and mental fatigue. Vital heart rate and heart rate variability measures are derived from the PPG signals. This data is then used to train machine learning algorithms from which information on the person state is obtained.

Process Flow

The Samsung gear band is worn by the subject which has integrated PPG sensors operating in the green channel to capture PPG signals at a sample rate of 20 Hz. The signals are binned into smaller time segments (15 sec) data and analysed for motion artefacts by data pre-processing, band pass filtering and transforming the signal into frequency domain using Welch transform. Time bins where there is a clear peak in the in the frequency range of 0.7 to 2.2 Hz are tagged as having good pulse quality index. Only these bins are retained for subsequent analysis. Various time and frequency domain measures are derived from the signals. These measures are then used to train machine learning algorithms to acquire the state of the subject. The outline of the process is depicted in Figure 1.

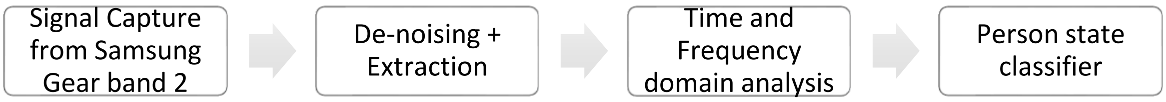


Figure 1: *Process flow diagram*

The detailed signal conditioning and noise correction process applied is elaborated in Figure 2. As an illustration, the analysed signal captured over 30 minutes is depicted to show regions with good pulse quality index (in green) and poor pulse quality index (in red).

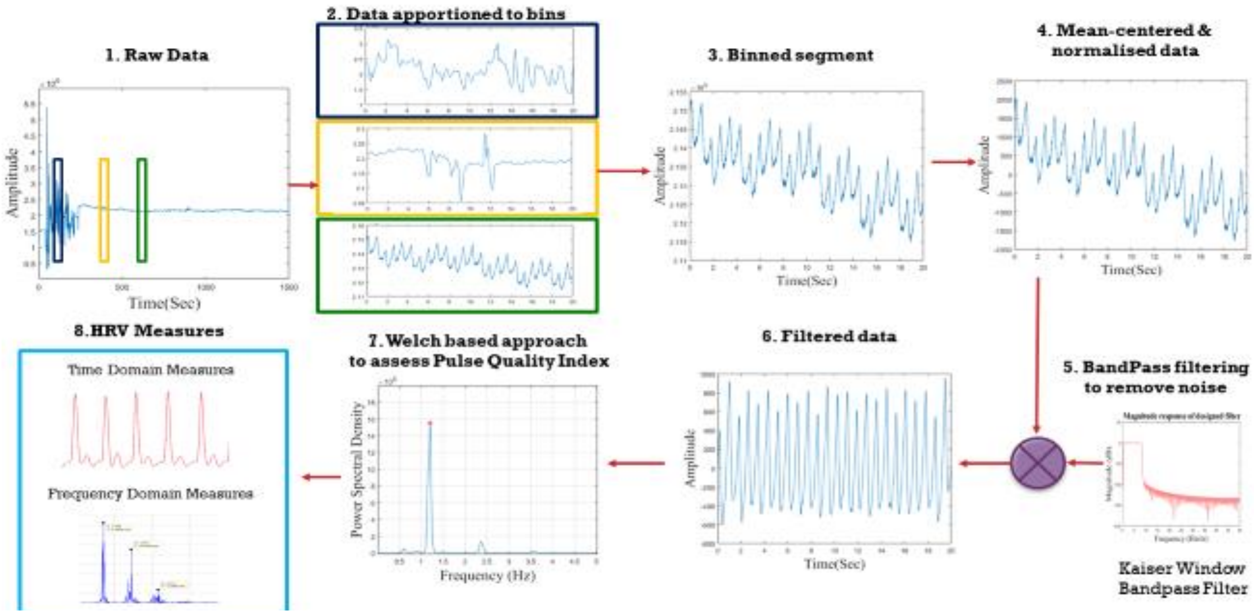


Figure 2: *Signal conditioning process flow for evaluation of pulse quality index*

Data Collection

Data was collected with a Samsung gear S2 device operating with a green-LED pulse sensor. The data was collected for a duration of about 30 minutes for different subjects under various states, such as, sedentary, sleep & mental fatigue. To simulate mental fatigue, the n-back test suggested by Tanaka et al[1] is performed by the subject. Over 50 hours of data has been collected with primarily 3 subjects under different states using standardised data collection procedure.

[1] Autonomic nervous alterations associated with daily level of fatigue. Tanaka M, Mizuno K, Yamaguti K, Kuratsune H, Fujii A, Baba H, Matsuda K, Nishimae A, Takesaka T, Watanabe Y. Behav Brain Funct. 2011 Oct 27; 7:46.

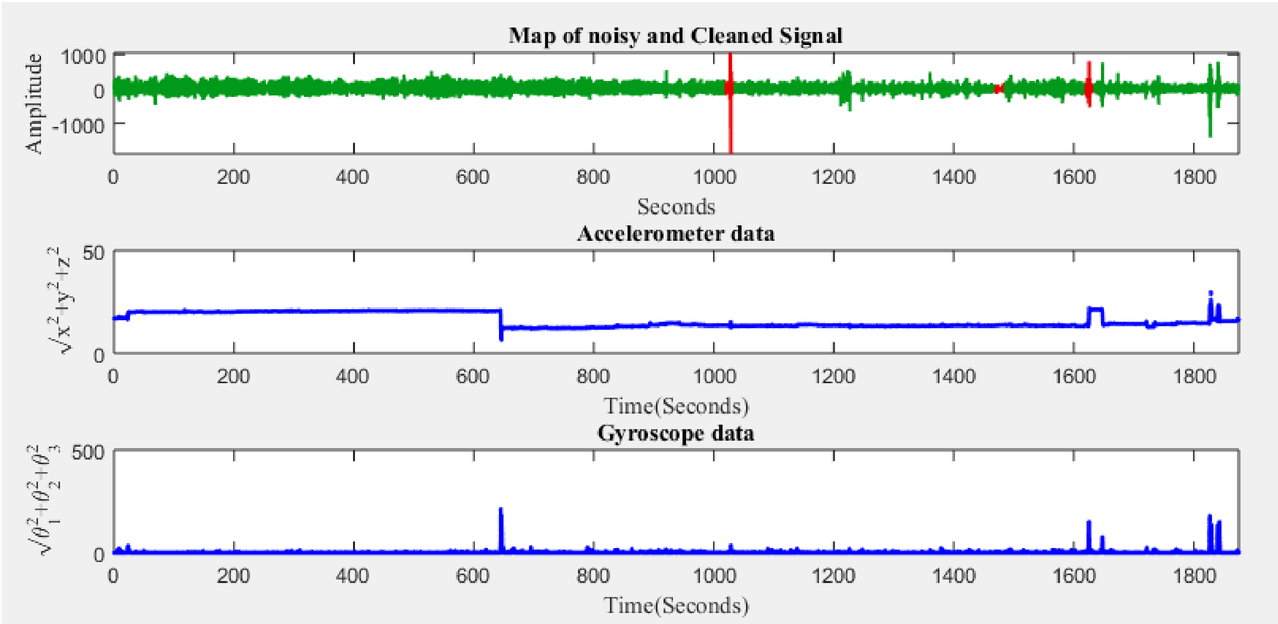


Figure 3: *Pulse quality index mapping for a typical PPG signa (shown on top). Accelerometer (middle) and gyroscope(bottom) data provide complementary information to deduce information about movements and to minimise motion artefacts.*

Heart rate and heart rate variability measures

Various heart rate and heart rate variability measures are derived from the PPG signals. Table 1 below provides brief description of the derived time and frequency domain measures.

Table 1*: HRV Measures and their description*

Parameter	Description
Time Domain Measures	
mHR	Mean of Instantaneous heart rate for 15 second interval (in bpm)
stdHR	Standard Deviation of Heart Rates (in bpm)
cvHR	Coefficient of variation of Heart rates. The ratio of the standard deviation to the mean of heart rate
RMSSD	Root mean square of successive differences between adjacent NN intervals (in ms)
pNNx (NN>x)	Proportion of NNx divided by total number of NN intervals greater than x milliseconds. The values of x considered are 50, 40, 30 & 20 ms.
Frequency Domain Measures	
nLF	Normalized Low Frequency power (0.04 Hz – 0.15 Hz)
nHF	Normalized High Frequency power (0.15 Hz – 4 Hz)
LHRatio	Ratio of Low frequency power to High frequency power

The derived HR and HRV measures for a single use-case is depicted Figure 4. The consolidated data collected for a single subject is plotted as 5-minute averaged data points in Figure 5.

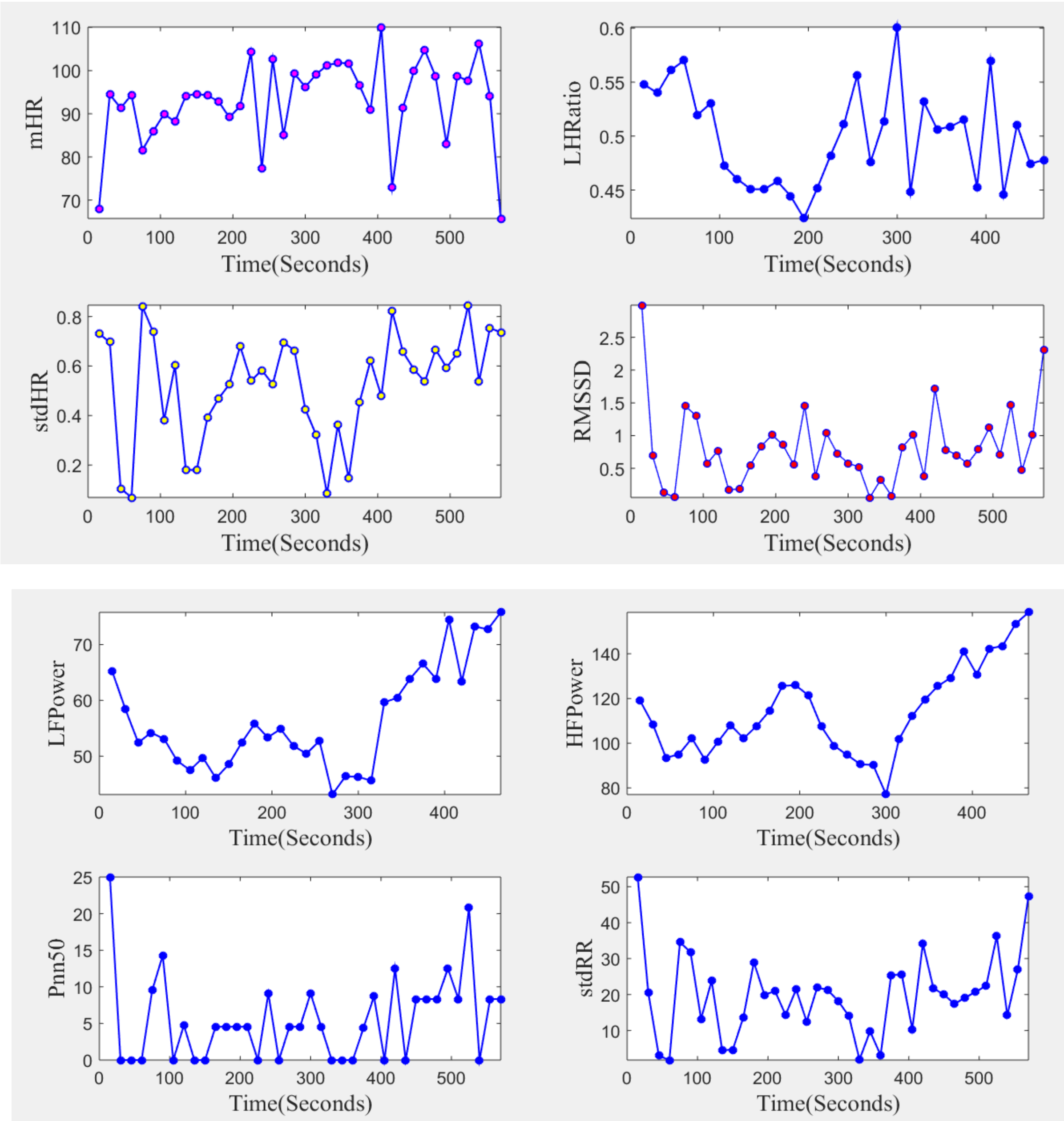
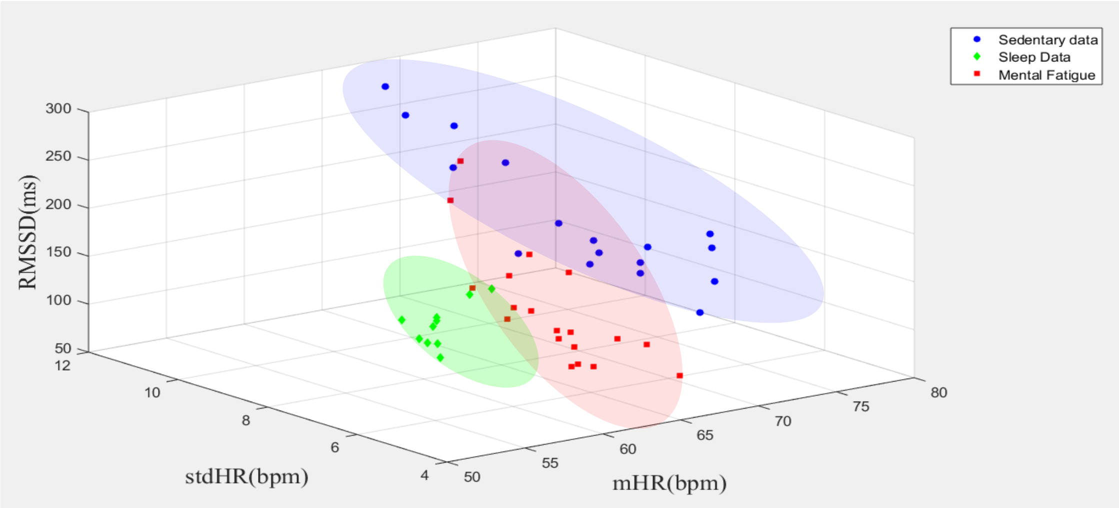
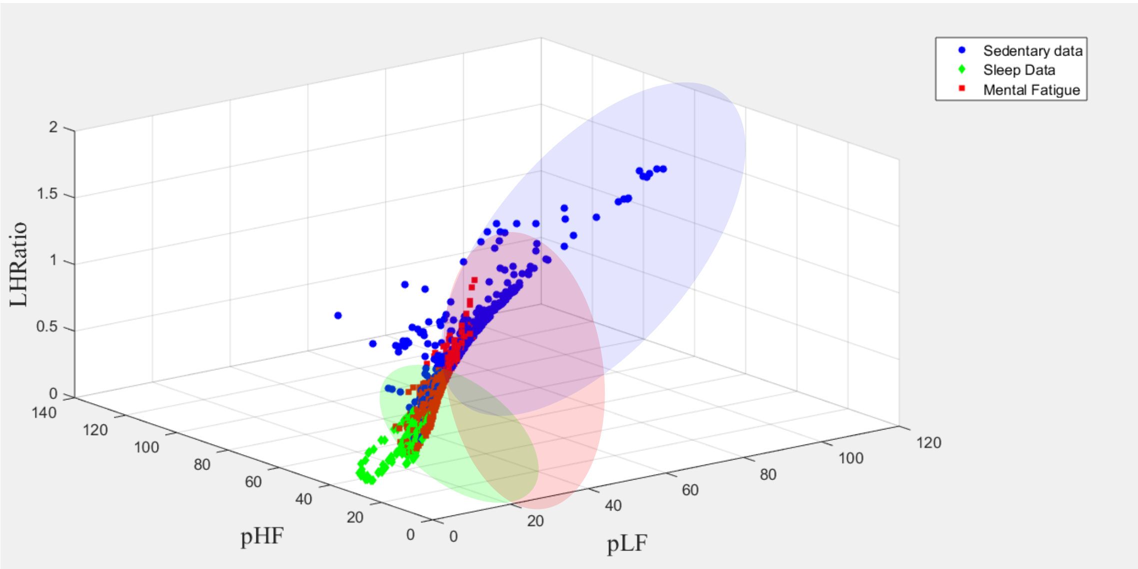


Figure 4: *Derived heart rate (HR) & heart-rate variability (HRV) measures derived from PPG signals. mHR – mean heart rate; stdHRD – Standard deviation of heart rate; RMSSD – Root mean Square of successive differences; LFPower – Power in Low frequency components; HFPower – Power in High frequency components*



(a)



(b)

Figure 5: *Scatter plots of data points constructed with HR/HRV measures, (a) in Time-domain, (b) Frequency-domain, for candidate subject under different states*

Data analysis using Machine learning algorithms

The 5 min HR and HRV feature sets are used for subsequent person state classification. Various machine learning algorithms are explored such as Support Vector Machines, Random Forest, Decision tree and KNN. Both person specific and consolidated dataset analysis has been carried out. The datasets used for the study is provided in Table 2. 70% of the dataset is used for training and 30% for validation. The results of the classification are depicted in Table 3, 4 & 5 for individual subjects and Table 6 for the combined dataset. We can clearly see from the results that the fatigue classification using person specific datasets yields an accuracy ranging from 60%-90% depending on the subject. Similarly, fatigue is classified with greater than 70% accuracy for the combined dataset.

Table 2: *Dataset used in the study*

State	Subject 1	Subject 2	Subject 3	Consolidated
Mental Fatigue	27	58	38	123
Sedentary	44	26	51	121
Sleep	63	94	89	246
Total	**134**	**178**	**178**	**490**

Table 3: *Fatigue classification methods and results for Subject 1*

Classifier	Training accuracy	F1_score, Precision, Recall w.r.t Fatigue class			F1_score, Precision, Recall w.r.t Sleep class			F1_score, Precision, Recall w.r.t Sedentary class			Test accuracy
SVM linear	73.91	0	0	0	0.71	63.16	80	0.54	78.57	40.74	54.76
Random Forest	**100**	**0.64**	**77.78**	**53.85**	**0.77**	**78.95**	**75**	**0.43**	**35.71**	**55.56**	**64.29**
Decision Tree	100	0.52	66.67	42.86	0.76	73.68	77.78	0.33	28.57	40	57.14
KNN 3	83.7	0.48	66.67	37.5	0.82	73.68	93.33	0.56	50	63.64	64.29
KNN 5	82.61	0.48	55.56	41.67	0.78	73.68	82.35	0.59	57.14	61.54	64.29

Table 4: *Fatigue classification methods and results for Subject 2*

Classifier	Training accuracy	F1_score, Precision, Recall w.r.t Fatigue class			F1_score, Precision, Recall w.r.t Sleep class			F1_score, Precision, Recall w.r.t Sedentary class			Test accuracy
SVM linear	75.61	0.17	11.11	40	0.76	93.1	64.29	0.88	87.5	87.5	65.45
Random Forest	98.37	0.7	83.33	60	0.83	75.86	91.67	0.71	62.5	83.33	76.36
Decision Tree	**100**	**0.83**	**83.33**	**83.33**	**0.87**	**89.66**	**83.87**	**0.71**	**62.5**	**83.33**	**83.64**
KNN 3	**91.87**	**0.86**	**83.33**	**88.24**	**0.93**	**93.1**	**93.1**	**0.94**	**100**	**88.89**	**90.91**
KNN 5	88.62	0.75	83.33	68.18	0.85	79.31	92	0.88	87.5	87.5	81.82

Table 5: *Fatigue classification methods and results for Subject 3*

Classifier	Training accuracy	F1_score, Precision, Recall w.r.t Fatigue class			F1_score, Precision, Recall w.r.t Sleep class			F1_score, Precision, Recall w.r.t Sedentary class			Test accuracy
SVM linear	75.61	0.48	50	46.15	0.88	85.19	92	0.73	75	70.59	74.55
Random Forest	99.19	0.52	50	54.55	0.93	96.3	89.66	0.71	68.75	73.33	78.18
Decision Tree	100	0.38	33.33	44.44	0.81	88.89	75	0.67	62.5	71.43	69.09
KNN 3	**81.3**	**0.52**	**50**	**54.55**	**0.88**	**85.19**	**92**	**0.8**	**87.5**	**73.68**	**78.18**
KNN 5	**82.93**	**0.67**	**58.33**	**77.78**	**0.93**	**96.3**	**89.66**	**0.73**	**75**	**70.59**	**81.82**

Table 6: *Fatigue classification methods and results (Consolidated)*

Classifier	Training accuracy	F1_score, Precision, Recall w.r.t Fatigue class			F1_score, Precision, Recall w.r.t Sleep class			F1_score, Precision, Recall w.r.t Sedentary class			Test accuracy
SVM linear	71.25	0.16	12.9	20	0.84	93.24	75.82	0.65	59.46	70.97	66.9
Random Forest	98.78	0.34	29.03	40.91	0.84	86.49	81.01	0.62	64.86	58.54	68.31
Decision Tree	100	0.35	32.26	38.46	0.75	75.68	73.68	0.62	64.86	60	63.38
KNN 3	**81.04**	**0.47**	**45.16**	**48.28**	**0.85**	**83.78**	**86.11**	**0.72**	**75.68**	**68.29**	**73.24**
KNN 5	**78.59**	**0.46**	**41.94**	**50**	**0.83**	**83.78**	**82.67**	**0.77**	**81.08**	**73.17**	**73.94**

Conclusions

PPG data for various subjects under different states were captured using the wearable Samsung gear S2. The signals captured were processed for noise reduction. Several time domain and frequency domain HR and HRV measures were derived from the PPG signals. The measures were then used for subsequent machine learning algorithms for person state classification. The preliminary investigations show promising results with 60-90% accuracy of classification for person specific analysis and over 70% accuracy of classification for consolidated analysis. Further studies are being carried out with more subjects of different age-groups, skin-tones and other advanced signal processing methods to further improve the classification accuracy.