Literature Review for Detection of Stress using Photoplethysmography Signals

Vishnu Kannan
vishnukanan@gmail.com

Ketki Ambekar
ambekar.ketki@gmail.com

Vaidic Joshi
er.vaidic@gmail.com

Pradeep Ramadasan
pradeep.ramadasan@gmail.com

Abstract

This paper presents a review of past literature on the topic of predicting psychological stress using commonly available Photoplethysmography (PPG) signals. After establishing the project goals and planned progression, a general survey of the problem space is presented, followed by a review of classical machine learning techniques applied to model various bio-markers from PPG data is presented. Then the role of Deep Learning in this problem space is presented along with the possibility of estimating PPG remotely (rPPG) using facial recordings. The reviewed publications are then compared and contrasted.

1 Introduction

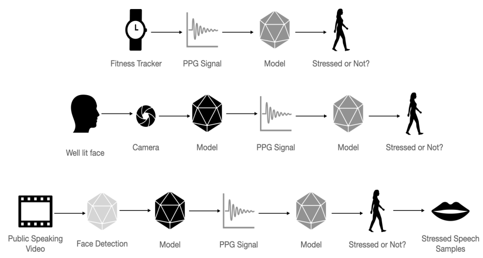
The goal of the project is to identify ways to automatically detect psychological stress in humans. PPG sensors are ubiquitous especially in the form of wearable electronics /citecastaneda2018review which has led to a lot of research around predicting various bio-markers based on blood volume pulse signals generated by PPG sensors. This includes predicting heart rate, respiration rate, ECG signal, psychological stress, identifying unique bio identities, more.

In this project we specifically look at identifying stressful moments for humans in their day to day life. Psychological stress occurs when an individual perceives that environmental demands tax or exceed his or her adaptive capacity [8]. Stress is intuitively known to lead to various illness, both physical and emotional, but there is yet to be strong data to prove causal relationships [7]. Stress is known to impact functioning of prefrontal cortex [2] which can lead to sub-optimal decision making. Even though there are several modalities to detect stress, recent research has centered around using bio-markers from wearables to detect stress [10]. This has led to several publicly available datasets that attempt to detect bio-markers while placing subjects in stressful situations [9, 15, 14, 11]. These datasets are useful in identifying relationship between heart function and psychological stress.

However, the need for a wearable device is limiting. To overcome that, recent advancements in deep learning have led to the advent of computer vision based remote Photoplethysmography (rPPG) [17].

Combined with speech, a model that can detect psycological stress from PPG signals captured remotely from a camera might help detect speech cues that are indicative of stress. Although there has been research in the past to detect stress directly from speech, there are no publicly available datasets to the best of our knowledge yet.

Figure 1: Project Plan



We are aiming to address the following sub-tasks in this project: a) Develop a model to predict stress from Blood Volume Pulse b) Develop a model to estimate PPG BVP signal from video and detect stress from Video data c) Use the previous model to identify speech patterns that are indicative of stress.

As future work beyond this project, we hope to use the speech patters to train a classifier to identify stress form speech data alone.

[4] presents several uses of PPG data along with most commonly extracted features that are used for modeling. [15, 11] each present several classical machine learning techniques employed to model stress from PPG signals. This includes both time domain and frequency domain features while compensating for motion induced noise. Most common ML techniques applied were linear regression, KNN and SVMs.

[14] presents use of Convolutional Neural Networks for modeling heart rate directly from PPG signals which shows the ability of CNNs to develop a representation of PPG signals.

[16] shows promising results in detecting Atrial Fibrillation using PPG signals.

[12] shows ability to employ representation learning for PPG data which is then be used to detect stress.

2 Concise Summary

2.1 A review on wearable photoplethysmography sensors and their potential future applications in health care [4]

Focus: The article describes the workings of photoplethysmography (PPG) devices, their benefits, their limitations, and how the recorded readings are used to understand information about the heart.
Key Ideas: The article describes The workings of PPG devices and their configurations. It also describes typical characteristics of a heart beat and gives a good understanding of what constitutes a normal heart rhythm. The paper suggests that data from device accelerometers should be used to eliminate Motion Artifacts that distort the readings, but more research is needed in this area.

2.2 Heart Rate Estimation From Wrist-Worn Photoplethysmography: A Review [3]

Focus: Understanding PPG devices and overview of mitigation of distortions introduced by Motion Artifacts.
Key Ideas: This article also (like the previous one) describes the workings of PPG devices, but emphasizes on their usage in ambulatory environments. It dives deeper into mitigating the distortions caused by Motion Artifacts. It enumerates certain publicly available databases that contain PPG data. The paper then further describes algorithms (machine learning and otherwise) to estimate Heart-Rate (HR) from the PPG signal.

2.3 Introducing WESAD, a multimodal dataset for wearable stress and affect detection [15]

Focus: Released a multi-modal dataset for stress and affect detection from Wearable electronic devices
Key Ideas: Identified the lack of pre-existing multi-modal datasets for affect stress detection with multiple affective states. Dataset contained various signals (blood pulse volume, ECG, heart EMG, Skin temperature, EDA, Acceleration data) using both chest worn and wrist worn devices across 15 subjects. By employing hand crafted feature extraction the authors show a classification accuracy of 93% in the stress vs non-stress task. They show the efficacy of wrist worn vs chest worn devices on predicting stress. They study the efficacy of predictions using various combinations of features to estimate the reliability and importance of each kind of signal. They notice that self reported stress levels can be used to personalize stress detection models which was called out as potential future work.

2.4 UBFC-Phys: A Multimodal Database For Psychophysiological Studies Of Social Stress [11]

Focus: Released yet another dataset for stress detection including video data of subjects along with wrist based wearable signals.
Key Ideas: Identified the potential use of videos for stress detection. In addition to blood volume pulse and EDA signals from a wrist worn device, the authors captured video data of study subjects. They developed a model that detects stress based on pulse rate variability. They show that PPG signals extracted from videos directly (using rPPG techniques) is able to predict stress amongst their test subjects with 85% accuracy.

2.5 Probabilistic Estimation of Respiratory Rate using Gaussian Processes.[13]

Focus: A method that uses the framework of Gaussian process (GP) regression to extract respiratory rate
Key Ideas: This article proposed a method that uses the framework of Gaussian process (GP) regression to extract respiratory rate from the different sources of modulation in ECG. It brings out

the advantages of a probabilistic approach: Uncertainty in the estimation is directly quantified; and the output consisted of a predictive posterior distribution, rather than a single estimate Finally, due to the generative nature of the approach, it was possible to generate data from the model, which could be useful for estimating the behaviour of the respiratory rate during periods of missing data.

2.6 Deep ppg: Large-scaleheart rate estimation with convolutional neural networks[14]

Focus: Demonstrate the effectiveness of Deep Learning techniques in predicting heart rate from PPG signals.

Key Ideas: This paper presents a thorough, detailed evaluation of estimating heart rate from PPG BVP signals obtained by wrist worn devices. The authors talk about the limitations of SoTA classical ML techniques that use hand crafted signal processing features. They talk about the lack of large public datasets to train deep learning models. To address this limitation they release a new dataset which contains data from Chest wrist worn devices across 15 subjects, with a total of about 36 hours of data. With this new data they test the effectiveness of a new CNN based deep learning model on predicting stress. They identify a suitable CNN architecture by following pre-established architecture guidelines for computer vision models and testing it on older smaller datsets. With a suitable architecture identified and frozen, they train a model with randomly initialized weights on their new dataset and show that the CNN based model can reduce mean absolute error in heart rate estimation from PPG signals by 30%. They also talk about the importance of leave one out cross validation as a means to measure the ability of a model to generalize.

2.7 Destress: Deep learning for unsupervised identification of mental stress in firefighters from heart-rate variability (hrv) data [12]

Focus: Demonstrate the efficacy of various unsupervised learning techniques in detecting mental stress amongst firefighter trainees. **Key Ideas:** The authors collected data from 100 firefighter trainees participating in a drill. They tried multiple unsupervised learning techniques to identify clusters of stressed subjects. They used hand crafted features like RMSSD, Max-HR, Mean-HR and LF-HF ratio and run KNN clustering. They then use auto encoders using both LSTMs and CNNs against time domain PPG data and evaluate the use of embeddings from the encoders for clustering using DBSCAN and KNN clustering techniques. They identify that CNNs perform the best for identifying 2-D representations of PPG data and perform clustering to identify stress. They use hand crafted derived features published in past literature as a means of tagging clusters with stress vs non-stress states. This paper presents an alternative approach to using PPG data by first learning representations prior to developing various models from the data.

2.8 Ambulatory atrial fibrillation monitoring using wearable photoplethysmography with deep learning.[16]

Focus: Detect Atrial Fibrillation using just PPG data

Key Ideas: Demonstrated the use of a deep 50 layer CNN models (ResNeXt architecture) to detect atrial fibrillation using PPG signals collected from 81 subjects where part of the data was annotated by clinicians and the rest was assumed to be from healthy subjects. The model thus trained had an accuracy of 95% which is one of the best results observed thus far as part of this literature review in the space of PPG based models. The authors identify the structures learned by the initial stages of the model and identify them to be first and second derivatives which has been the common hand crafted features identified to be useful in past literature. The authors also show the ability for CNNs to not be impacted by motion artifacts which have been a source of noise in most previous PPG data standard models.

2.9 Assessing mental stress from the photoplethysmogram: a numerical study.[5]

Focus: Identifying features in PPG that are indicative of mental stress

Key Ideas: A method for assessing mental stress is to extract an index of stress from the photoplethysmogram (PPG). The PPG signal is a valuable source of physiological information, since it is influenced by the cardiac, vascular and autonomic nervous systems, which are all affected by stress. For instance, changes to parameters such as heart rate, blood pressure, and heart rate variability would be expected to influence the PPG signal. In addition, the PPG can be easily acquired using pulse oximeters, which are frequently used in healthcare to measure arterial blood oxygen saturation and pulse rate. Furthermore, the PPG can be acquired by a wide range of ubiquitous devices such as smartphones, tablets, and fitness devices. If it was possible to extract a measure of mental stress from the PPG then it may have great utility. The primary aim of this study was to identify features of the PPG pulse wave which are indicative of mental stress. Secondary aims were to compare different PPG measurement sites for assessing stress, and to analyse the physiological determinants of features which changed with stress. The study was performed using a novel approach to simulate PPG pulse waves numerically at different levels of stress.

2.10 Video-based stress detection through deep learning.[18]

Focus: Detect stress using video cameras using facial expressions and gestures.
Key Ideas: This article explores the use of videos for stress detection. The deep learning model(TSDNet) proposed in the article is to use the facial expressions and gestures that the subject performs in the video. The deep learning model is able to predict stress with overall accuracy of 85.42%. The article also brings out that the F1 score can be improved by about 7% when both facial expressions and gestures are used to predict stress. The authors have also created a dataset consisting of labelled video clips that is used to evaluate the performance of TSDNet.

2.11 Respiratory rate estimation from face videos.[6]

Focus: Detect respiration rate remotely using remote photoplethysmography obtained from face video.
Key Ideas: The authors propose a method to monitor simultaneously the respiration rate(RR), heart rate(HR) and HR variability(HRV) using the face video remotely. The proposed method uses motion compensation, a two-phase temporal filtering, and signal pruning to reduce the noise in the video. The model attains a peek accuracy of about 73%. The paper establishes that proposed method is feasible and effective in measuring RR remotely when the video is captured at rest.

2.12 Smartphone-based respiratory rate estimation using photoplethysmographic imaging and discrete wavelet transform. [1]

Focus: Detect respiration rate(RR) using video of skin surface.
Key Ideas: The proposed method is able to predict respiration rate (RR) with an accuracy of about 97.8% using video of the skin surface. The dataset comprises of video of fingertips using mid-range smartphone, along with Plethysmography signals using dedicated hardware for validation. The method uses three-level discrete wavelets transformation to make the prediction.

3 Compare and Contrast

Until the last few years, hand crafted signal processing features have been the mainstay of research around predicting bio-markers and effective states from commonly available PPG data. These features are often representative of the temporal distributions of the underlying data. Many SoTA techniques use frequency domain estimates to develop spectral graphs which are then used for modeling. Overall these techniques either require strong domain knowledge (of the vascular system), or experience with common signal processing techniques. They are tedious to follow and estimate, and do not offer consistent results across various datasets as shown in [14].
Recent research from ([14, 16, 12] show the ability for CNNs to identify patterns in PPG data and learn representations which can be used for various tasks including stress detection. With the release of larger datasets containing PPG signals, deep learning models can play a major role in improving the usefulness of wearable devices and open up more avenues for identifying further bio-markers from PPG data.

Comparing [4] with [3], both the papers describe characteristics of the PPG devices. The former however focus on describing the features of the heart beat which help us identify regular v/s. irregular rhythms. The latter dives deeper into some of the topics such as types of LEDs used, configurations of PPG devices with better terminology.

[4] describes that the PPG devices can monitor Heart Rate Variability (HRV), glucose measures, blood pressure readings, etc. while being characterised by simplicity, mobility and cost effectiveness, and limited by inaccurate readings dur-

ing physical exercises, activities and motion artifacts. The article describes the major components and configurations of of PPG devices. It further describes characteristics of a typical heartbeat - anacrotic i.e. systole (rise) and catacrotic i.e. diastole (fall). The second derivative of the wave reveals a lot of information about the heart including illnesses.

While [4] only touches on the surface of mitigating distortions introduced by Motion Artifacts, merely suggesting use of an accelerometer to mitigate the same, [3] explores the topic in length and breath, touching upon common MA removal techniques and evaluation metrics, algorithms that emphasize on reduced complexity. The ML algorithms explored in [3] are a helpful addition over [4]. But both the papers do a good job of expanding our domain knowledge about PPG devices so that we can understand what the features mean in the dataset.

[3] lays emphasis on computational lightness because of the size constraint of the PPG devices. They found that random forest gave a good performance, where a three layer network of Restricted Boltzmann Machines gave an accuracy of 95.4% on the SPC training dataset. They also got good results on using Deep Learning models like CorNET in terms of Average Absolute Error (AAE). The Paper also talks about detection of other heart diseases like Atrial Fibrillation (AF). It talks about a research done by Philips that used a first order Markov Model to study the probability of AF causing Irregular Rhythms with $97 \pm 2\%$ sensitivity and $99 \pm 3\%$ specificity (dataset unavailable). Another research performed classification in time domain features and applied SVM was able to achieve an accuracy of 93.85%.

One of the main constraints of deep learning models is the amount of compute needed for predictions as the models are often very large. [14] shows the possibility of shrinking both the model and performing quantization to make them work reasonably on embedded devices.

The proposed methods in [18, 1, 6] explores the possibility of obtaining estimates of respiratory rate from videos. All the three approaches were able to obtain good accuracy, however they were all susceptible to noise. The uncertainty associated with the estimated value cannot be directly quantified, due to the nature of the algorithms employed. The failure of existing methods to estimate respiratory rate accurately in actual patients, rather than healthy volunteers, motivated the probabilistic approach in [13]. This method used a framework of Gaussian process (GP) regression to extract respiratory rate from the different sources of modulation in a single-lead ECG. This brings all of the advantages of a principled, probabilistic approach, and the output may consist of a predictive posterior distribution, rather than a single estimate. This is useful if the estimate of the respiratory rate is to be used as the input to a subsequent probabilistic inference system, where knowing the full distribution of the input is more informative than a point estimate. Since it is generative in nature, it is possible to generate data from the model, which can be useful for estimating the behaviour of the respiratory rate during periods of missing data.

4 Future Work

[14] used frequency domain (FFT) features while [16] used the time domain PPG signals directly. In this project, the usage of time domain features will be explored since it is a) proven to work for a related use case, b) involves less computation, c) can represent temporal relationships, and d) called out as an exploratory task in [14].

The application of representation learning is especially interesting because it can potentially help build simpler models to detect various biomarkers from PPG data without having to build task specific models. Development of embeddings have been key for the recent advancements in Natural Language Processing. As part of this project we will evaluate development of PPG embeddings using autoencoders and then apply both classical machine learning techniques like SVMs and GMMs, as well as deep neural networks to evaluate their efficacy in predicting stress from PPG data and compare it with the benchmark results published for individual datasets. To cross-validate the efficacy of the embeddings, they can be used on the heart rate prediction task benchmarked in [14].

[14] suggests the importance of using Leave-one-out cross-validation where in the case of PPG data segmentation is tied to test subjects as each individual has different cardiac functional characteristics. Models can often be tuned for a specific combination of dev and test sets which isn't a good measure of generalization. To counter this, as part of this project, we will have a dedicated dataset that will be useful solely for testing generalization of the

model.

Meanwhile, the main dataset used for training will be split into dev, validation and test sets where each segment of the test data will be used as a test set just once. The natural boundary for splitting the dataset will be based on test subjects as each one has varying heart characteristics.

References

[1] Maha Alafeef and Mohammad Fraiwan. "Smartphone-based respiratory rate estimation using photoplethysmographic imaging and discrete wavelet transform". In: *Journal of Ambient Intelligence and Humanized Computing* 11.2 (Feb. 2020), pp. 693–703. ISSN: 18685145. DOI: 10.1007/s12652-019-01339-6.

[2] Amy FT Arnsten. "Stress signalling pathways that impair prefrontal cortex structure and function". In: *Nature reviews neuroscience* 10.6 (2009), pp. 410–422.

[3] Dwaipayan Biswas et al. "Heart Rate Estimation From Wrist-Worn Photoplethysmography: A Review". In: (2019).

[4] Denisse Castaneda et al. "A review on wearable photoplethysmography sensors and their potential future applications in health care". In: *International journal of biosensors & bioelectronics* 4.4 (2018), p. 195.

[5] Peter H Charlton et al. "Assessing mental stress from the photoplethysmogram: a numerical study." In: *HHS Public Access* (2018). DOI: 10.1088/1361-6579/aabe6a.

[6] Mingliang Chen et al. "Respiratory rate estimation from face videos". In: *2019 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2019 - Proceedings*. Sept. 2019. ISBN: 9781728108483. DOI: 10.1109/BHI.2019.8834499. arXiv: 1909.03503. URL: http://arxiv.org/abs/1909.03503%20http://dx.doi.org/10.1109/BHI.2019.8834499.

[7] Sheldon Cohen, Denise Janicki-Deverts, and Gregory E Miller. "Psychological stress and disease". In: *Jama* 298.14 (2007), pp. 1685–1687.

[8] Sheldon Cohen, Ronald C Kessler, Lynn Underwood Gordon, et al. "Strategies for measuring stress in studies of psychiatric and physical disorders". In: *Measuring stress: A guide for health and social scientists* (1995), pp. 3–26.

[9] "Cup I.S.P. Heart Rate Monitoring During Physical Exercise using Wrist-Type Photoplethysmographic (PPG) Signals." In: (2015). URL: https://sites.google.com/site/researchbyzhang/ieeespcup2015.

[10] Giorgos Giannakakis et al. "Review on psychological stress detection using biosignals". In: *IEEE Transactions on Affective Computing* (2019).

[11] Rita Meziatisabour et al. "UBFC-Phys: A Multimodal Database For Psychophysiological Studies Of Social Stress". In: *IEEE Transactions on Affective Computing* (2021).

[12] Ali Oskooei et al. "Destress: deep learning for unsupervised identification of mental stress in firefighters from heart-rate variability (hrv) data". In: *Explainable AI in Healthcare and Medicine*. Springer, 2021, pp. 93–105.

[13] Marco A.F. Pimentel et al. "Probabilistic Estimation of Respiratory Rate using Gaussian Processes". In: *35th Annual International Conference of the IEEE EMBS* (2013).

[14] Attila Reiss et al. "Deep ppg: Large-scale heart rate estimation with convolutional neural networks". In: *Sensors* 19.14 (2019), p. 3079.

[15] Philip Schmidt et al. "Introducing wesad, a multimodal dataset for wearable stress and affect detection". In: *Proceedings of the 20th ACM international conference on multimodal interaction*. 2018, pp. 400–408.

[16] Yichen Shen et al. "Ambulatory atrial fibrillation monitoring using wearable photoplethysmography with deep learning". In: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2019, pp. 1909–1916.

[17] Arindam Sikdar, Santosh Kumar Behera, and Debi Prosad Dogra. "Computer-vision-guided human pulse rate estimation: a review". In: *IEEE reviews in biomedical engineering* 9 (2016), pp. 91–105.

[18] Huijun Zhang et al. "Video-based stress detection through deep learning". In: *Sensors (Switzerland)* 20.19 (2020), pp. 1–17. ISSN: 14248220. DOI: 10.3390/s20195552.

xcs229ii-scpd

More unreads

introductions
lecture-questions
problemset1
problemset2
problemset3
project-experimentalproto...
project-finalpaper
project-litreview
project-proposal
teamformation-projectideas
project_team
Add channels

Direct messages

Slackbot
Ketki Ambekar you g...
Andrey Koch (CF)
er.vaidic guest
er.vaidic, Petra Parikova, Pr...
Hamima Nasrin guest
insop (CD)
Khalid El-Awady (CF)
Pradeep Ramadasan guest
Suraj Menon (CF)
Vishnu Kannan guest

#project-litreview 104

Yesterday

Today

Vishnu Kannan 00:06

Peeps, here's our literature review on the topic of detecting psychological stress from commonly available PPG data which can be estimated using wearable sensors or remotely from skin captures using rPPG techniques. We learned a lot as part of this review process. If you are curious about wearables, biomarkers and health analysis, this might be worth a glance.

PDF

XCS_229ii_project_literature_reviev
221 kB — Click to view

Literature Review for Detection of Stress using Photoplethysmography Signals

Vishnu Kannan vishnukannan@gmail.com
Ketki Ambekar ambekar.ketki@gmail.com
Vaidic Joshi er.vaidic@gmail.com
Pradeep Ramadasan pradeep.ramadasan@gmail.com

Abstract

This paper presents a review of past literature on the topic of predicting psychological stress using commonly available Photoplethysmography (PPG) signals. After establishing

datasets that attempt to detect bio-markers while placing subjects in stressful situations [9, 15, 14, 11]. These datasets are useful in identifying relationship between heart function and psychological stress.

1 2 1

Jim Samuel 00:55

Folks, Please find attached our XCS 229ii Lit. Review for Machine Learning Based Textual Data Distributions, Topics Generation & Alignment on Vaccine & Stock Data.
By:

Message #project-litreview

Aa