A sparse generative model for Heart rate signals.

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1 Introduction

For many years the human heart has been considered as the primary source of emotion courage and wisdom but as new research frontiers are explored it is brought to light that the human heart is not only an efficient pump that sustains life but an access point to the source of intelligence, a highly complex information processing center with its own functional brain. [1]. A deeper understanding of the neural and other communication pathway between the heart and the brain has led to the belief that stressful emotion affect the Autonomic Nervous System(ANS) in ways so as to make the beat-to-beat interval vary over time. Ranging from social engagement to highly strenuous physical activity the ANS mediates in most aspects of our life via its two main branches i.e the Sympatheitc Nervous System(SNS) and the Parasympathetic Nervous system(PSNS). While our response in flight or freeze scenarios have been attributed to the SNS our social behaviour can be largely attributed to the activity of the Vagal nerve mediated by the PSNS.

Heart rate estimated at any given instant represents the total effect of the neural output of the parasympathetic (vagus) and the sympathetic nerves. In a denervated human heart in which there are no connections from the ANS to the heart the intrinsic rate generated by a pacemaker (SA node) is about 100 BPM. Parasympathetic activity predominates when HR is below this intrinsic rate during normal daily activities and when at rest or sleep. When HR is above 100 BPM, the relative balance shifts and sympathetic activity predominates. The average 24-hour HR in healthy people is 73 BPM. The high frequency HR variations are often attributed to parasympathetic activities and is frequently called the respiratory band because it corresponds to the HR variations related to the respiratory cycle known as respiratory sinus arrhythmia.(RSA) Hence heart rate and its variance can be excellent markers of one's social functioning. It can also serve as an assessment tool for many cardiovascular disease diagnosis and a non-invasive method for assessing autonomic functioning [2].

Traditionally, heart rate has been known to be calculated from a dedicated medical electrograph but recently hand held devices like mobile phones have been shown to be very usefeul to collect Heart Rate(HR) data. [3] extracted HRV from Photoplethysmograms obtained by the camera of smartphone. Therefore, with the shift in the data collection modalities there has been a deluge of heart rate data.

2 Proposed Activities

- Most of the statistical models so far have not taken the arythmic component into account while building the generative model.The arythmic component or the Vagal component is an important modulator of the heart rate. The arythmic component is largely affected by the respiratory cycle. The arythmic component, more prominent during relaxation, has been known to be a pre-cursor of the PSNS. Some of the papers have tried to separate the component using Respiratory belt signal as a control input to an adaptive filter [4]. This seems to be a more or less supervised method of separating the arythmic component. We propose to remove the arythmic component in an unsupervied manner. We use the Respiratory belt signal only to validate our estimate.

- We propose a sparse generative model to learn the latent patterns present in the PRV data. We will validate our model with experimental data obtained from the DEAP dataset[5]. The data set has various arousal scales we divide the aroual scale into low, neutral and high. For each catergory we use knoweledge based dictionary to learn the latent pattern in the category.Therefore, given a category of arousal we use a linear combination of the learned kernels for that category to simulate the HR time signal.

- We further propose to predict audience's rating of the video clip from their Heart rate responses.We validate our prediction against the feedback given by the audience after each video clip.

References

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