

Application of Heart Rate Variability (HRV) in Congestive Heart Failure (CHF) Detection and Quantification

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Declaration

I, Wenhui Chen declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and IT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

Congestive heart failure (CHF) is one of the most important cardiovascular syndrome and end stage of all kinds of heart diseases. Due to high mortality and morbidity, risk assessment of patient suffering CHF has attracted many attentions. The existing research about CHF assessment mainly focused on disease detection using ECG signals, especially with 24-h/5-min heart rate variability (HRV), both in mechanism analysis and classification. A significant relation between different ECG components and disease condition had been proved. Furthermore, a good classification performance had been achieved in CHF detection using HRV. However, there is not much attention focusing on multilevel assessment of CHF, i.e. disease detection and quantification. Also, sleep apnea and CHF are two of the most common diseases and interrelated, which are hard to differentiate from the syndrome. But there is no research in differentiating the two diseases. Besides, RR intervals are sensitive to physiological activity and rhythm, increasing unstable analysis and results. Thus, this research will devote to ECG analysis and multi-level risk assessment model construction to achieve robust, convenient and accurate CHF detection and quantification, as well as underlying mechanism analysis.

In this research, 116 RR interval data were downloaded from MIT/BIH database, including 72 normal persons and 44 CHF patients. First, we analyzed 24-h RR intervals and proposed a series of novel indices of HRV - dynamic indices - to better describing difference among different risk levels of CHF patients in a day. Then we applied the decision-tree based support vector machine and backward elimination algorithm to construct a 4-level risk assessment model for CHF assessment. Results showed a total accuracy of 96.61% with only two misclassified samples. This demonstrated the stratifying risk assessment model of CHF in our research has the potential to be a

reliable and objective prognostic marker for the routine clinical application (especially daily health nursing) in the future.

Then, we applied 5-min RR intervals into a unsupervised sparse-auto-encoder based deep learning algorithm to explore CHF detection performance under short cycle in big data condition. A total of 30592 5-min RR intervals was obtained from 72 healthy persons and 44 CHF patients. This algorithm first extracts unsupervised features using a sparse auto-encoder neural network from the raw RR intervals. Then a two layers' neural network model was constructed. Various hidden node settings were compared to optimize classification performance. Results showed an accuracy of 72.44% in CHF detection under the constructed 2-layer neural network, and optimal nodes setting is (200, 50). This result indicated that short-term RR intervals have the potential for CHF detection but is sensitive to body condition.

Next, we analyzed different time scale of HRV from 5-min to 24-h to explore optimal time scale for CHF detection and quantification. Statistical analysis between 3-level risk-groups was applied under 10 classical HRV measures to evaluate differentiating power in risk assessment of CHF for the optimal time scale. With the optimal time length, we used classical classifiers with these classical HRV measures in 3-level risk level classification of CHF, to prove the usage in risk assessment. The statistical analysis of HRV measures showed that 2-h RR interval data has the optimal performance in differentiating three risk levels. The classification performance showed that the optimal timescale of 2-hour for CHF assessment, yielded an comparable accuracy of 87.88% and 81.13% for classifying the healthy from patients and lower risk from higher risk patients, respectively. This research demonstrated that the optimal measurement timescale (2h) has potential in providing convenient and reliable CHF assessment in the future application, especially in-home monitoring.

Finally, we analyzed whole night Polysomnography (PSG) data to differentiating congestive heart failure and sleep apnoea patients, which are two of the most tightly interrelated and common diseases in cardiopulmonary system. Twenty whole night PSG data from the Sleep Heart Health Study database were included in this study. The Pan-Tompkins algorithm was applied to the electrocardiograph signal to detect R peaks of the QRS complex. The whole night R peaks data were then manually checked and

segmented into 1895 5-minute epochs to calculate three frequency domain and three nonlinear heart rate variability measures. All these measures were analyzed for their statistical differences between groups (sleep apnea with and without CHF). Finally, a binary support vector machine classifier and extreme search method were performed to construct the model. Results showed that an accuracy of 81.68% was achieved in distinguishing sleep apnea patients with and without CHF. This indicated that HRV measures from PSG had the potential to help distinguish sleep apnea patients with and without CHF reported.

In conclusion, with all these analyses of ECG signals in congestive heart failure classification, we proved the potential of HRV from ECG in robust, accurate and convenient congestive heart failure assessment using intelligent methods, which can be applied in home-monitoring with wearable ECG measurement equipment.

Publications

The contents of this thesis are based on the following papers that have been published, accepted, or submitted to peer-reviewed journals and conferences.

Journal Papers:

1. Wenhui Chen, Lianrong Zheng, Kunyang Li, Qian Wang, Guanzheng Liu, and Qing Jiang. "A novel and effective method for congestive heart failure detection and quantification using dynamic heart rate variability measurement." *PloS one*, 11(11), e0165304, 2016.
2. Wenhui Chen, Guanzheng Liu, Steven Su, Qing Jiang, and Hung Nguyen. "A CHF detection method based on deep learning with RR intervals." 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2017.
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4. Wenhui Chen, Qing Jiang, Steven Su, and Hung Nguyen. "Automatic Risk Assessment of Congestive Heart Failure Using ECG at Optimal Time scale." (Submitted for publication).

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2. Wenhui Chen, Prof. Yifan Chen, MD B. Uddin, Prof. Hung Nguyen, Chin M. Chow, and Steven W. Su. "An Automatic Method to Differentiate Sleep Apnea Patients with and without Congestive Heart Failure using Polysomnography Records." In The 13th IEEE-EMBS International Summer School and Symposium on Medical Devices and Biosensors (MDBS' 2019), IEEE, 2019.

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