Background

Tuberculous pericarditis is found in 1 to 2% of instances of pulmonary TB and is the most common cause of pericarditis in Africa [1]. Up to 40% of patients die of sudden cardiac death in the first few months following diagnosis due to fluid build up on the heart. Treatment typically involves antibiotics and, in cases of tamponade (severe compression of the heart due to fluid in the pericardium), pericardial drainage. In rural and low-resource, with limited access to health facilities, patients often die before they can come into the clinics for treatment.

One of the earliest physiological compensatory mechanisms for the reduced stroke volume caused by a rise in pericardial pressure is the increase in heart rate (HR). Therefore, the aim for the reduced stroke volume caused by a rise in pericardial drainage.

Remote HR Monitoring

- Patient monitoring & self-management
- Record heart sounds
- Transmit via GSM network
- Automated heart rate monitoring
- Early warning of patient deterioration

Auscultation using smartphones

Chen et al. adapted the well-known Pan & Tompkin’s QRS detection algorithm [2] for identifying S1 and S2 heart sounds in audio recordings made using an iPhone 3GS and a HTC G1 smart phones [3]. S1 and S2 heart sounds were classified using a inter-heart sound interval distribution approach that resulted in 88.4% positive predictivity and 92.1% sensitivity for S1 detection in an clinical data set. An example of the algorithm performance is shown in the figure below.

Heart sound recording using low-cost mobile phones

- Nokia 1202 Classic (£10)
- Connect hands-free kit to ‘stethoscope’ based on prototype proposed by [4]
- Stethoscope made from egg cup, rubber o-ring and transparency sheet
- Record heart sounds via VoIP over GSM network

HR monitoring

The adaptive thresholding was introduced into the algorithm, proposed by Chen et al [3]. Furthermore, k-means heart sound classification was implemented to detect S1, S2 and missed beats. The heart rate was determined by firstly using a 9-point median filter of the S1-S1 intervals and S2-S2 intervals. The heart rate is judged to be the average of the median S1 and S2 heart rates.

Results

The HR estimation algorithm was assessed on a clinical data set comprising of simultaneous ECG and heart sounds recordings from 148 health adult volunteers [5]. The heart rate was determined for both the ECG (using Pan & Tompkin’s QRS detection [2]) and the estimation procedure described above.

Figure 1 shows a Bland-Altman plot of ECG and audio HR estimates

Conclusion

The HR estimation algorithm found a mean difference of 3 bpm across all 148 patients, with an R² value of 0.68 within the 98% confidence interval. The feasibility of using low-cost mobile phones to monitor HR in low-resource areas is hopeful.

References


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