THE ACCURATE ASSESSMENT OF HEMORRHAGE IN THE FIELD USING SIMILARITY BASED MODELING

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BACKGROUND

Accurate and early assessment of hemorrhage in the field is essential for the initiation of optimal prehospital care. At present this is done using clinical signs and symptoms. Stroke volume (SV) is a primary indicator of the degree of central blood volume, but measurement is not feasible in the field. The purpose of this study was to assess the efficacy of similarity based modeling (SBM) in predicting SV based on data collected from a noninvasive wearable sensing device.

METHODS

10 subjects wore a wearable sensing device during lower body negative pressure (LBNP), an experimental model of hemorrhage used in conscious humans. The device measures: activity, heart rate (HR), HR variability, pulse transit time, respiratory rate, O_2 saturation and tidal volume. A progressive LBNP protocol was applied which produced profound central hypovolemia; LBNP was stopped at the point of cardiovascular collapse (i.e., presyncope). A finger cuff blood pressure monitoring device (Finometer) provided a reference beat-to-beat measurement of SV. SBM was trained using the sensing device data and subsequently to generate off-line estimates of SV. The reference SV measurements were used to assess the accuracy of the SBM model.

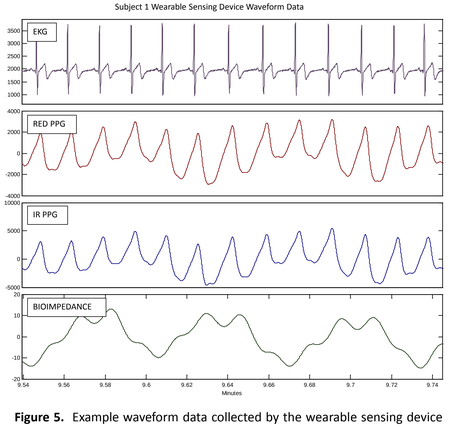

Figure 5. Example waveform data collected by the wearable sensing device (Figure 3) for subject 1 during the LBNP experiment. The data shown are sampled at 256 Hz. 3D accelerometer data are as acquired at a sampling rate of 100 Hz. The physiological features are generated from these waveform data.

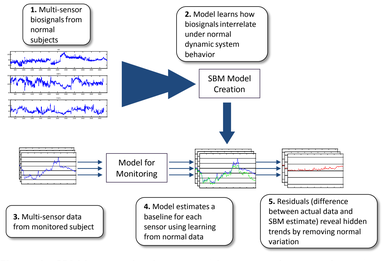

Figure 1. SBM is a multivariate data driven modeling technique that is most often used to monitor complex systems in order to detect anomalous behavior. An example is the human cardiopulmonary system. Historical data representative of normal (or baseline) system behavior are used to train SBM for subsequent use during monitoring. Anomalous behavior is detected by examining the differences between the input variables and the corresponding SBM estimates of those inputs.

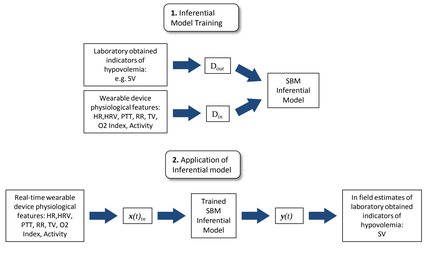

Figure 2. In this study SBM was used in a less typical modeling mode than described in Figure 1. The goal was to generate an estimate of a variable that cannot effectively be measured in the field but is a good indicator of the progression of hypovolemia [1, 2]. SBM was trained to provide an inferential estimate of SV based on a set of physiological feature variables that can be noninvasively measured in the field using a wearable sensing device. To train SBM, data collected during LBNP experiments were used from both the wearable device and the laboratory blood pressure device (for measuring SV).

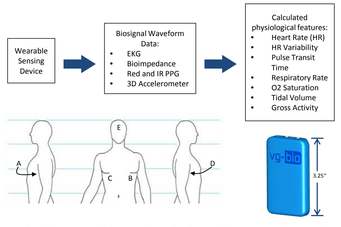

Figure 3. The wearable sensing device collects waveform data from chest electrodes (A, B, C, D) and a forehead reflectance PPG sensor (P). The outer electrodes (A and D) provide a high frequency low current source for measuring bioimpedance. The inner electrodes (B and C) measure the response to the source current from which impedance across the lower chest is calculated. The B and C electrodes are used simultaneously to capture EKG waveform data. Both Red and IR PPG waveforms are captured by the reflectance sensor on the forehead (E). The set of physiological features used as input to the SBM model are generated from the acquired waveform data.

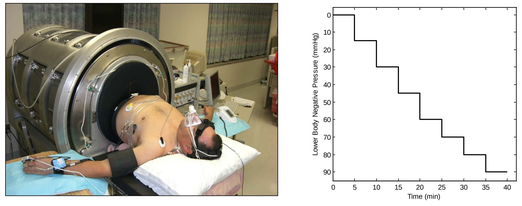

Figure 4. A subject in the LBNP device and experimental protocol. The pressure inside the LBNP chamber is first reduced by steps of 15 mmHg for 5 minute intervals. Once the pressure is reduced by 60 mmHg the pressure reduction steps are reduced to 10 mmHg. The protocol progresses until the point of presyncope (decrease in blood pressure and/or presyncopal symptoms)

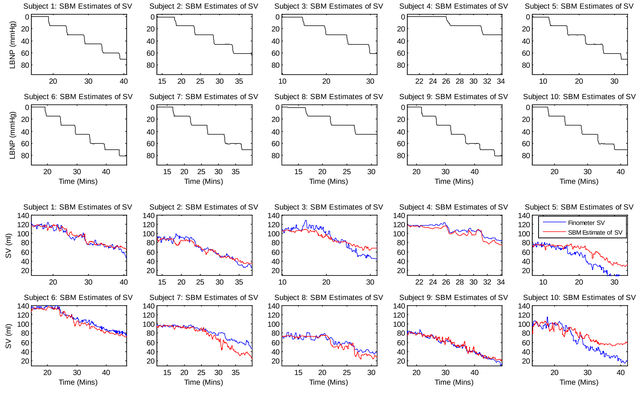

Figure 6. LBNP experiment results. The top two rows show the stages of the LBNP protocol that each subject progressed to. In each case, the experiment was stopped at the point of presyncope. The bottom two rows show the corresponding SBM estimated and reference SV values for each subject. Given the relatively small sample size for the study, a "leave-one-out" cross-validation approach was used to generate separate SBM models for each of the 10 subjects using data from the remaining 9. Utilizing this approach avoids over-fitting to a subject's own acquired data while maximizing the SV range covered by the training data. This is also representative of how SBM would be applied in the field, i.e. SBM trained using laboratory data and then applied to patients in the field that were not part of the laboratory data collection experiments.

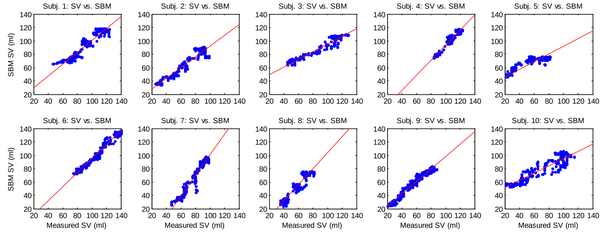

Figure 7. Plots of the SBM SV estimate versus the reference measurement of SV are displayed in blue. A regression line is shown in red. These results demonstrate good correlation between the SBM SV estimate and reference SV. However, the SBM SV estimates for Subjects 3, 5, 7 and 10 showed bias during a portion of the data (stronger nearer to the end of the experiment) as evidenced in Figure 6 and the fact that the regression line des not go through the origin. This is not unexpected given the small sample size.

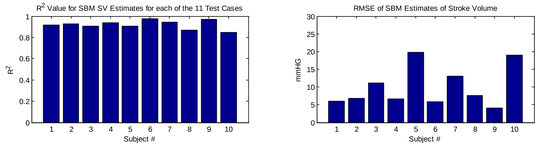

Figure 8. The left bar graph shows the R^2 values for the SBM SV estimates compared to the reference SV values for each subject. The mean and median values for the R^2 values were 0.92 and 0.93 respectively with p-values << 0.001. The standard deviation of the R^2 values was 10 ml. The right graph shows the corresponding RMSE values for each case.

RESULTS

SBM estimates of SV were highly correlated with reference SV measurements. The mean and median r^2 values for the SBM estimates were 0.92 and 0.93 respectively (p-values << 0.001) and the standard deviation was 10 ml. The SBM SV estimate results for 4 out of the 10 subjects showed bias towards the end of the experiment. This is because the variation in the data increases as the LBNP experiment progresses due to the differences in each subjects physiological response to the protocol. A larger sample size would provide additional training data samples during this time of increased variation, which would likely reduce the biasing effects. Nonetheless, clear SV trends indicative of central hypovolemia were apparent in all subjects.

CONCLUSION

SBM-based estimates of SV were highly correlated with reference measurements of SV. SBM-based algorithms could easily be embedded into noninvasive, wearable devices for real-time determination of SV in the field.

ACKOWLEDMENTS

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2. Cooke WH, Ryan KL, Convertino VA, Lower Body Negative Pressure as a Model to Study Progression to Acute Hemorrhagic Shock in Humans, *J Appl Physiol* 96: 1249-1261, 2004.