Monitoring of Stroke Volume through Impedance Cardiography Using an Artificial Neural Network

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***Abstract*—Impedance cardiography is a noninvasive technique for estimation of stroke volume (SV), based on monitoring the variation in the thoracic impedance during the cardiac cycle. The current SV calculation methods use parameters obtained by ensemble averaging of the waveform along with equations based on simplified models of the thoracic impedance and aortic blood flow profile. They often result in inconsistent estimates when compared with the reference techniques. An investigation is carried out for beat-by-beat monitoring of SV using an artificial neural network with a set of input parameters as used in the different SV equations. A three-layer feed-forward neural network is used and the impedance cardiogram parameters are obtained using an algorithm for beat-by-beat automatic detection of the characteristic points. The training and testing are carried out using the SV values obtained from Doppler echocardiography as a reference technique after alignment of the signals from the two techniques. Results from the data from six subjects with recordings under rest and post-exercise conditions show the neural network based estimation to be more effective than the estimations based on SV equations.**

Keywords— artificial neural network; impedance cardiography; stroke volume

I. INTRODUCTION

Stroke volume (SV) is the amount of blood ejected by the ventricle in one cardiac cycle [1] and it is an important parameter for assessing the functioning of the cardiovascular system. Cardiac output (CO) is the amount of blood pumped by the heart in one minute and is obtained by multiplying SV with the heart rate [2]. The conventional techniques to estimate stroke volume are based on Fick, dye dilution, and thermo-dilution [3]. In addition to being invasive and non-continuous, they also have limitations of use in many heart patients due to the risks involved in the clinical procedure [2]. Doppler echocardiography and esophageal echocardiography are the more commonly used techniques for SV estimation [4], [5].

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Impedance cardiography is a noninvasive technique for SV estimation by monitoring the variation in thoracic impedance during the cardiac cycle [2], [6]. The first derivative of the variation in thoracic impedance is known as impedance cardiogram (ICG). As the ICG signals are contaminated by motion and respiratory artifacts, ensemble averaging of the sensed waveform is generally employed to suppress the artifacts [2], [7]. It leads to averaging of latencies and distortion in the ICG features and therefore the estimated parameters from ICG may not be well related to SV. Several equations have been proposed for SV estimation and these are generally based on a model of the variation of the thoracic impedance. These equations have considered blood flow profile only at the start of the ejection along with the person-specific scaling factors, which may lead to biased estimation. To address these shortcomings, we propose the use of an artificial neural network trained with beat-by-beat data for tracking the relationship between the ICG parameters and SV without using models of the thoracic impedance and aortic blood flow profile.

A review of SV estimation methods using equations is presented in the second section. The third section describes the use of artificial neural network for SV estimation. Experimental methods are presented in the fourth section and the results and discussion are presented in the fifth section, followed by conclusion in the last section.

II. EQUATIONS FOR SV ESTIMATION

The ICG waveforms are characterized by characteristic points; A, B, C, X, and O as shown in Fig. 1. The C point is the maximum rate of change in thoracic impedance $\left(-dZ/dt\right)_{\max}$. The B point is the deflection preceding the C point and coincides with the aortic valve opening. The X point is the lowest point after the C point and is associated with the aortic valve closure. The A point is the deflection before the B point and it normally (under steady-state condition) coincides with the contraction of atria [8], [9]. The O point is the peak

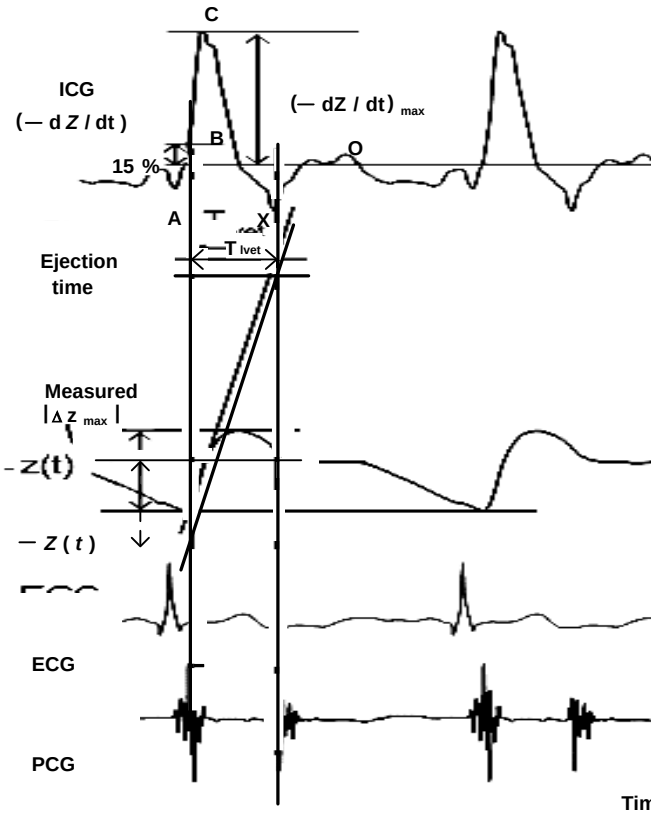

Fig. 1. ICG and other related signals, adapted from [6].

after the X point and it normally coincides with the wide opening of mitral valve.

Nyboer *et al.* [10] modelled the body segment under measurement as a cylindrical conductor to determine the segmental blood volume using impedance plethysmography and related change in impedance with change in volume of the body segment during the cardiac cycle as

$$\Delta V = -\rho \frac{L^2}{Z^2} \Delta Z \tag{1}$$

where, ΔV = volume change (mL), L = length of the thoracic segment modelled as a conductor of fixed length (cm), Z = total impedance of the segment (Ω), ρ = resistivity of blood (Ω-cm), ΔZ = maximum change in the impedance (Ω).

Subsequent to Nyboer's work, several SV equations have been proposed: some are based on physiological models and some are empirically obtained. Kubicek *et al.* [2], using a parallel conductor model of the thorax, developed the following equation for calculating SV from the left ventricular ejection time and maximum value of impedance cardiogram:

$$\mathrm{SV}_{\mathrm{Kubicek}} = \rho \frac{L^2}{Z_o^2} \left(-\frac{dZ}{dt} \right)_{\max} T_{\mathrm{lvet}} \tag{2}$$

where, L is the distance between the voltage sensing electrodes (cm), Z_0 is the basal impedance (Ω), $\left(-dZ/dt\right)_{\max}$ is the maximum value of rate of change in impedance (Ω/s), and T_{lvet} is the left ventricular ejection time (s).

Sramek and Bernstein [11] replaced the cylindrical conductor in the parallel conductor model of thorax with a truncated cone and used scaling factors based on height and weight as a correction to the Kubicek equation resulting in the following equations:

$$\mathrm{SV}_{\mathrm{Sramek}} = \frac{L^3}{4.25} \frac{\left(-dZ/dt\right)_{\max}}{Z_0} T_{\mathrm{lvet}} \tag{3}$$

$$\mathrm{SV}_{\mathrm{Sramek\text{-}Bernstein}} = \frac{\delta L^3}{4.25} \frac{\left(-dZ/dt\right)_{\max}}{Z_0} T_{\mathrm{lvet}} \tag{4}$$

where, δ is the ratio of the actual body weight to the ideal body weight. Later Bernstein *et al.* [12] modelled thorax as a multi-component parallel conductor for deriving SV equation. They used empirically derived intra-thoracic blood volume approximated as function of weight and a square root transform of the maximum value of impedance cardiogram normalized with the basal impedance as the following:

$$\mathrm{SV}_{\mathrm{Bernstein}} = \frac{V_{ITBV}}{\zeta^2} \sqrt{\left(-dZ/dt\right)_{\max} / Z_o} \; T_{\mathrm{lvet}} \tag{5}$$

where, V_{ITBV} is the intra-thoracic blood volume approximated as $16W^{1.02}$ with W the body weight (kg), ζ is the index of transthoracic conduction given as

$$\zeta = \left[Z_c^2 - Z_c Z_o + K \right] \Big/ \left[2Z_c^2 + Z_o^2 - 3Z_c Z_o + K \right]$$

with Z_c as a critical impedance taken empirically as 20 Ω. None of the above reported equations have been established for giving accurate estimation of SV under clinical conditions.

Several researchers have reported the usefulness of ICG for beat-by-beat monitoring of SV particularly during transient states, and its clinical significance [2], [13]-[17]. Kim [18], reported the possibility of diagnosing the cardiovascular diseases related to pulmonary artery, dilated cardiomyopathy, aortic stenosis and other valvular diseases by monitoring the SV during exercise. A study by Zang *et al.* [19], reported that ICG can be used to monitor cardiovascular function under transient conditions, involving ECG and ICG recordings from healthy volunteers in supine, upright, and sitting positions. Sherwood *et al.* [20], reported that the ICG may be useful for assessing the effect of physical exercise, sleep, and use of drugs on the cardiovascular system. A study by Wong *et al.* [21], involving 22 normotensive subjects, reported that ECG and ICG together can be used for monitoring the systolic blood pressure. Due to lack of high repeatability in the results and somewhat poor agreement of the results with those obtained from the reference methods, ICG is still not considered as a replacement for the existing methods for clinical diagnosis, continuous monitoring in intensive care unit, and in emergency departments. The limitations of

impedance cardiography in SV estimation can be primarily attributed to the fact that the existing SV estimating equations are derived from simplified models of thoracic impedance with several assumptions. Since artificial neural network (ANN) based models can track the nonlinear relationship between input and output, it is proposed that an ANN model based SV estimation can be used to avoid the assumptions in the existing thoracic impedance model based methods.

III. ANN BASED SV ESTIMATION

It has been reported [22] that a three-layer feed-forward neural network with Levenberg-Marquardt or gradient decent class of learning algorithm can track a nonlinear input-output relationship. Normally, input layer consists of neuron units equal to the number of inputs in the parameter set and output layer has a single neuron. The hidden layer typically consists of optimal number of neurons with a nonlinear transfer function [23].

Ajitkumar *et al.* [24] proposed ANN model for SV estimation to better address the nonlinear relationship between the ICG parameters and SV. A three-layer feed-forward neural network was used and trained using back propagation algorithm [25]. The study was conducted with data from 20 healthy subjects. For each subject, the data were collected in three body positions: horizontal, supine 10° head-down, and 30° head-up. In each position, the subject was asked to breath normally for 15 s followed by 5 s of breath-hold, the ICG and simultaneous Doppler echocardiography recordings were carried out during the breath-hold interval and this process was continued for six times over a period of two minutes. A data set consisting of height, weight, age, and gender, along with L, Z_o, V_{EPT} (volume of electrically participating thoracic tissues), $\left(-dZ/dt\right)_{\max}$, T_{lvet}, heart rate, and Doppler SV was prepared from the ICG and Doppler recordings obtained during each breath-hold interval, resulting in a total number of 360 data-sets (20 subjects × 3 positions × 6 data sets). With Doppler SV values as the reference, correlation coefficients were 0.32 for $\text{SV}_{\text{Kubicek}}$, and 0.34 for $\text{SV}_{\text{Sramek}}$, and 0.87 for SV_{ANN}, indicating ANN to be a better method for SV estimation using ICG.

In a US patent by Baker *et al*. [26], it is proposed to use a feed-forward neural network model for semi-continuous calculation of cardiac output with the thermodilution technique. The network was trained with the inputs from the measurements of blood temperature thermal curves and the trained ANN model was used for direct estimation of cardiac output from the invasive measurement of blood temperature. Standard error of the estimation was 0.84. L/min. In a US patent by Baura [27], it is proposed to use an ANN model for continuous cardiac output monitoring using ICG parameters. A three-layer feed-forward neural network, with six inputs, three neuron units in the hidden-layer with tan-sigmoid activation functions, and an output layer, was used and trained using back propagation algorithm. ICG recording were carried out in tetra-polar electrode configuration. The input parameters were heart rate, basal impedance, $\left(-dZ/dt\right)_{\max}$, left ventricular ejection time, and thoracic length. The CO values obtained from thermodilution technique were used as the reference values during the training phase. Number of subjects and the quantitative improvement in the estimation accuracy have not been reported.

These earlier proposed ANN models for SV estimation have been designed with the input parameters obtained from ensemble averaged ICG. The training and testing have been reported for the data across the subjects. It is proposed to use an ANN model for SV estimation, with ICG parameters from a large number of cycles without ensemble averaging as the inputs and the corresponding cycle-by-cycle SV values from Doppler echocardiography as the reference, for cycle-by-cycle SV estimation and to evaluate the system for datasets within the subject and across the subjects.

IV. EXPERIMENTAL METHOD

A. Data Recording

The recordings were carried out at two hospitals: Madhavbaug Ayurvedic Cardiac Hospital (Khopoli, Raigad, Maharashtra, India) and Hardas Heart Care (Pune, Maharashtra, India). For echocardiography, the first hospital had “MyLab 25 Gold” from Esaote (Genova, Italy) and the second hospital had “ iE33” from Philips Ultrasound (Bothell, WA, USA). The recordings were carried out after approval from the Ethics Committee of the hospital. The subjects were informed about the study and they read and signed the consent form for participating in the study. The echocardiograms of aortic blood flow velocity profile were recorded using a 2.5 MHz phased-array probe placed on the chest in a five chamber apical long axis view of the ascending aorta, with an ultrasound gel applied for good contact with skin. The subjects were checked for normal health on the basis of ECG report, not having past history of cardiovascular diseases, and physical examination by a cardiologist. The gender, age, height, and weight of the subject were noted. The distance between the voltage sensing electrodes was also noted.

The signals ECG, Z_0, $z(t)$, and $-dZ/dt$ were recorded using “HIC-2000 Bio-electric Impedance Cardiograph” from Bio-Impedance Technology (Chapel Hill, NC, USA) with 100 kHz excitation current of 1 mA and impedance sensing calibration of 40 mV/Ω. Four-electrode configuration with Ag-AgCl disposable ECG spot electrodes was used for current injection as well as voltage sensing. The analog output signals from the ICG instrument were digitized using 8-channel, 16-bit data acquisition card “KUSB-3100” from Keithley Instruments (Cleveland, Ohio, USA) at a sampling frequency of 500 Hz. The ICG and Doppler echocardiograms were recorded simultaneously, for beat-by-beat analysis.

B. Subjects and Exercise Protocol

The ICG, ECG, and Doppler echocardiograms were recorded from six healthy male subjects with age of 18 – 50 years (mean = 27.3 years, SD = 12.0 years), height of 161 – 173 cm (mean = 167.8 cm, SD = 4.2 cm), and weight of 58 – 88 kg (mean = 67.33, SD = 11.0 kg). ICG and

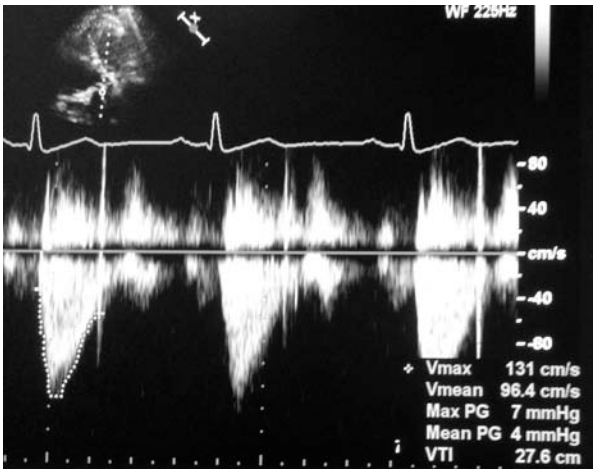

Fig. 2. An example of the Doppler echocardiogram and VTI estimation. Upper section: apical five-chamber view. Middle section: ECG. Lower section: Doppler spectrum representing the left ventricular outflow tract velocity profile. The envelope of the ejection phase in the first cycle is traced and the calculated values are shown in the right bottom side of the figure.

Doppler echocardiography recordings were carried out under rest and post-exercise conditions. An exercise protocol was followed to introduce large cardiac variability. Recordings under rest were carried out with the subject lying in the left-lateral supine position with slight folding of the right leg. Subject was asked to exercise for about ten minutes and the post-exercise recording was carried out with the subject lying again in the left-lateral supine position. No restrictions were placed on breathing by the subject during both recordings. Subject was advised to avoid any movement during the recordings in order to minimize motion artifacts.

C. Artifatcs Suppression and Detection of ICG Points

A wavelet-based denoinsing technique reported by Pandey *et al.* [28], involving scale-dependent thresholding using discrete Meyer (demey) wavelet, was used for suppression of respiratory artifacts in ICG. A technique for automatic detection of ICG characteristic points using ECG-R peaks as reference, as reported in [29], was used for beat-by-beat calculation of ICG parameters.

D. SV from Doppler Echocardiography

In the Doppler echocardiography technique, SV is calculated by multiplying velocity time integral (VTI) by cross-sectional area at the corresponding site [30]. The most frequently used site is the left ventricular outflow tract (LVOT). Its diameter was measured from parasternal long-axis view at the level of aortic annulus during mid-systole. The LVOT blood flow velocity profile (Doppler spectrum) was measured in apical five-chamber view by using continuous-wave Doppler beam placed at the center of the aortic annulus. The VTI was calculated as the integration of instantaneous peak velocities over the ejection period. It is equal to the area below the base line and envelope of the Doppler spectrum and it was measured with the built-in software of the Doppler echocardiography machine by tracing the envelope of the Doppler spectrum using a track ball. An example of the recording and VTI estimation is shown in Fig. 2.

Table 1. ANN models used for SV estimation.

ANN Model	Description	Input Parameters
NNKB	Input parameters of Kubicek equation (2)	L^2, $1/Z_0{}^2$, $(-dZ/dt)_{\max}$, T_{lvet}
NNSR	Input parameters of Sramek equation (3)	$L^3/4.2$, $1/Z_0$, $(-dZ/dt)_{\max}$, T_{lvet}
NNSB	Input parameters of Sramek-Bernstein equation (4)	δ, $L^3/4.2$, $1/Z_0$, $(-dZ/dt)_{\max}$, T_{lvet}
NNBR	Input parameters of Bernstein equation (5)	V_{ITBV}, ζ^2, $\sqrt{(-dZ/dt)_{\max}/Z_0}$, T_{lvet}
NNCI	Superset of input parameters used in all the SV equations	V_{ITBV}, ζ^2, $L^3/4.2$, $1/Z_0$, $1/Z_0{}^2$, $(-dZ/dt)_{\max}$, $\sqrt{(-dZ/dt)_{\max}/Z_0}$, T_{lvet}

E. ANN Model Implementation

A three-layer feed-forward neural network was used for implementation of ANN models. The hidden-layer of the network structure consisted of 20 neuron units with tan-sigmoid activation functions and one unit in its output layer with linear activation function. The number of neuron units in the input layer was same as number of the inputs. The parameters L, Z_0, $(-dZ/dt)_{\max}$, T_{lvet} from ICG along with person's height and weight were used as inputs. Beat-by-beat stroke volume values measured from the simultaneously recorded Doppler echocardiogram were used as reference output. Networks were trained using parameters from the original ICG as well as those from the denoised ICG, i.e. after processing for suppression of respiratory artifacts. The input parameters and the target output were transformed to have zero mean and unity variance to make each parameter to contribute equally in generalization of the ANN model.

For tabulation and reporting of the results, the SV estimations using the equations are referred to as EQKB for Kubicek, EQSR for Sramek, and EQBR for Bernstein. The estimations using ANN network are referred to as NNxx with "xx" indicating the input parameters, as shown in Table 1. The ANN training and testing was carried out using the data from the individual cardiac cycles without ensemble averaging. There were a total of 371 cardiac cycles after pooling of the pre-exercise and post-exercise recordings from the six subjects. For each subject, 60% of the cycles were selected randomly for training and the remaining 40% were used for testing. The Levenberg-Marquardt learning algorithm was used in training the ANN [22]. The criteria for network

training stoppage were root mean square error and maximum iteration count.

V. Results and Discussion

Information on the subjects, aortic diameter, and mean and standard deviation of R-R intervals of ECG and SV estimation using Doppler echocardiography are given in Table 2. Closeness of the SV values obtained from ICG with those obtained from Doppler echocardiography was quantified by calculating the mean ($\overline{\varepsilon}$) and standard deviation (SD) of the errors and correlation coefficient (*r*) for beat-by-beat values. The results are given in Table 3, for estimations using equations as well as those using ANN models. The estimation methods with "1" at the end indicate use of the parameters obtained without ICG denoising, while those with "2" indicate use of parameters obtained after ICG denoising. The results were obtained by applying the training and testing of the ANN models on the data from individual subjects as well as on the data from across the subjects. In each case, the training of the ANN model was carried out using 60% of the cardiac cycles and the remaining cycles were used for testing, as described earlier.

It is seen that all the equation based methods result in high values of mean and SD of the errors and low values of correlation coefficients for individual subjects and across the subjects. With reference to an average SV of 80 mL, the SD of errors in estimation using Kubicek equation were 16.3% – 36.1%. The correlation coefficients were 0.07 – 0.57. Similar results were obtained in the estimations using Sramek equation indicating no significant effect of modification of the Kubicek equation, i.e. correction factor related to height in place of sensing electrode distance. Estimations using Bernstein equation also resulted in large SD of errors (12.4% – 27.9%) and low correlation coefficients (0.08 – 0.39). The use of ANN methods decreased the errors to about one-fourth of the corresponding values from

Table 2. Information on subjects along with R-R interval and SV estimated using Doppler echocardiography under resting condition. Ao: aortic annulus (cm), RR: R-R interval of cardiac cycles (ms), SV: stroke volume (mL), SD: standard deviation.

Sub-ject code	Age	Ao dia. (cm)	RR and SV under resting condition				
			No. cycles	RR		SV	
				Mean	SD	Mean	SD
AB	30	1.8	41	866	35.8	76	2.7
AK	18	1.9	19	877	48.9	65	4.1
BG	50	1.8	18	995	18.6	60	6.7
KU	19	2.5	74	920	63.0	90	6.3
MD	26	2.2	20	869	28.3	76	5.4
PR	21	2.4	21	756	29.2	83	4.9

Table 3. Results of SV estimation methods. Error: differences between the SV values obtained from ICG and those using Doppler echocardiography; $\overline{\varepsilon}$: mean of errors and SD: standard deviation of errors. *r*: correlation coefficient between the SV values obtained from ICG and those using Doppler echocardiography.

Est. method	Subject AB			Subject AK			Subject BG			Subject KU			Subject MD			Subject PR			Across subjects		
	Error (mL)		*r*	Error (mL)		*r*	Error (mL)		*r*	Error (mL)		*r*	Error (mL)		*r*	Error (mL)		*r*	Error (mL)		*r*
	$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD		$\overline{\varepsilon}$	SD	
EQKB1	-14.2	30.1	0.10	-2.9	14.0	0.06	-4.6	17.4	0.15	-5.3	25.9	0.23	-4.1	15.5	0.20	-2.5	17.2	0.56	-29.6	17.2	0.22
EQKB2	-12.6	28.9	0.07	-2.4	13.0	0.10	-5.3	18.6	0.11	-1.4	19.5	0.37	-4.1	15.4	0.21	-2.1	17.0	0.57	-28.0	18.7	0.24
EQSR1	-14.2	30.1	0.10	-2.9	14.0	0.06	-4.6	17.4	0.14	-5.3	25.9	0.23	-4.1	15.5	0.20	-2.5	14.6	0.50	-19.7	19.6	0.21
EQSR2	-12.6	28.9	0.07	-2.4	13.0	0.10	-5.3	18.6	0.11	-1.4	19.5	0.37	-4.1	15.4	0.21	-2.1	14.2	0.51	-18.0	16.4	0.21
EQBR1	-7.9	23.7	0.11	-2.4	12.6	0.16	-2.3	13.4	0.16	-2.2	21.4	0.28	-1.4	9.9	0.16	-1.8	16.0	0.57	-31.4	16.2	0.24
EQBR2	-6.8	22.3	0.08	-2.0	11.8	0.13	-2.6	14.2	0.12	-0.7	18.3	0.39	-1.4	9.9	0.18	-1.6	16.0	0.57	-30.9	15.4	0.25
NNKB1	1.5	2.5	0.66	-0.6	2.8	0.60	0.9	5.3	0.66	3.0	5.7	0.77	0.0	2.4	0.63	0.6	4.1	0.57	-1.0	3.8	0.65
NNKB2	1.8	7.6	0.60	0.3	2.8	0.65	-4.0	8.5	0.68	3.8	7.4	0.65	0.3	5.4	0.78	3.9	12.2	0.58	0.9	7.3	0.66
NNSR1	1.3	7.2	0.64	1.6	7.2	0.64	1.7	4.6	0.79	-1.6	5.1	0.81	-0.8	4.8	0.77	3.7	8.7	0.48	-2.7	6.3	0.69
NNSR2	2.9	4.7	0.58	-2.5	4.1	0.75	-0.6	5.8	0.69	-0.3	5.6	0.77	3.7	4.6	0.70	2.5	8.0	0.44	-1.4	5.5	0.66
NNSB1	2.1	2.4	0.70	-2.4	2.4	0.72	0.6	6.4	0.66	0.1	5.7	0.78	-0.3	5.2	0.71	2.2	5.9	0.45	-0.7	4.7	0.67
NNSB2	4.6	5.0	0.60	-4.9	6.1	0.65	-0.7	8.0	0.70	0.3	6.2	0.71	-0.8	4.1	0.66	7.5	10.3	0.57	0.8	6.6	0.65
NNBR1	1.3	3.1	0.81	-4.7	3.4	0.64	-0.5	4.7	0.75	-1.8	4.9	0.84	0.0	4.9	0.67	0.5	4.5	0.55	0.1	4.2	0.71
NNBR2	-0.1	2.8	0.74	-0.7	2.5	0.70	0.0	6.7	0.62	-4.7	5.5	0.80	2.1	4.5	0.57	3.5	4.2	0.59	0.2	4.4	0.67
NNCI1	0.9	1.9	0.85	0.8	3.6	0.73	-0.2	7.8	0.67	-5.6	5.0	0.91	-1.5	4.5	0.67	0.5	2.4	0.64	-0.2	4.2	0.75
NNCI2	-3.2	2.0	0.83	-3.3	3.7	0.71	-0.1	8.1	0.64	-6.7	6.3	0.87	-0.5	3.8	0.70	0.3	2.2	0.77	0.8	4.4	0.75

equations. The correlation coefficients also improved significantly.

Use of denoising does not appear to have a significant effect on the estimations, which may be due to absence of significant respiratory artifact in the recordings or due to robustness of the signal processing technique employed for automatic detection of ICG characteristic points. It needs to be examined with recordings of longer durations.

The best results were obtained using NNCI2, which combined the inputs as used in different SV equations. With this method, the SD of errors were 2.0 – 8.1 mL, i.e. about 2.5% – 10.1% for SV of 80 mL. The correlation coefficients were 0.63 – 0.87. These results are very promising for use of ICG for beat-by-beat SV estimation. In our study, implementations have not been optimized for the number of hidden layer neuron units required to fit the network. Use of additional parameters and their transformations also needs to be investigated for the possibility of further improving the estimation.

VI. Conclusion

The results of our investigation have shown that ANN-based SV estimation using ICG can be an effective technique for beat-by-beat SV estimation. Further investigations are needed for optimization of the network and studying the effect of including more ICG parameters as inputs. The investigations need to be extended to data from a larger number of subjects and different postures during recording.

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