Noninvasive Radial Pressure Waveform Estimation by Transfer Functions Using Particle Swarm Optimization

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*Abstract: - -*Waveforms of blood pressure contain very important signals of life. Although blood pressure can be continuously measured by an intra arterial catheter, this invasive method introduces risks to patients. Knowing that blood pressure can change in just a few seconds or minutes without a sensible feeling, the waveforms of blood pressure are capable of conveying substantial cardiovascular information. Traditional Chinese medicine also uses radial pressure information in the form of pulses to diagnose diseases by sensing the signals from the fingertips. Therefore, a noninvasive method in measuring blood pressure waveforms is proposed in this paper, based on which we can use the signals of fingertip photoplethysmogram to reconstruct radial pressure waveforms. Characteristics of various photoplethysmogram will be categorized into 3 clusters by using fuzzy C-mean clustering. A particle swarm optimization scheme is then esblihed to search for an optimal transfer function model for estimating the radial pressure waveforms. Experiment results show that correlation ratio of the transformed waveforms can be as high as 0.89, much better than the results via the ARX technique.

Key-Words: - Noninvasive, radial pressure waveform, photoplethysmogram, particle swarm optimization, transfer function, correlation ratio.

1 Introduction

With traditional blood pressure measurement, we can only obtain systolic pressure, diastolic pressure and heart rate that couldn't effectively help finding and preventing early signs of cardiovascular diseases. In the past, intrusive inspection (like cardiac catheterization) was usually adopted to get further detailed information for specific functions of the heart and blood vessels. Because there was a lot of important physiologic information (such as vascular sclerosis degree, cardiac contractility etc.) hidden in the blood pressure waveforms, these valuable information certainly help doctors or patients better perceiving the cardiovascular physiological status. From the perspective of Chinese medicine, pulse diagnosis/taking is one of the most important methods for diagnosing diseases, in which the pulse signals due to the collision of radial artery blood on the walls of blood vessels are sensed for further diagnosis. At present, the acquisition of the continuous blood pressure and waveforms in ICU were both intrusive and it must be operated by

professional medical staff. Meanwhile there was the risk of causing thrombosis and infection. With the growth of aging population, non-invasive blood pressure waveforms picking devices were worth vigorously developing and applying in order to reduce the reliance on professional medical staff. On the other hand, transfer function can be identified based on frequency-domain [1]-[3] or time-domain [4]-[5] techniques. In comparison to complicated operation of spectrum transformation in the frequency domain, time-domain techniques have an advantage in achieving real-time processing because convolution operations can be performed efficiently with far less computation. In this paper, a noninvasive method for measuring blood pressure waveforms based on signals of fingertip photoplethysmogram (PPG) is therefore proposed. When the PPG signals of various characteristics become available, an optimization scheme based on particle swarm optimization (PSO) [6]-[7] is proposed to derive a transfer function bank for reconstructing continuous radial pressure waveforms for other patients. Because

of the noninvasive nature in the reconstruction of the continuous radial pressure waveforms, the proposed approach has made contributions in clinical monitoring. Experiments have confirmed that the proposed approach is not only simple to implement but also capable of on-line processing. The optimization scheme based on PSO has successfully derived a set of transfer function banks with satisfactory performance in providing estimates for actual blood waveforms. Thanks to the capability of global search of PSO, the difference between the actual and estimated waveforms of the blood pressure obtained is much smaller than that via the ARX model.

The organization of this paper is as follows: Section 2 introduces the materials and methods used, including pre-processing of the information source. Rationale in selecting a suitable order for the transfer function is described in this section. How PPG signals are categorized for use by a PSO-based optimization scheme to derive an optimal transfer function model is also given in this section. Section 3 presents the experiment results and discussions, where simplicity and viability of the proposed approach can be validated in this section. Conclusions are drawn in Section 4.

2 Derivation of transfer functions based on PPG and BP

2.1 Materials and Pre-processing

Blood pressure (BP) and PPG signals from 20 volunteers aging between 19-65 years old are taken and recorded for a period of five minutes. IO-tech 16-bits DAQ boxes were adopted to acquire the BP and PPG signals with a sampling frequency of 200Hz. The BP signals were produced from a Colin BP-508 radial tonometry, while PPG signals were produced from our self-made devices using the Pulse oximeter finger sensor of Novamerix. All BP and PPG signals were filtered by a 4th-order Butterworth low-pass filter having a cutoff frequency of 20Hz.

2.2 Selection of transfer function order

It is important in the selection of the transfer function (TF) order. According to the perspective of spectrum analysis, transfer functions with lower orders generally result in smooth power spectrum and may not suitably represent the actual dynamics of the system. However, high-order transfer functions might introduce noises in various forms into the derivation data set and thus result in poor predictive performance. From the previous research [3], we realize that finger PPG-radial pressure TF spectrum had a peak between 0-10 Hz, indicating that this system should at least be a 2nd-order one with a pair of complex poles. The residual analysis made it clear that the energy of residual items will reduce as the orders increased. When reaching the best order, the residual energy came to a stable condition. Based on this concept, a series of criteria were developed, such as AKaike information criterion (AIC) and Final prediction error (FPE) and Minimum description length (MDL) [8]. These criteria were used to validate the selection of the highest order for the system model. In this paper, the highest order of the transfer function model can be selected based on the AIC. For better clarity, the formula of the criteria is listed below:

$$AIC = \ln[(1 + \frac{2n}{N}) * V] \qquad (3)$$

, where n stands for the order of the system, N represents the number of points of the test signals. V is the loss function, which sums the square prediction errors between the model and actual outputs

$$V = \frac{1}{2N} \sum \varepsilon^2(t) \qquad (4)$$

, where ε is the residual error between the real and simulation outputs. Figure 1 shows ten simulation runs of the loss function according to the AIC criterion. When the system order is higher than 6, standard deviation of the loss function increases as demonstrated in Fig. 1. As a result, the system order is adopted as $n_a = n_b = 6$.
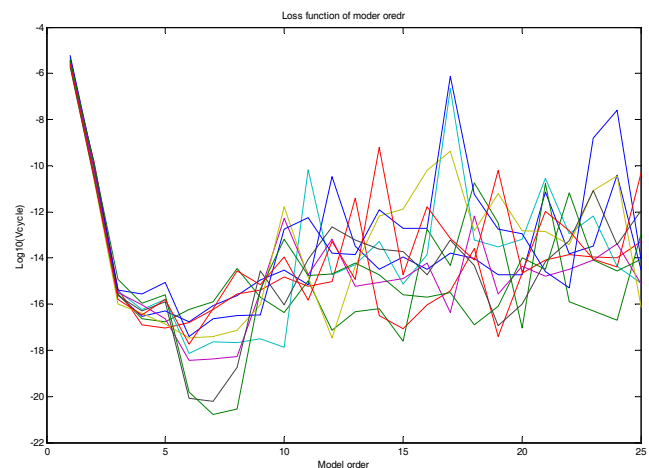

Fig. 1 Ten simulation runs of the loss function according to the AIC criterion.

2.3 Classification of transfer function bank

Note that PPG signals reveal different characteristics depending on the sources of the samples. To achieve

the objective for a minimum modeling error, the use of a transfer function bank comprising individual transfer functions, each corresponding to a particular cluster of PPG signals, is a desired approach in practice. Also, it is impractical for us to know the radial artery blood pressure waveforms without resorting to an invasive method. By using the concept of transfer function bank, we can establish exclusive transfer functions according to the characteristics of the test signals. We used the Fuzzy C-mean algorithm to categorize the signals of the PPG waveforms into three clusters after normalization. For signals belonging to the same cluster, the original PPG signals were taken as the input signals and BP signals as the output signals. Based on the input and output signals, a particle swarm optimization algorithm is then proposed to identify the optimal transfer function model for each cluster.
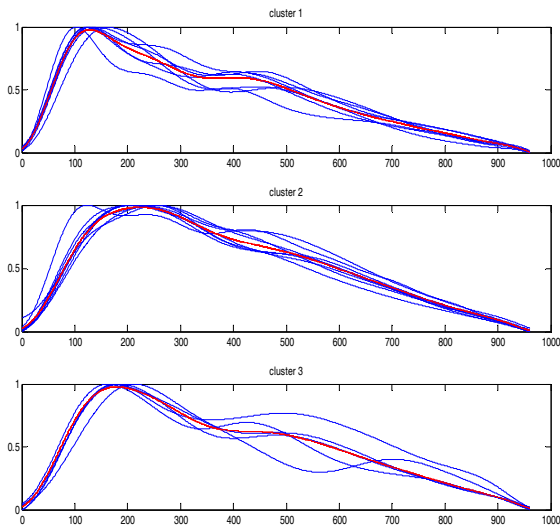

Fig. 2 Classification of PPG waveforms (red lines indicating the central vector of this cluster).

2.4 Transfer function derived via a PSO-based optimization scheme

The particle swarm optimization (PSO) algorithm was first introduced by Kennedy and Eberhart in 1995 [6]-[7]. Through simulation of a simplified social system, the PSO has been successfully applied to nonlinear optimization problems. Basically, the PSO simulates the behavior of swarm as a simplified social system. Like fish schooling and bird flocking, the social behavior of such organisms can be treated as an optimization procedure. With the use of PSO, each particle tries to search the best position with time in a multidimensional space while adjusting its position in light of its own experience and the experiences of neighbors, including the current velocity and position and the best previous position experienced by itself and its neighbors.

Evolution process of the PSO consists of, at each time step, changing the velocity of each particle toward its global best (*Gbest*) and individual best (*Pbest*) locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *Gbest* and *Pbest* locations. Evolution is directed in such a way that the velocity of the *j*th particle with respect to the *k*th dimension at time *t* is updated according to the following equation [6]:

$$V_{i,j}^{(t+1)} = w \times V_{i,j}^{(t)} + c_1 \times rand \times (Pbest - x_{i,j}^{(t)})$$
$$+ c_2 \times rand \times (Gbest - x_{i,j}^{(t)})$$
$$x_{i,j}^{(t+1)} = x_{i,j}^{(t)} + V_{i,j}^{(t+1)}$$
$$i = 1,2,...,n, \quad j = 1,2,...,m$$

, where *n* is the number of particles at time *t* , *m* is the number of members in a particle. The *j*th particle at time *t* is represented as $x_{i,j}^{(t)}$, the best position that the *j*th particle ever recorded is represented as *Pbest*, and the best position among all of the individual best positions achieved so far is *Gbest*, the rate of the position change for particle *j* is presented as $V_{i,j}^{(t)}$, *rand* is a random number between 0 and 1, *w* is the inertial weight constant, and c_1, c_2 are acceleration constants, respectively.

Figure 3 shows the proposed framework in deriving an optimal transfer function model based on the input/output relationship of PPG and BP. The rationale is to search for an optimal set of the coefficient parameters for the transfer function model such that the objective function in terms of error function as an aggregated error is minimized.
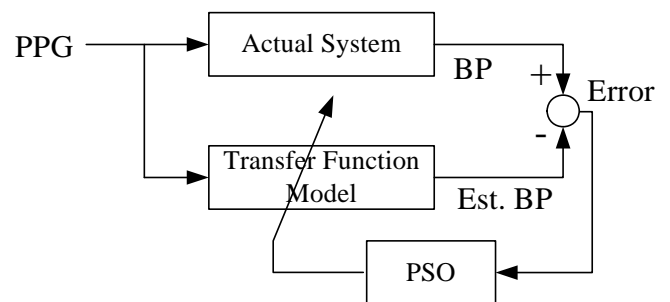

Fig. 3 Framework of the PSO-derived transfer function model.

3 Results and discussions

In this paper, two indexes have been established to evaluate the resemblance between the waveforms of the actual and estimated blood pressure. The first one is a fitness function defined as:

$$fit = 100 \cdot \frac{1 - norm(yh - y)}{norm(y - mean(y))} \tag{3}$$

, where *norm* is the operation to calculate the Euclidean length of the variable, yh is the estimated BP waveform signal, and y is the measured radial artery waveforms after normalization. The other evaluation index is the correlation ratio, R, defined as follows:

$$R = corrcoef(yh, y) = \frac{\text{cov}(yh, y)}{\sqrt{\text{cov}(yh) \cdot \text{cov}(y)}} \tag{4}$$

, where *cov* is the operation to derive the covariance. Fig. 4 shows waveforms of hypertension's BP and PPG signals, in which the top one is the radial artery pressure waveform and the bottom one is the fingertip photoplethysomghy waveform. By the transformation of the derived transfer function, estimated radial artery pressure waveforms can be obtained for comparison with the original signals of hypertension pressure waveforms as shown in Fig. 5.
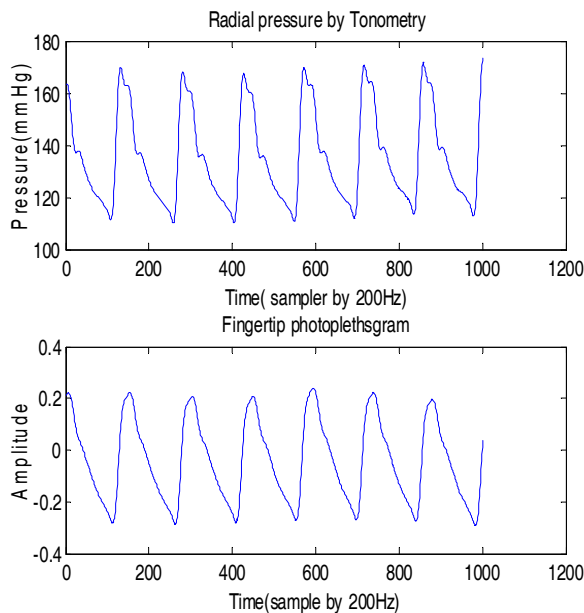

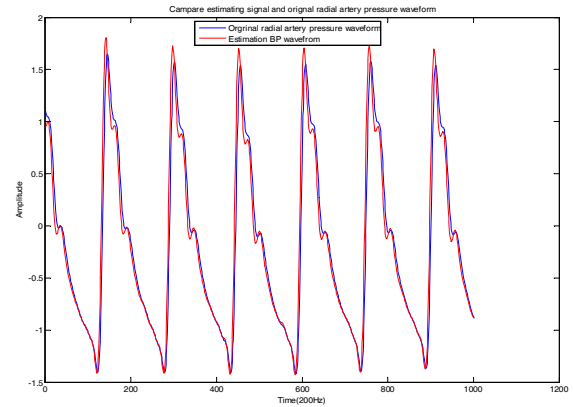Fig. 4 Waveforms of hypertension's BP and PPG signals.

Fig. 5 Comparison of the estimated and original signals of hypertension pressure waveforms.
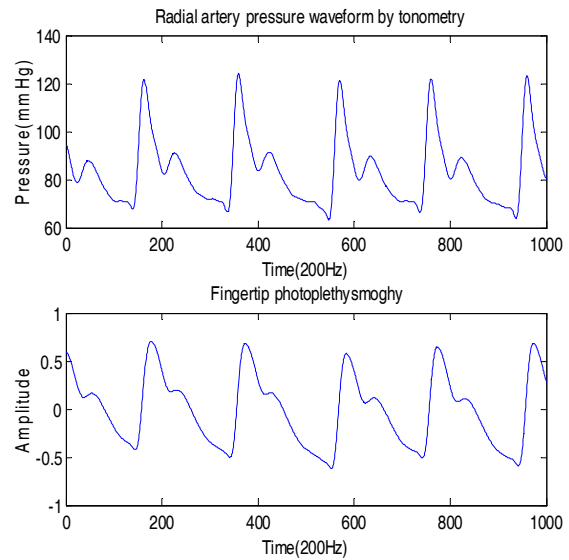

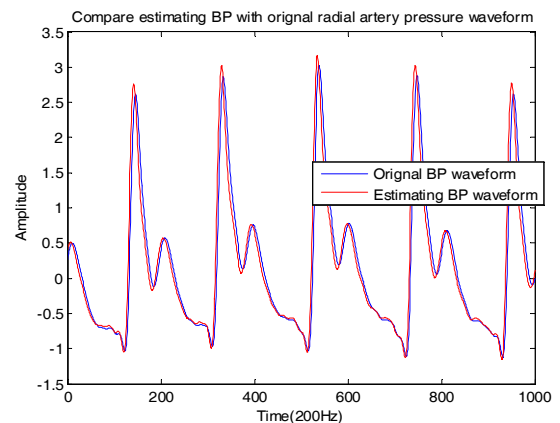Fig. 6 Waveforms of normal BP and PPG signals.

Fig. 7 Comparison of the estimated and original signals of normal pressure waveforms.

Figure 6 shows the waveforms of normal BP and PPG signals. By the transformation of the derived transfer

function, estimated radial artery pressure waveforms can be obtained for comparison with the original signals of hypertension pressure waveforms as shown in Fig. 7. Table 1 shows the comparison results in terms of estimation accuracy of waveforms generated by transfer functions obtained via the PSO derived and ARX models, respectively, for 20 testing sample sets. The mean of correlation ratio of the PSO-derived model is as high as 0.89, in comparison to 0.86 obtained via the ARX model. The index of mean value of best fit is 56.0 by PSO in comparison to 48.3 via the ARX model, clearly indicating the improvement by using the PSO-derived model. Although there are few cases where the ARX model works well in estimating the waveforms, the overall performance of the PSO-derived model is far better than the ARX model as demonstrated in the Table. This comes as no surprise because PSO is capable of locating the global optimum while the ARX model can only achieve local optimum as expected.

non-invasive monitoring systems, for example, non-invasive instruments for measuring blood pressure waveforms proposed in this paper, is of significance and urgently required. With the use of non-invasive monitoring systems, the possibility of getting infected of medical staff can be significantly reduced. The demands of a large number of medical staff can therefore be greatly relaxed. Based on the proposed approach, cardiovascular parameters of patients can be obtained via the blood pressure waveforms. As demonstrated in the experiments of this paper, the estimate of continuous blood pressure waveforms via the proposed non-invasive approach incorporating PPG and PSO-derived transfer function has reached a satisfactory performance of 0.89 in terms of correlation ratio. In the future, improvements will be made to enlarge testing samples and establish a more effective classification of clusters for PPG to enhance the measuring system for providing clinical values in the diagnosis process.

Table 1 Performance comparison results of the PSO-derived and ARX models

No	PSO model		ARX model	
	Best Fitting	Correlation Coefficient	Best fitting	Correlation Coefficient
1	67.7	0.93	58.1	0.91
2	60.4	0.85	37.7	0.80
3	72.3	0.95	57.6	0.90
4	71.1	0.94	71.0	0.94
5	48.9	0.86	39.3	0.81
6	58.9	0.92	60.0	0.92
7	49.2	0.87	39.4	0.82
8	58.9	0.91	49.2	0.88
9	64.1	0.93	57.6	0.90
10	49.2	0.87	39.4	0.82
11	45.4	0.85	42.5	0.83
12	67.9	0.94	70.0	0.94
13	58.1	0.91	57.5	0.90
14	60.1	0.92	39.4	0.92
15	59.5	0.87	48.6	0.87
16	44.2	0.84	37.7	0.80
17	44.2	0.84	39.4	0.82
18	45.6	0.85	37.6	0.80
19	48.7	0.87	44.1	0.84
20	45.1	0.84	39.3	0.81
Mean value	56.0	0.89	48.3	0.86

4   Conclusion

As senior population is dramatically increasing over the past years, requirements of quality home care are in strong demand. As a result, monitoring systems are getting more and more important for the welfare of the senior people. The development of

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