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Optimization of a generalized radial-aortic transfer function using parametric techniques

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ABSTRACT

The central aortic blood pressure (cBP) waveform, which is different to that of peripheral locations, is a clinically important parameter for assessing cardiovascular function, however the gold standard for measuring cBP involves invasive catheter-based techniques. The difficulties associated with invasive measurements have given rise to the development of a variety of noninvasive methods. An increasingly applied method for the noninvasive derivation of cBP involves the application of transfer function (TF) techniques to a non-invasively measured radial blood pressure (BP) waveform. The purpose of the current study was to investigate the development of a general parametric model for determination of cBP from tonometrically transduced radial BP waveforms. The study utilized simultaneously measured invasive central aortic and noninvasive radial BP waveform measurements. Data sets were available from 92 subjects, a large cohort for a study of this nature. The output error (OE) model was empirically identified as the most appropriate model structure. A generalized model was developed using a pre-specified derivation cohort and then applied to a validation data set to estimate the recognized features of the cBP waveform. While our results showed that many relevant BP parameters could be derived within acceptable limits, the estimated augmentation index (AI) displayed only a weak correlation compared to the invasively measured value, indicating that any clinical diagnosis or interpretation based on estimated AI should be undertaken with caution.

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1. Introduction

Cardiovascular disease remains the world's greatest health problem and is responsible for more deaths than any other disease group [1]. Hypertension is well recognized as a key cardiovascular risk factor and the central aortic blood pressure (cBP) waveform is an important component of cardiovascular function as it represents left ventricular afterload. Traditional blood pressure (BP) measurement at the brachial artery, while convenient, is considered a poor representation of cBP [2]. One reason for this is the occurrence of pulse pressure amplification associated with increasing stiffness of vessels associated with progression along the arterial tree [3]. The gold standard for measuring cBP involves invasive catheter-based techniques however invasive procedures are impractical in large cohorts and are not free from complications. As a result, interest in noninvasive methods for measuring cBP has increased and has resulted in the introduction of a number of different techniques [4,5].

Noninvasive methods of cBP estimation have predominantly focused on the application of a so-called vascular transfer function (TF) to non-invasively obtained radial BP waveforms. This method has gained support among a number of researchers [4,6,7] and has given rise to the introduction of commercial devices in this field, the most utilized being the SphygmoCor device (SphygmoCor; AtCor, Sydney, Australia) [8]. The SphygmoCor system utilizes applanation tonometry to measure the radial artery pressure waveform and applies a generalized TF to provide an ensemble averaged cBP wave. The study from which the SphygmoCor TF approach was derived relied on data obtained from 14 patients undergoing clinically indicated cardiac catheterization [9]. Simultaneous radial and cBP were obtained and a TF was derived using Fourier analysis techniques.

Perhaps the most pertinent report in this area is that from Fetics, Nevo, Chen and Kass [4]. Fetics et al. evaluated the performance of an autoregressive exogenous (ARX) model to estimate cBP parameters based on noninvasive radial tonometry measurements. Acknowledging earlier methods based on the Fourier transform, Fetics et al. aimed to compare the performance of a frequency domain-based technique with an ARX model.

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Simultaneous central aortic and radial BP waveform measurements were obtained from 39 patients and utilized in their study. 20 of these patients were grouped as Group 1, estimation data, and the remaining 19 as Group 2, validation data. Although 39 patients represents a considerable sample size, it is not the largest sample recorded for a study of this nature [10]. The validity of the ARX model approach was confirmed by Fetics et al. with their developed model of order 10. The findings of their study showed improvement over the Fourier transform approach but with some limitations to the derivation of the secondary parameter, pressure augmentation index (AI).

Other noninvasive methods have continued to be proposed, one of the most recent being from Hahn et al. who presented a physics-based approach to determine a subject and state specific individualized TF [5] aimed to determine cBP based on a single peripheral measurement. Another recent study is from Rashedi et al. [11] in which single-tube and two-tube models are assessed for the reconstruction of cBP.

The approaches thus far have also varied in regard to the number of patient data available for estimation and validation. For comparison, the TF reported by Karamanoglu et al. [9] was developed with 14 patients, Fetics et al. utilized data from 39 patients and Hahn et al. utilized data from 13 patients [12]. One aim of our current work is therefore to determine whether any improvement in the derivation of cBP parameters is achieved with an increase in the number of subjects used in model derivation.

Our study refocuses on the application of a generalized TF with the use of simultaneous radial and central aortic data obtained from 92 subjects. Data obtained from an earlier study by Hope et al. [13] was utilized. This paper describes the development of a unique parametric model to assess the full range of cBP waveform parameters which is then assessed against invasive gold standard measurements. In addition to providing one of the few parametric models developed for this application, this study is unique in being based on invasive data available from 92 subjects, the largest data set reported for the development of a parametric model of this nature.

2. Methods

2.1. Data and preprocessing

Simultaneous invasive measurements of cBP and noninvasive radial BP waveforms were obtained from 92 patients, 64 of whom were males. The invasive cBP measurements were obtained by means of a high fidelity solid state catheter positioned in the ascending aorta with the noninvasive radial measurements obtained via applanation tonometry. Chart for Powerlab (ADInstruments) was used to acquire the waveforms at 200 Hz. Hope et al. assessed the number of subjects required to produce an optimal TF. Their study utilized up to 30 randomized subjects for derivation and concluded that there was minimal change in the resultant TF with a validation group of more than 20 [13]. The same derivation data group was utilized in this study to develop the generalized TF. The derived model was evaluated on data from the remaining 62 patients which were not included in the model estimation stage. The presence of this second set of data, validation data, is a significant factor in validating any model as it avoids over-fitting the data and provides a means to assess how the model will perform in practice.

2.2. Model structure

Due to the complexity of the human arterial system, it cannot simply be described by its impulse or step response. Previous studies have shown that parametric approaches are superior to the Fourier transform approach [4]. The model structure used in this study is of the form [14]:

$$y(t) = \frac{B(q)}{F(q)}u(t - n_k) + e(t) \tag{1}$$

where $u(t)$ is the input, $y(t)$ is the output and $e(t)$ is the modeling error, which is similar to the ARX equation error model.

B(q) and *F(q)* are polynomials with reference to the backward time-shift operator q^{-1} defined as $q^{-1}u(t)=u(t-T)$ and T is the sampling interval. For simplicity, T is assumed to be 1 and the shift operator is defined as $q^{-1}u(t)=u(t-1)$. The polynomials are written as

$$B(q) = b_1q^{-1}+...+b_{n_b}q^{-n_b} \tag{2}$$

$$F(q)=1+f_1q^{-1}+...+f_{n_f}q^{-n_f} \tag{3}$$

These parameters are further defined as:

n_b – order of the B polynomial $+1$ which is also the number of zeros. Eq. (2) describes the filtering of the input of the system.
n_f – order of the F polynomial which is also the number of poles. Eq. (3) describes the filtering of the output of the system.
n_k – the input delay, expressed as the number of samples.

Note that although Eq. (1) is similar to Eq. (4.25) from Ref. [14], the error term $e(t)$ denotes the modeling error in this work and not the disturbance in the system due to white noise as in [14]. In this case, the model is similar to the ARX equation error model.

2.3. Criterion of fit

A suitable or “good model” is one which can predict the observed output with small error. Therefore, a criterion to assess and choose between candidate models is to minimize the prediction errors. The prediction error method (PEM), which is suitable for polynomial models, was used in this analysis as it describes the model as the one-step-ahead output prediction, that is, as a prediction of the next output:

$$\hat{y}_m(tt{-}1) = f(Z^{t-1}) \tag{4}$$

Now $\hat{y}_m(tt-1)$ is the one-step ahead output prediction, Z^{t-1} is the set of all measured input and predicted output data up to time $t-1$ and f is an arbitrary function [15]. The set Z^{t-1} is defined below:

$$Z^{t-1} = \left\{ u(1), \hat{y}(1), u(2), \hat{y}(2),...u(t-1), \hat{y}(t-1) \right\} \tag{5}$$

where $u(t)$ and $\hat{y}(t)$ are the input and predicted output at time t respectively. Eq. (4) is then parameterized with respect to the parameter vector θ where:

$$\theta = \left[b_1,...,b_{n_b}, f_1,...f_{n_f} \right]^T \tag{6}$$

resulting in,

$$\hat{y}(t\theta) = f(Z^{t-1}, \theta). \tag{7}$$

With the OE model in Eq. (1), the prediction function f is given by:

$$\hat{y}(t\theta) = \varphi^T(t\theta)\theta \tag{8}$$

$$\text{where } \varphi = [\mathrm{u}(t-1)...\,\mathrm{u}(t-n_b) - \hat{y}(t-1,\theta)... - \hat{y}(t-n_f,\theta)]^T \tag{9}$$

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