USING SPEECH PROCESSING METHODS TO MODEL BLOOD FLOW SIGNALS

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ABSTRACT

This paper shows how the multipulse method from digital speech processing can be used to accurately model signals obtained from blood pressure and flow velocity sensors. This model produces very good modelling of the signals on a resolution that allows analysis between heartbeats. The AR coefficients can be transformed to reflection coefficients and tube radii associated with digital wave guides, as well as pole-zero representation. These parameters permit additional insight and interpretation that will produce deeper insight into the biological control mechanisms.[1]

1. INTRODUCTION

During postural change from sitting to standing, blood is pooled in the lower extremities as a result of increased gravitational potential. A response to the shift in blood volume causes a decrease in cardiac output as well as a reduction of blood flow to the brain, which can cause transient 'black outs' or dizziness. The ability to analyze and predict the level of cardiovascular regulation would enhance the ability to design better treatments that may prevent cognitive loss, falls, and syncope.

We show that signals for blood pressure recorded in the finger and for blood flow velocity recorded in the left middle cerebral artery (MCA) can be modelled independently of each other using the multipulse method, which has proved to be useful in speech signal processing, see [1], for example. Previous work in this area is based on measurements of blood flow velocity and pressure that are averaged over each cardiac cycle. Our method produces a sequence of the input pulses while at the same time computing an AR model. This allows us to model the signal at high resolution between beats. Because of this, we can track the changes of the vascular system on a much finer time scale than previous methods. Furthermore, the use of the AR model permits interpretation by the use of other derived system parameters, such as reflection coefficients, tube radii, poles and zeros.

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2. METHODS

Representative pressure and flow velocity signals are shown in Fig. 1. One can note drop in pressure and flow velocity around 60 seconds when the subject stands. The body compensates through control mechanisms that lead to a steady state after about 80 seconds.

The signals in Fig. 1 show properties that are common in voiced speech signals, e.g., an almost periodic form and a natural decay after an initial peak. The multipulse model can be modified for this case. The premise of the multipulse model is that the signal, $y(n)$, can be represented using the standard autoregressive model (AR)

$$y(n) = \sum_{k=1}^{P} \alpha(k) y(n-k) + x(n); \qquad x(n) = \sum_{i=1}^{I} b_i \delta(n-p_i). \tag{1}$$

where P is the order of the model, $\alpha(k)$ is the k^{th} AR coefficient, and $x(n)$ is the input. The *multipulse* innovation is that the input, $x(n)$, to the AR system is a series of discrete impulses $\delta(n-p_i)$ at times p_i with amplitudes b_i. The problem is to solve simultaneously for the AR coefficients $\alpha(k)$, the pulse positions $\Omega_{pp} = \{p_1,\ p_2, \ldots p_I\}$, and amplitudes $\{b_i\}$ that minimize the squared error during some time interval. Iterative schemes have been found to produce acceptable solutions.

An important difference between the blood signals and speech signals is the difference in baselines of the signals. Speech signals have values that vary about a mean of zero. Blood pressure and flow signals vary above a baseline pressure or velocity. The natural decay of the AR system when no pulses are present produces the correct asymptotic value of zero for speech. Since the AR model produces a signal that naturally decays to zero in the presence of no input, it is natural to remove the nonzero baseline values. To do this, we fitted a low order polynomial to the minimum values of the signals over the region of interest. We subtract this minimum function to produce a secondary signal that is suitable for multipulse modelling. This minimum function is added back in to complete the reconstruction of the signals after the multipulse parameters are found and the output according to (1) is computed.

A common trade-off is between using enough samples to get accurate estimates of the parameters by averaging out the noise, and using few enough samples to be able to track time-varying phenomena. After some initial experiments, we decided to use overlapping segments of four periods (heartbeats). The process is as follows: four periods are modelled at a time, then there is a shift of one period and the next four are modelled. For each set of four periods (about 100 samples), a fourth order AR model was computed with 32 pulses. In order to generate a reconstructed signal, the pulses for each set were filtered with the AR coefficients and the detrending polynomial was added.The results associated with each period were the average of the results for each of the four overlapping data sets.

3. ANALYSIS

Fifty-eight total data sets were processed for three types of subjects. Sample errors of the pressure and flow velocity signals are shown in Fig. 1 along with the computed input pulses superimposed on the detrending polynomial.

It is a large advantage of the multipulse model to allow the inclusion of variable pulse positions. This allows the model to handle irregular heartbeats and signal anomalies without distorting the AR model of the vascular system. This importance is shown when we show the various modelling parameters as a function of time. We will see a smooth transition in those values around such irregularities.

The AR coefficients may be used to develop other mathematical descriptions of the system. An alternative characterization of the system is given in terms of reflection coefficients, $\{K_i\}$, which are computed from the AR coefficients suing the Schur-Cohn recursion. Reflection coefficients are useful because they can be related to fluid flow through a series of tubes of varying radii or so-called digital waveguides. The tube radii $\{R_i\}$ is associated with the interface between the i^{th} and $(i+1)^{th}$ segments and are related to the reflection coefficients by

$$K_i = \frac{R_i - R_{i+1}}{R_i + R_{i+1}}. \tag{2}$$

The details can be found in common DSP texts. The length of the tube segments corresponds to two sampling intervals and is related to the speed of sound in the medium under investigation, in this case blood.

These three system characterizations (AR coefficients, reflection coefficients, and tube radii) are plotted in Fig. 2 for a pressure signal and a flow velocity signal. Since we used a fourth order model, there are five AR coefficients, with the zeroth order coefficient normalized to unity. Similarly, the radius of the first tube was taken as one, and the rest were computed from the reflection coefficients. Each asterisk represents the corresponding AR coefficient for an individual period.

The tube radii parameters has the potential to yield results that relate to physical quantities. The graphs indicate that the parameter tend to behave in a more stable way than the other two. The interpretation of these results is beyond the scope of this paper, which is to introduce the multipulse method for analyzing the data. However, it is intriguing to see the difference in the behavior of the three parameters.

An alternative frequency domain representation of the AR model can be developed by taking the z-transform of the model in (1). One can consider system poles, which give insight into the dynamic behavior of the computed model. The fourth order model gives four poles that must be real or occur in conjugate pairs. The data sets analyzed in this paper never gave four real poles. The most prevalent combination was two real poles and one conjugate pair.

The phase of a complex pole gives the frequency of oscillation in the time domain associated with that pole, while the magnitude gives the degree of damping. Most of the data sets have a high frequency pole, $\omega_h > 3Hz$. A low frequency pole, $\omega_l < 3Hz$, appeared more often in the data sets for old normotensive subjects. In the sets for young normotensive subjects, it was commonly the case that two real poles were obtained instead of a lower frequency complex pair. A plot of the pole variation for a sample blood pressure signal is shown in Figs. 3. This plot shows both the distribution of poles within the unit circle and the behavior of the poles as a function of time. As in the case of the three time-domain parameters, the pole behavior is closely correlated with the transition to standing.

4. DISCUSSION

In Fig. 2, we see a change in the AR coefficients that represent the blood pressure signals during the transition region (60-80 sec), while there is no noticeable difference in the AR coefficients that represent the blood flow velocity signals. The tube radii parameters look quite different in the transition region. The tube radii show distinct increases during the transition for young subjects, little for the healthy elderly subjects and only a slight change for the hypertensive elderly subjects (not shown here). For the blood flow velocity signals only young subjects shows a distinct change. This might be due to the effect of autoregulation, which maintains blood flow velocity under a changing blood pressure. For both signals, our analysis show a significant difference between young subjects and two classes of elderly subjects. For the young subject, the tube radius vary significantly more than for the elderly subjects. This may be explained from the fact that elderly people and especially people with hypertension have stiffer arteries that do not

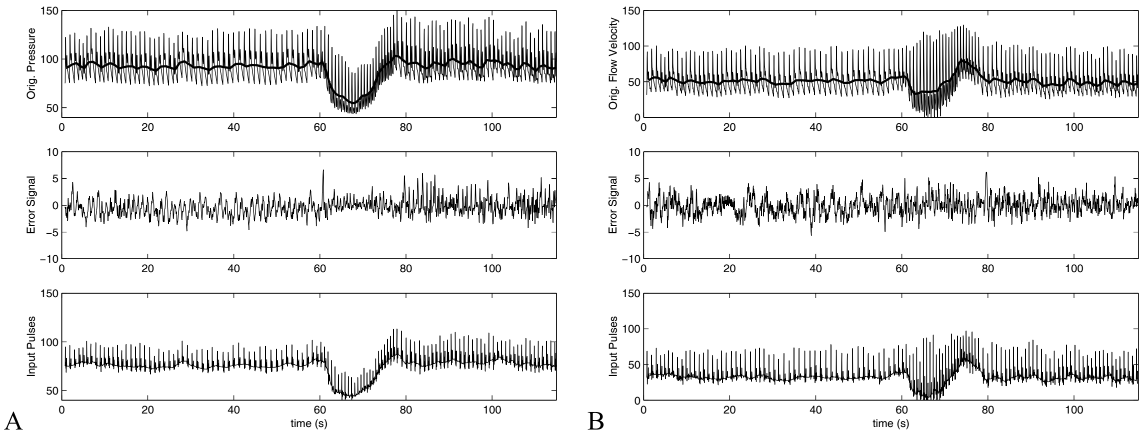

Fig. 1. Example signals with error signals and input pulses. The error signal is defined as the difference between the original signal and its reconstruction. The input pulses are superimposed on the detrending polynomial. Blood pressure and flow velocity for a young subject are shown in A and B respectively.

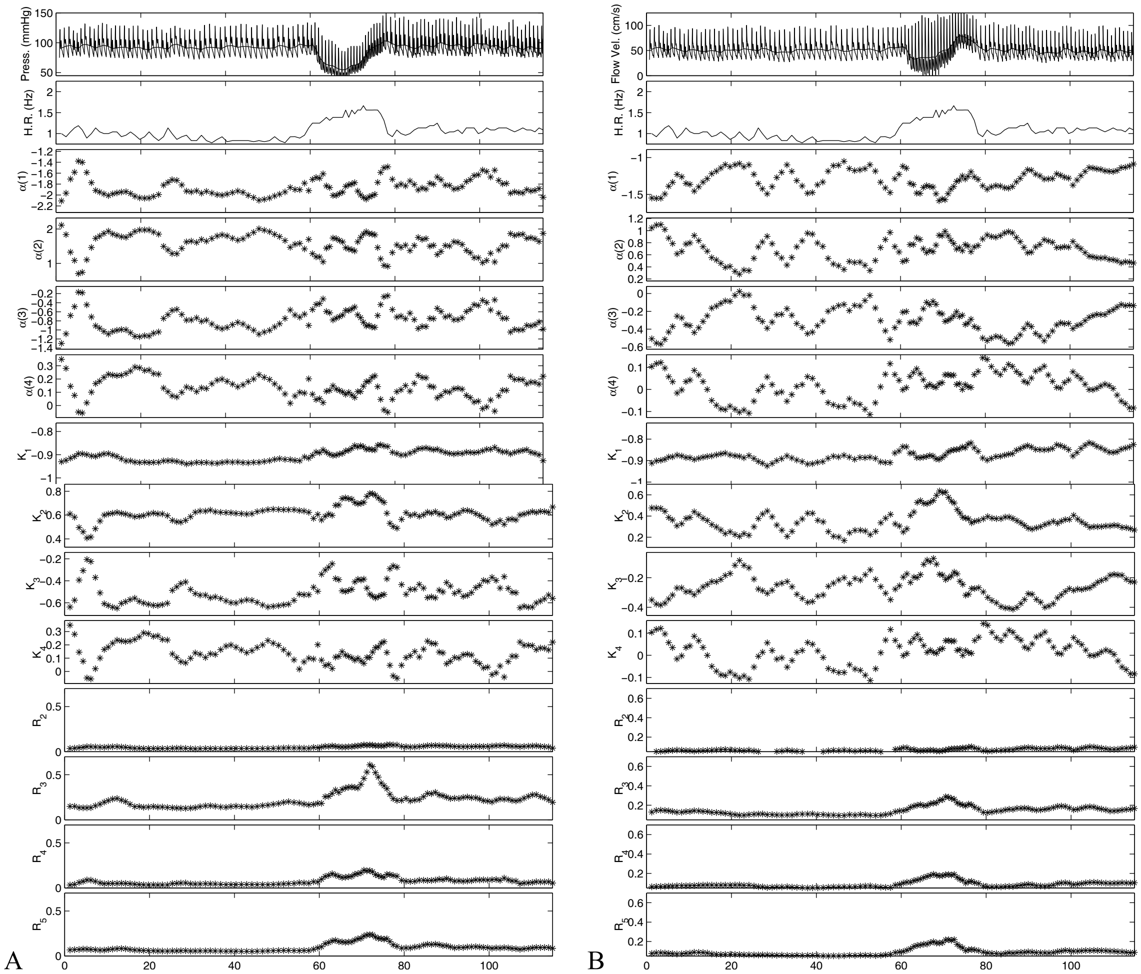

Fig. 2. Time variation of model parameters for pressure A and flow velocity B. The original signals are shown along with the heart rate (HR) for comparison. Each star in the plot represents the computed parameters averaged for a single period. The different representations are shown: AR coefficients ($\alpha(1) - \alpha(4)$), reflection coefficients ($K_1 - K_4$), and tube radii($R_2 - R_5$, R_1 is normalized to unity).

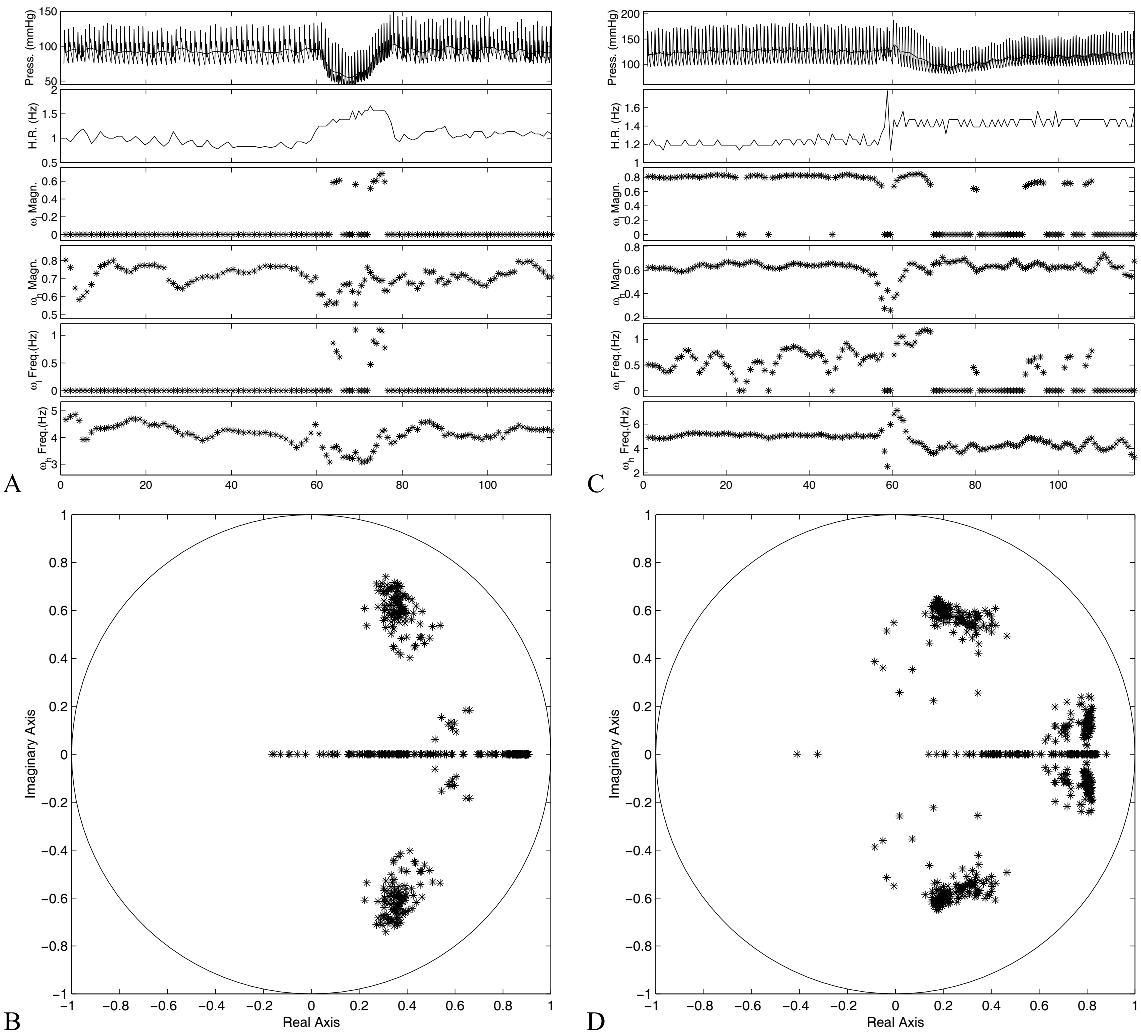

Fig. 3. Time variation of system poles for a young subject (pressure) is shown in A, and a scatter plot of the poles in the complex plane is shown in B. Similar plots for an elderly hypertensive subject (pressure) are shown in C and D.

change as much. Furthermore, for the elderly subjects the heart-rate changes more (it increases and stay increased). This indicates that the regulation mainly affects the heart-rate, while the resistances are effected to a lesser degree.

The plots of the system poles shown in Figs. 3 also vary significantly between the groups. A significant variation in the high frequency pressure pole ω_h is noted, especially over the transition region (60-80 sec). There is a change in both magnitude and frequency of ω_h, however, the magnitude drop appears to lead the frequency drop.

We found that the behavior of the blood flow velocity signal does not appear to follow the pressure signal. For young subjects, we observed a significant change in both magnitude and phase, whereas the elderly subjects did not show any significant difference either in magnitude or in frequency. Finally, it is also observed that the ω_h frequency is typically higher for the blood flow velocity signals, than for the corresponding blood pressure signals.

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5. REFERENCES

[1] T. Quatieri, *Discrete-Time Speech Signal Processing*. Upper Saddle River, NJ: Prentice Hall PTR, 2002.