Multi-Channel Blind System Identification of the Arterial Network Using a Hemodynamic Wave Propagation Model

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Abstract –A new model has been developed to incorporate significant features of arterial wave propagation theory into a multi-channel blind system identification algorithm that will be applied to the cardiovascular system. The new model will reduce the sensor requirement of the algorithm and provide more physiologically meaningful parameters.

I. INTRODUCTION

Integration of information from noninvasive cardiovascular sensor signals such as blood pressure and blood volume waveforms at the extremities could be used to reveal important variables describing the central hemodynamic state. The authors have found that Multichannel Blind System Identification (MBSI) provides a powerful methodology and framework to allow this type of noninvasive cardiovascular monitoring [1].

The cardiovascular system is topologically analogous to a multi-channel dynamic system. Pressure and flow waves emanating from a common source, the heart, are broadcast and transmitted through the many vascular pathways. Therefore noninvasive circulatory measurements taken at different locations can be treated as multi-channel data and processed with an MBSI algorithm.

The salient features of MBSI are that the vascular channel dynamics and the common input can be identified in real-time based on output data alone. This technique distinguishes itself from other techniques that apply a predetermined transfer function to interpret sensor data. These other techniques cannot account for individual differences nor can they account for dynamic changes in the subject's physiologic state.

The identified vascular channel dynamics can reveal important mechanical and physiological properties of the cardiovascular system such as peripheral resistance and compliance and significantly improve estimation of cardiac output using strictly non-invasive wearable sensors.

Existing MBSI theory, however, is not directly applicable to the cardiovascular system, having several shortcomings:

- □ The method requires co-prime channels, but the dynamics of the arterial network are not co-prime, containing common poles that result from all channels initially traveling a common path.
- □ Models representing the complex cardiovascular dynamics tend to be of high order, placing too

large a demand on the uncontrolled input in order to meet the necessary persistence of excitation requirements [5].

Blind system identification using an ARMA model requires at least three distinct sensor measurements, which is difficult to accommodate with wearable sensors given the anatomy of the arterial system.

The first limitation has been removed with a new method that identifies the distinct part of the channel dynamics separately from the common dynamics [1]. The goal of this paper is to begin to resolve the second and the third problems, which have acted as a major bottleneck for reliably using the MBSI method in this context.

The approach taken in this paper is to integrate knowledge from physics based hemodynamic models into the MBSI algorithm. Thus, rather than applying a generic black box ARMA model of unknown order for each channel, a more physiologically relevant FIR model structure is specified for each channel based on features derived from arterial pulse wave propagation theory.

II. MBSI

The MBSI algorithm [3,4] can be explained by considering a linear system consisting of two distinct channels connected to the same input.

$$y_1(n) = h_1(n) * u(n)$$
 And $y_2(n) = h_2(n) * u(n)$

From the outputs alone we can determine the input, u(n) and the channel dynamics, $h_1(n)$, $h_2(n)$. By exploiting their relationship with the common input we can obtain the following correlation condition, which the observed outputs must satisfy: $h_2(n) * y_1(n) = h_1(n) * y_2(n)$.

III. HEMODYNAMIC MODEL

Arterial pulse wave propagation models [2] have been shown to accurately reconstruct the complexities of the pressure/flow relationship along the arterial tree. From these models we can identify three main features that are inherent in the dynamics of the cardiovascular system and could be incorporated into a model used in the MBSI algorithm.

Wormsley's equation describes the relationship between the oscillatory pressure and flow in the artery using characteristic input impedance Z_0 . Substitution of physiologically relevant values into the definition of Z_0 reveals that the impedance of any vascular branch features slow decaying dynamics related to the terminal resistance of the microcirculation.

Analogous to a transmission line, pulse waves in the arterial system produce wave reflection at points of impedance mismatch such as vessel bifurcation and vessel radius change. The major reflection sites occur when pulse waves reach the level of the microcirculation. Therefore, any pressure or flow measured in the arterial system results from a combination of the incident wave and a reflected version of the incident pulse wave $P(x) = P_{in}(x) + RP_{in}(x)$, where R is a complex reflection coefficient based on the impedance mismatch.

The third feature, transport time delay, results because of the distance a pulse wave must descend along the arterial pathway to the measurement location.

IV. MODEL BASED MBSI FORMULATION

Incorporating knowledge of the slow decaying dynamics into the system identification problem can be accomplished using a suitable change of basis and is the subject of continuing work.

In this paper a new model structure has been developed that integrates pressure wave reflection and a transport time delay into the MBSI algorithm.

Based on these two inherent features the finite impulse response of each channel is transformed into the gray box model shown in Figure 1.

The FIR impulse responses for the incident wave (h_{in}) and reflected wave (h_{re}) can be written as:

$$h_{in} = \begin{bmatrix} b_{0,in} & b_{1,in} & \dots & b_{N-1,in} \end{bmatrix}, \text{ N coefficients}$$
$$h_{re} = \begin{bmatrix} b_{0,re} & b_{1,re} & \dots & b_{M-1,re} \end{bmatrix}, \text{ M coefficients}$$

The incident pressure wave (yin) can be expressed as:

$$y_{in}(n) = h_{in}(n) * u(n)$$

The reflected pressure wave (y_{re}) can be expressed as a function of the incident wave involving a time delay, k_{re} :

$$y_{re}(n) = h_{re}(n) * y_{in}(n - k_{re})$$

Substituting the equation for the incident pressure wave into the expression for the reflected wave, it can be expressed as a function of the input.

$$y_{re}(n) = h_{re}(n) * h_{in}(n - k_{re}) * u(n)$$

A new impulse response, h_D can now be defined.

$$h_D(n) = h_{re}(n) * h_{in}(n - k_{re})$$
$$h_D = \left[0 \dots 0 \ b_{k_{re}} \dots b_{k_{re}+M+N-2,D}\right]$$

Where the impulse response, h_D has $k_{re}+M+N-1$ coefficients and y_{re} can be expressed as:

$$y_{re}(n) = h_D(n) * u(n)$$

To simplify by letting the final time delay, $k_T = 0$, the measured output can be expressed directly as the sum of the incident and reflected waveforms.

$$y(n) = y_{in}(n) + y_{re}(n)$$

$$\underbrace{u(n)}_{h_{in}(n)} \underbrace{y_{in}(n)}_{z^{-k_{T}}} \underbrace{y_{1}(n-k_{T})}_{y_{re}(n)}$$
Figure 1 Gray Box Arterial Model

Figure I Gray Box Arterial Model

$$y(n) = h_{in}(n) * u(n) + h_D(n) * u(n)$$

$$y(n) = (h_{in}(n) + h_D(n)) * u(n)$$

We finally arrive at a revised formulation for the black box impulse response.

$$h(n) = h_{in}(n) + h_D(n)$$

Where the FIR coefficients for h(n) can be expressed using the impulse responses of the incident and reflected waves.

$$h = [b_{0,in} \dots b_{N,in} \ 0 \dots 0 \ b_{k_{re},D} \dots b_{k_{re}+M+N-2,D}]$$

This final form of the impulse response has $k_{re}+M+N-1$ coefficients and the MBSI equality can be written in the familiar form:

$$h_1(n) * y_2(n) = h_2(n) * y_1(n)$$

The MBSI problem can be simplified by removing the columns that correspond to the zero valued impulse response coefficients in the discrete convolution.

V. CONCLUSION

The conventional MBSI algorithm suffers from some inherent problems when applied to the cardiovascular system. We assert that these issues can be resolved from restructuring the identified model and incorporating salient features derived from arterial wave propagation theory. The model structure used in the MBSI algorithm has been refitted to include knowledge of transport time delay and wave reflection. Future work will consist of incorporating a suitable basis function into a model used in the MBSI algorithm to treat the slow decaying dynamics of the arterial system.

VI. REFERENCES

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