Transforming Artifact to Signal: A Wavelet-Based Algorithm for Quantifying Neonatal Movement

Ian Zuzarte-*IEEE Member,* Courtney Temple, Premananda Indic-*IEEE Member,* and David Paydarfar

***Abstract*— In neonatal research, physiological signals are often degraded by an artifact generated by movement of the infant. Portions of these movement embedded signals are commonly excluded in the analysis of the relevant physiological signal. However, movement may be a significant marker of physiological development of the infant. Here we present results from a wavelet-based algorithm that quantifies neonatal movement, using recordings from the pulse plethysmograph. We suggest that movement-induced artifactual signal can yield important physiological information regarding neonatal physiology.**

I. Introduction

Apnea of prematurity is a common developmental disorder in preterm infants that is implicated in long-term neuro-developmental deficits. Preventative clinical interventions would benefit from quantitative indices that predict risk of apnea, hypoxia and bradycardia [1]. As with many nonlinear dynamical systems, information indicating the underlying parameters or state of a system can be hidden within the observed signals. In physiological systems, disentangling these underlying parameters can be complicated by the interaction of multiple subsystems.

There is currently no routine method for monitoring gross body movements in hospitalized critically ill infants. Here we describe an algorithm for quantifying somatic movement. The idea that gross body movements might be a precursor to apnea has been described previously [1-5]. A number of physiological perturbations result from spontaneous movement, including increased oxygen consumption due to metabolic demands, movement-induced hyperventilation and hypocapnea, and disruption of quiet sleep. These perturbations can lead to a destabilizing effect on ventilatory control and hence the occurrence of movement might serve as an important physiological marker that anticipates apnea episodes.

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Ian Zuzarte is with the Department of Neurology, University of Massachusetts Medical School, MA 01655, USA (phone: 508-856-6227; fax: 508-856-6778; e-mail: ian.zuzarte@umassmed.edu).

Courtney Temple is with the Department of Neurology, University of Massachusetts Medical School, MA 01655, USA (e-mail: Courtney.Temple@umassmed.edu).

Premananda Indic is with the Department of Neurology, University of Massachusetts Medical School, MA 01655, USA (e-mail: Premananda.Indic@umassmed.edu).

David Paydarfar is with Department of Neurology, University of Massachusetts Medical School, MA 01655, USA and also with Wyss Institute for Biologically Inspired Engineering, Harvard University, Boston, MA 02115, USA. (e-mail:David.Paydarfar@umassmed.edu).

We propose a model using the wavelet transform [6] to detect the time varying movement signal from a routinely recorded signal, the pulse plethysmograph (Pleth). We studied the distribution of the movement signal and its characteristics.

II. Methods

A. Experimental Data

A prospective study was performed on 10 preterm infants (gestational age <35 wks) at the Neonatal Intensive Care Unit (NICU), University of Massachusetts Memorial Healthcare. Infants with congenital malformation, chromosomal disorders, congenital or perinatal infection of the central nervous system, intraventricular hemorrhage (>grade II) and hypoxic-ischemic encephalopathy were excluded. Infants were studied while spontaneously breathing room air or receiving supplemental oxygen through nasal cannulae at a fixed flow rate. The protocol was approved by the University of Massachusetts Medical School Institutional Review Board for Human Subjects.

Pulse oximeter plethysmographic waveforms for 10 subjects were recorded and displayed using a bedside monitor (Intellivue MP70, Philips Medical Systems) and streamed to a personal computer using data acquisition software (TrendfaceSolo, Ixellence GmbH in 9 subjects; VueLogger, Wyss Institute, Boston in 1 subject) at a sampling rate of 125 Hz. One-hr data segments for each of the 10 infants were selected from recording periods between feeding periods.

B. Wavelet Based Model for the Detection of Movement Signal from Plethysmograph data

The pulse oximeter is a device that measures the change in the volume of arterial blood with each heart beat. This signal is detected from a sensor attached to the hand or foot of the infant.

The sensor is also highly sensitive to movement, revealed as rapid fluctuations in plethysmograph signal with waveforms that are visibly distinct from the pulse-induced waveform. As a result of these fluctuations, the signal becomes highly non-stationary with rapid changes in amplitude and time scale. To capture only the fluctuations caused by the movement from the Pleth signal, we considered a framework with wavelet transform and developed a procedure to capture the movement signal.

Given a discrete Pleth signal $x(n\Delta t)$, we obtain a wavelet transform of the given discrete signal by the convolution of the data with the scaled and translated version of a mother wavelet $\psi_o(\gamma)$. Thus the wavelet transform is defined as

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$$W_n(s) = \sum_{n'=0}^{N-1} x(n\Delta t)\, \psi_o^*\left(\frac{(n'-n)\Delta t}{s}\right) \quad (1)$$

where N is the number of data points. As described previously [6], convolution is done N times using a wavelet function that has been normalized to have unit energy. We used a dyadic representation of scales as

$$S_j = s_o 2^{j\delta j} \quad j = 1,2,\ldots\ldots J \quad (2)$$

with $s_o = 2\Delta t$, $\delta j = 1/32$ and $J = 256$

Of the different choice of wavelets available, we considered Paul wavelet described as

$$\psi_o(\gamma) = \frac{2^m i^m m!}{\sqrt{\pi(2m)!}}(1 - i\gamma)^{-(m+1)} \quad (3)$$

where $i = \sqrt{-1}$ and order $m = 4$. This wavelet captured the onset of movement accurately compared to other wavelet functions.

We determined the wavelet power spectrum (scalogram) and the maximum value in the scalogram at each instant of time in the period greater than 1.5s. The instantaneous variation of this signal is defined as the movement signal *A(t)* which represents the intensity of movement.

We also determined the duration of each movement burst from the movement signal by setting a threshold of 20 to yield a binary signal as a marker of movement.

$$D(t) = \begin{cases} 1 & A(t) > 20 \\ 0 & otherwise \end{cases} \quad (4)$$

All inter-movement burst durations less than 5s was set to 1 to get a revised marker for the calculation of movement duration.

III. Results

A. Detection of Movement Signal from Plethysmograph

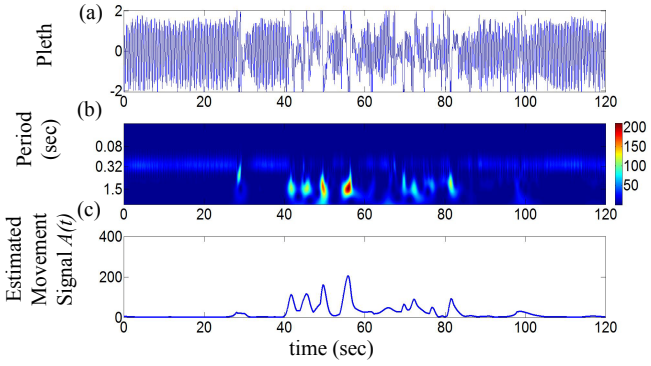

Figure 1. (a) Plethysmograph signal (Pleth). (b) Time-frequency representation of the Pleth signal and (c) Predominant power in the range of 1.5-5Hz extracted from (b)

Fig. 1 represents the time-frequency representation of the Pleth signal and the estimated movement signal. As it can be seen, the movement of the infant is captured in the Pleth signal.

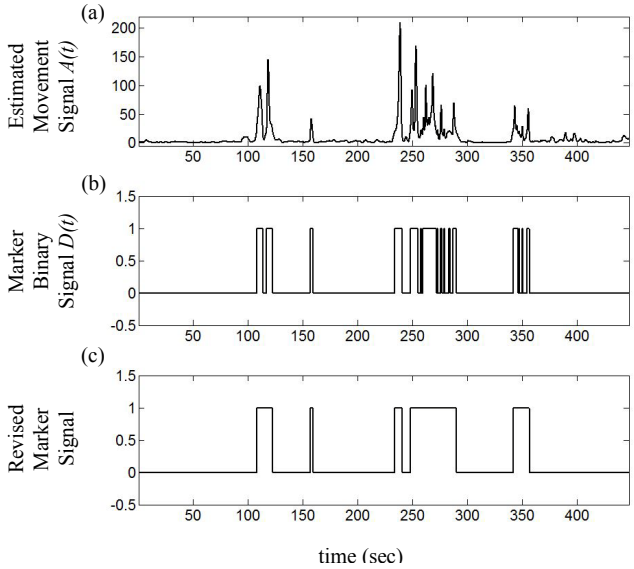

Figure 2. (a) Estimated movement signal *A(t)* derived from the Pleth signal. (b) Marker signal *D(t)* obtained based on setting an arbitrary threshold on *A(t)* (c) Revised marker signal

B. Characterization of Movement Signal

To understand the characteristics of the movement signal, we plotted the distribution of the signal. We found that the distribution follows a long tail, suggesting that the movement signal is not random. Such long tail distributions have also been found as a feature of breathing patterns, i.e., the distribution of interbreath intervals[7,8].

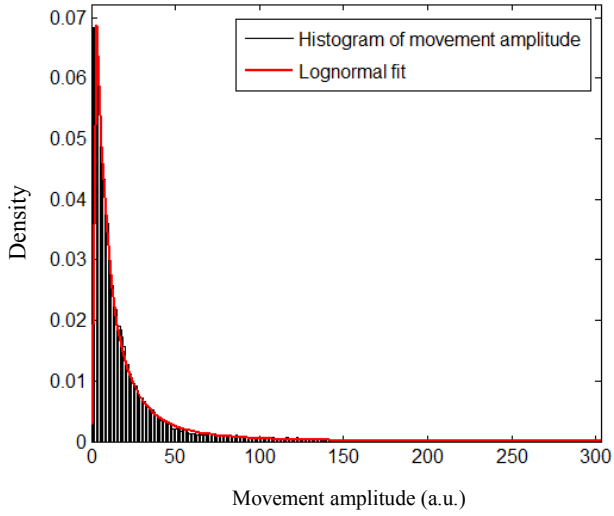

Figure 3. Distribution of the estimated movement signal amplitude, *A(t)* along with the best function fit using lognormal function

We found that the lognormal distribution fits the distribution well in terms of goodness of fit compared to other distributions (Fig. 3). We also estimated the duration of the movement signal estimated from Fig. 2c as the time interval the movement signal remains continuously above zero. The distribution of movement durations also showed a long tail distribution with lognormal function as the best fit (Fig. 4). We considered one hour recordings from 10 infants

and estimated the parameters of the lognormal distribution as shown in Table I.

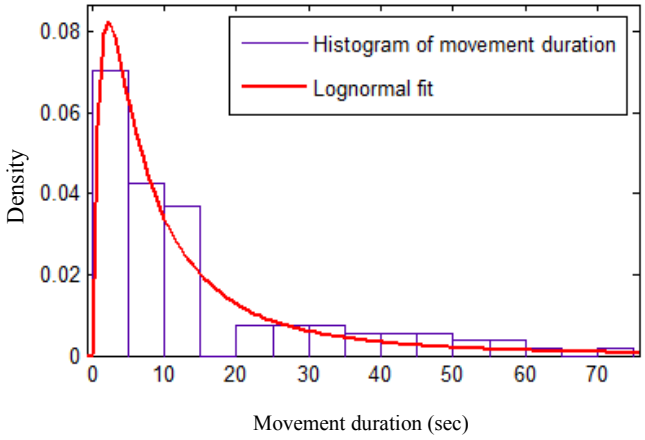

Figure 4. Distribution of the estimated movement signal duration, *D(t)* along with the best function fit using lognormal function

TABLE I. ESTIMATED MEAN (μA) AND STANDARD DEVIATION (σA) OF THE MOVEMENT SIGNAL AND ESTIMATED MEAN (μD) AND STANDARD DEVIATION (σD) OF THE MOVEMENT DURATION ALONG WITH DAY OF LIFE OF 10 INFANTS

Subject #	Day of life (days)	μA	σA	μD	σD
1	25	2.57	1.96	2.32	1.07
2	5	2.25	1.23	1.39	1.35
3	7	2.39	1.44	1.88	1.17
4	8	2.09	1.47	1.56	1.38
5	6	1.79	1.69	1.86	1.31
6	8	2.11	1.70	1.71	1.21
7	3	3.14	1.40	2.10	1.47
8	6	0.74	1.64	1.31	1.35
9	14	0.64	2.05	1.15	1.14
10	15	2.24	1.59	1.71	1.17

C. *Relationship of Movement Characteristics with Infant Physiology*

We calculated the day of life as the difference of post conception age and gestational age. We studied whether the characteristics of the distribution has any relationship with day of life. We found a strong correlation of day of life with the estimated standard deviation of the fitted lognormal distribution of the movement signal (Fig. 5).

We also found a strong correlation of day of life with the estimated standard deviation of the movement duration (Fig. 6). However we did not find any correlation between the estimated mean of either the signal or the duration and the day of life. The exact significance of such a relationship is not known, however it may reflect the maturation of the infant.

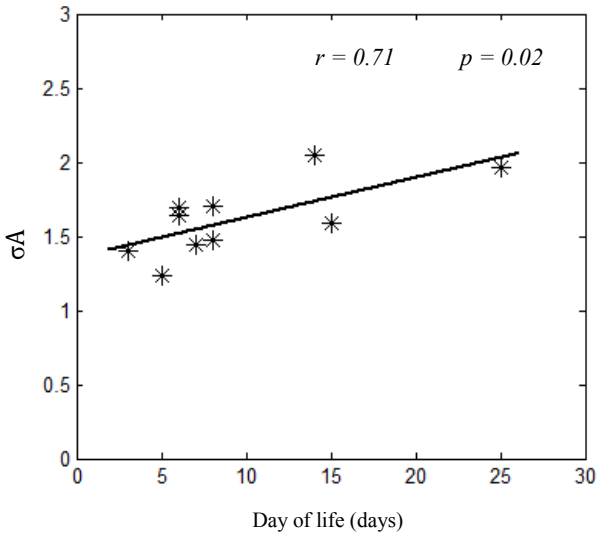

Figure 5. Correlation of day of life with the estimated standard deviation of the fitted lognormal distribution of the movement signal (n=10)

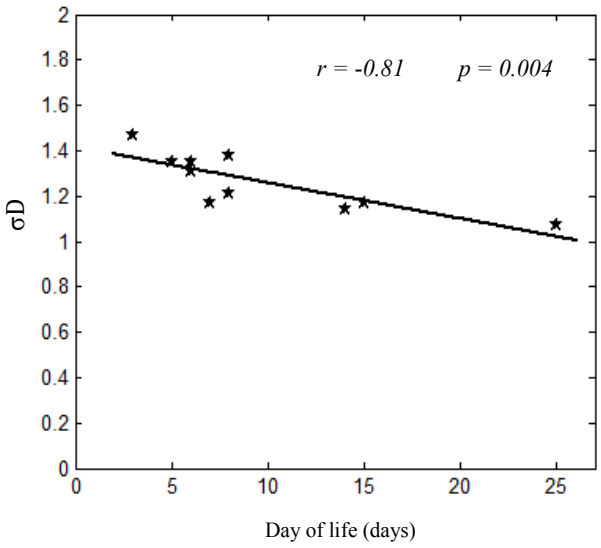

Figure 6. Correlation of day of life with the estimated standard deviation of the fitted lognormal distribution of the movement burst duration (n=10)

IV. CONCLUSION

In hospitalized critically ill infants, there is no routine method for monitoring gross body movement, which appears to be a physiologically important index for infant health and a precursor for life-threatening events [3]. Here we have shown, using a wavelet based algorithm, that movement can be detected from the pulse plethysmograph signal. The distribution of the movement signal as well as duration of movement bursts follows a lognormal function. We found that the estimated standard deviation of the lognormal function correlates with the infant's day of life. This suggests that analysis of movement can serve as an important physiological marker that may be relevant to growth and development.

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