A Comparative Analysis of Methods for Baseline Drift Removal in Preterm Infant Respiration Signals

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A Comparative Analysis of Methods for Baseline Drift Removal in Preterm Infant Respiration Signals

A thesis submitted in partial fulfillment of the requirements for the degree of Masters of Science at Virginia Commonwealth University.

By

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Abstract

A COMPARATIVE ANALYSIS OF METHODS FOR BASELINE DRIFT REMOVAL IN PRETERM INFANT RESPIRATION SIGNALS

By Pallavi Ramnarain

A thesis submitted in partial fulfillment of the requirements for the degree of Masters of Science at Virginia Commonwealth University.

Virginia Commonwealth University, 2010

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Breathing is a vital function intrinsic to the survival of any human being. In preterm infants it is an important indicator of maturation and feeding competency, which is a hallmark for hospital release. The recommended method of measurement of infant respiration is the use of thermistors. Accurate event detection within thermistor generated signals relies heavily upon effective noise reduction, specifically baseline drift removal. Baseline drift originates from several sensor-based factors, including thermistor placement within the sensor and in relation to the infant nares. This work compares four methods for baseline drift removal using the same event detection algorithm. The methods compared were a linear spline subtraction, a cubic spline subtraction, a neural network baseline approximation, and a double differentiation of the thermistor signal. The method yielding the highest event detection rate was shown to be the double differentiation method, which serves to attenuate the baseline drift to zero without approximating and subtracting it.
1. Introduction

A. Respiratory Patterns

Breathing is a vital function intrinsic to the survival of any human being. With preterm infants it is an important indicator of maturation and feeding competency, which is a hallmark for hospital release. Respiratory patterns in infants vary greatly from adults. The increased metabolic rate of newborn mammals, including human infants, necessitates an increase in ventilation [1]. This increase in ventilation can result from an increase in tidal volume, an increase in breathing frequency, or a combination of the two. All of the options have mechanical constraints. An increase in tidal volume results in an increase in the elastic component of breathing work and an increase in the distortion of the compliant chest wall. An increase in breathing frequency results in an increase in the frictional work of breathing, and it requires strenuous efforts during inspiration to adequately ventilate the lungs in a shorter period of time. The time constant of respiratory systems in newborn infants is approximately 220 ms [1]. The breathing pattern in newborn infants is highly variable. It can consist of occasional deep or very shallow breaths, slow breathing periods, rapid bursts, short apneas and interruptions of expiratory flow [1].

Preterm infants switch suddenly between breathing patterns as a function of state of consciousness [2]. There are two primary respiratory patterns in preterm infants: regular and periodic. Periodic refers to periods of ventilation that are interrupted by brief apneas [2]. Cohen et al established measurements of periodicity as important features to be included in classification of the maturation of preterm infants.
Respiratory patterns in preterm infants during feeding change as a function of maturation. Swallow influences respiration through the shared musculature and anatomical spaces involved. At the onset of feedings Vice & Gewolb noted a reduction in breathing rate and tidal volume, and as the feeding progressed the respiratory airflow pattern increased in irregularity [3].

B. Anatomy & Physiology of Respiration

The purpose of respiration is to balance oxygen and carbon dioxide levels in the blood to adapt to changing metabolic needs. The rhythmic movement of the diaphragm and skeletal muscle drive respiration. Air exchange occurs in the alveoli of the lungs. The rhythmic drive for the respiratory system originates in the brain stem. There are two types of sensors involved in respiration: chemoreceptors, which sense acid/base levels and oxygen/carbon dioxide levels, and mechanoreceptors, which relay information regarding the volume of air in the lungs and the resistance to airflow, thereby modulating the rate and depth of respiration [4]. There are six main functional anatomic components to the respiratory system: the central nervous system, the upper airways, the lower airways, the lung parenchyma, the pleural space, and the bones and muscles surrounding the lungs [4]. It used to be believed that infants had to breathe through their nose only because the oropharynx is occluded by the joining of the tongue and soft palate at rest. It has since been shown that while nasal breathing is favored in infants, it is not obligatory [5].
The primary anatomical regions involved in respiration are the nasal cavity, pharynx, larynx, trachea, and lungs. The nasal cavity serves as the primary air inlet in infants [5]. The anterior boundary is composed of nasal cartilage. The inferior boundary is comprised of the bony structure between the nasal and oral cavities, namely the palatine process of the maxilla and palatine bones [4]. The superior boundary is a combination of the nasal, frontal, ethmoid,
and sphenoid bones [4]. The interior of the nasal cavity is divided vertically by the nasal septum, ethmoid bone, and vomer [4]. Turbinates known as the nasal conchae line the nasal cavity with horizontal orientation [4]. Their primary purpose is to direct airflow. The posterior boundary of the nasal cavity consists of choanae, which mark the junction of the nasal cavity with the pharynx [4].

Figure 2: The Nasal Cavity Innervated by Cranial Nerve V (CN V) [6]

The pharynx is a soft tube connecting the nasal cavity to the larynx. Its shape and dimensions are determined by the sleeve of pharyngeal constrictor muscles, the soft palate, the tongue, and the suspension of laryngeal cartilages [5]. The pharynx is divided into three portions [5]. The first portion is the nasopharynx, which extends from the nasal choanae to the elevated soft palate. The second section is the oropharynx, which is bridged to the nasopharynx.
by the faucial arches and extends from the soft palate to the epiglottis. The final portion of the pharynx is the laryngopharynx which extends from the base of the epiglottis to the cricopharyngeal sphincter.

Figure 3: Nasopharynx Depicted from the Left Side of a Cadavar Dissected Along the Saggital Plane [6]
Figure 4: Oropharynx Depicted from the Left Side of a Cadavar Dissected Along the Sagittal Plane [6]
Figure 5: Laryngopharynx Depicted from the Left Side of a Cadavar Dissected Along the Saggital Plane [6]

The larynx serves as the gateway to the trachea. It is a cartilaginous structure suspended by muscular and ligamentous attachments to the hyoid bone and cervical vertebrae. During phonation the larynx modifies airflow. It also serves to protect the airway during swallowing.

The trachea is a semirigid tube composed of semicircular cartilaginous rings connected by ligamentous membranes. The posterior wall runs up against the esophagus. The trachea branches into two primary bronchi that go into each lung.
Figure 6: Trachea Depicted from the Left Side of a Cadavar Dissected Along the Saggital Plane [6]

There are a series of valves that control the flow of air into the lungs and prevent food from occluding or entering the airways. The first of these is in infants is a combination of the soft palate and tongue. The infant tongue is shaped to fit the soft palate, and when the two are closed, air flows from the nasopharynx to the trachea. When the soft palate is elevated, it combines with the pharyngeal constrictors to seal the nasopharynx, preventing food from entering the nasal passages. The next valve is the epiglottis. At rest it is elevated, allowing air to flow to the larynx and trachea. The final valve is the cricopharyngeal sphincter. It remains
tonically closed and serves to prevent food in the esophagus from coming back into the pharynx and also keeps air from filling the esophagus.

Figure 7: Eppiglotic Cartilage Depicted from the Left Side of a Cadavar Dissected Along the Saggital Plane [6]

There are 22 primary nerves involved in the control and management of respiration [4]. Their roles are divided into sensory and motor control. Cranial Nerve V, also known as the trigeminal nerve, is primarily sensory, receiving inputs from the scalp, face, teeth, tongue, oral membranes, palate, nose, and nasal sinuses [4]. Cranial Nerve IX, known as the glossopharyngeal nerve, provides both sensory and motor functions. It innervates the pharynx, posterior third of the tongue, and the carotid sinus [4]. Cranial Nerve X, known as the vagus nerve, also provides both sensory and motor functions [4]. Its motor innervations include the
pharynx, larynx, and esophagus. It has the parasympathetic function of regulating autonomic fibers to the lungs. It also receives sensory input from the pharynx, larynx, trachea, and lungs. In addition to the cranial nerves mentioned, cervical nerves 1-7 and thoracic nerves 1-12 control motor functions of the diaphragm and relay sensory information from the lungs.

Figure 8: Cranial Nerve Innervation of the Upper Respiratory Airways [6]
Figure 9: Depiction of Cervical Nerve Placement for Respiratory Innervation and Control [6]

Figure 10: Depiction of Thoracic Nerve Placement for Diaphragm Innervation and Control [6]
Neural and brainstem control of respiration exists at three levels: afferent sensory control, brainstem organization, and efferent motor control [4]. Afferent, or sensory, control involves the relay of sensory data from respiratory organs to the brainstem. As air enters the respiratory system through the nose, sensory information is collected and sent from the nasal mucosa travels to the nucleus tractus solitaries (NTS) in the brainstem[4][5]. There the information can effect changes in the size of the nasal lumen to improve nasal respiration or trigger protective responses. Sensory receptors in the larynx respond to mechanical and chemical stimuli for airway protection and airflow modulation. Afferent signals from the nose and larynx go from CN X to the NTS. The lungs contain mechano- and chemo- receptors that respond to stretch and the presence of irritants. The carotid and aortic bodies contain chemo receptors to sense pH, oxygen and carbon dioxide levels. They relay this information over the vagal and glossopharyngeal nerves[4][5].

The organization of the brainstem plays an important role in effective modulation of respiration. The NTS in the medulla receives information about gas exchange and ventilation mechanics from the lungs, carotid and aortic bodies, and the larynx through CN IX and CN X [4][5]. This information converges on the central rhythm generator (CRG) in the medulla. The precise location and exact neurons involved in the CRG are still debated. Premotor and intermotor neurons are concentrated in two bilateral sites in the tegmentum of the medulla: the dorsal respiratory group (DRG) and the ventral respiratory group (VRG). The DRG is in the NTS, while the VRG is in the nucleus ambiguous (NA) [5]. Both of them project to the contralateral phrenic and intercostals motoneurons in the spinal cord. The DRG and VRG are
driven by neurons in the CRG, and they function to stimulate changes in breathing rate and depth of breathing to accommodate other motor and autonomic activities in the body.

Efferent motor control involves the relay of information from the brainstem to the various respiratory organs to initiate the motoric movements associated with respiration. The spinal cord is the final common pathway of neural control of respiration and is the pathway for the bulk of motoric information related to respiration. The diaphragm is enervated by cervical nerves 3-5, and thoracic and lumbar nerves enervate the intercostal and abdominal muscles. Also the NA enervates the skeletal muscles of the pharynx and larynx to coordinate with movements of the thoracic muscles to ensure appropriate and smooth airflow [5].

The respiratory system have several protective mechanisms and reflexes integrated within it. These can be separated into two main categories: airway defense reflexes and airway maintenance. Airway defense reflexes serve to keep foreign substances out of the airways by preventing further inhalation or expelling them. These reflexes are triggered in response to signals from mechanoreceptors and chemoreceptors. Responses to these signals include coughing, swallowing, and cessation of respiration. For the purposes of this work, respiratory apneas include any cessation of respiration resulting from the stimulation of these receptors [5]. Apneas can be caused by occlusion or closure or the larynx or by centrally inhibiting respiration. Long apneas can lead to hypoxia and bradycardia. Chemoreceptors in the nose can trigger sneezing, increased mucous secretion, or apneas. Stimulation of nasal mechanoreceptors mainly results in sneezing. Irritation in the upper airways (pharynx and larynx) can trigger coughing, apneas, swallowing, laryngeal adduction, bronchoconstriction, mucous secretion, and subsequent bradycardia. In preterm infants the larynx is highly
sensitive to the presence of fluid [5]. When fluids are sensed in the larynx, the response consists of an apnea during which a swallow occurs and after which a cough occurs. The lungs contain chemo- and mechano- receptors that trigger mucocilliary clearance of foreign materials or irritants, augmented breaths, and coughing [5].

The second category or protective mechanisms provide for airway maintenance. Airway maintenance is a function of the neuromuscular and structural mechanisms responsible for maintaining airway patency [4]. Airway stability is a term that refers to the ability of an airway to resist collapse. The negative pressure generated during breathing can create airway constricting forces, while the airway muscles counteract to providing a dilating force. Neck flexion can also lead to airway constriction, which has implications in infant posture during feeding as craniocervical posture and pharyngeal airway stability are inherently interconnected due to the proximity of the anatomical structures involved in breathing.

There are several maturational considerations that impact the functioning of the respiratory system in preterm infants. At birth, the respiratory structures get positional stability from their close proximity and the infant’s large amounts of subcutaneous fat [5]. As the infant grows it starts to have postural stability. The anatomical structures involved in respiration move apart but are stabilized by an increase in connective tissue, cartilage, and more specialized muscle control [5].

An accurate assessment of respiration in preterm infants must measure one or more variable factors of respiration. There are several variable factors in respiration. The first is respiratory rate, defined as the number of breaths per minute. The rate itself can change, as can the amount of time spent in the various breath stages. Depth of respiration is another
variable factor. The amount of air moved in and out of the lungs with a given breath is referred to as tidal volume. It can be affected by the strength of the muscles associated with respiration. The work of breathing, defined as the amount of work or effort per breath, is another variable factor [5]. It is composed of two parts. The first is the work needed to activate the muscles that cause the lungs to expand, and the second is the work needed to overcome the resistance in the lung tissues and airways for proper respiration to occur. Another variable factor is overall heart function. Stroke volume and heart rate can change the oxygen and carbon dioxide levels in blood. The final variable factor is respiratory drive, which is composed of the complex interconnections between the afferent and efferent nervous signals involved in regulating the drive to breathe.

C. Sensor Description

The inherent variations in respiratory patterns necessitate the use of a measuring device capable of accurately measuring these dynamic changes. Thermistors provide a semiquantitative, indirect way to measure respiration [7]. A thermistor is a device where electric resistance varies as a function of temperature [8]. As the speed of airflow passing the thermistor increases, the change in the thermistor’s temperature increases and approaches that of the passing air [8]. Also, thermistors are recommended by the American Thoracic Society Guidelines for the measurement of airflow in pediatric applications [9].

Thermistors are classified as semiquantitative because the flow output signal they provide is not a direct measurement of actual nasal airflow. Instead it is a combination of nasal airflow and the time constant of the sensor. In 1998 Farre et al found that thermistors could not accurately measure actual flow, and that the relationship between the peak to peak amplitude
of thermistor and respiration signals was nonlinear [10]. They also found that the response of a thermistor depends heavily on the airflow pattern, distance from nose and section of nostrils. The thermistor output signal is a direct measurement of the change in temperature of the actual thermistor, and, with correct placement, an indirect measure of nasal airflow resulting from the change in temperature between inspiration and expiration. The amplitude of the output signal is not an accurate reflection of actual airflow magnitude because of the effects of the associated time constant [9]. The temperature change sensed by a thermistor results from convective heat transfer, and Farre et al found that the true breathing airflow signal and the sensor temperature signal were related by a nonlinear differential equation [10]. They also found that the most influential factor affecting the accuracy of the thermistor output was air convection around the device. Respiratory efforts can be inferred from thermistor measurements, but they are really a measurement of nasal airflow. It has been found that thermistor measurements significantly underestimate apneic events [7]. Also, the presence of a nasal cannula can significantly increase the nasal airway resistance in subjects with narrow nares or deviated nasal septums [7].

The physical geometry of the thermistor sensor can also play a role in its response time and accuracy. Primiano et al found that when the surface temperature of the thermistor was less than the dew point of the gas it was measuring, a small layer of condensation coated the sensor, delaying its response time [11]. As the temperature reaches the dew point, the sensor output stabilizes until the condensation evaporates, and the resulting dry thermistor tracks temperature properly. This is less of concern with the thermistors used in this study as the surface area of the sensing portion was so small that any condensation effects were negligible.
In 2009 Series et al found that current thermistor technology is accurate enough to detect apneas [12]. They also noted, though, that a decrease in thermistor output could be the result of either an apnea or mouth breathing. Their definition of an apnea was a 50% decrease in thermistor signal for 10 seconds or more and/or an accompanying 2% decrease in SaO2.

The temperature difference within a thermistor is so small that it is negligible, and as such a lumped heat capacity model can be used when modeling its response [13]. Storck found that the thermistor temperature does not directly describe the respiratory phase in a meaningful way, but its time derivative illustrates respiration well [13]. This is because the derivative describes heat flux, which changes more rapidly than temperature.

D. Signal Description

One of the biggest challenges in processing nasal airflow signals obtained from thermistors is accurately eliminating artifact. Artifact is evident primarily as signal offset and baseline drift, although at times 60 Hz powerline interference can also be observed. The closest physiologic signal comparison is the electrocardiogram (ECG). ECGs often exhibit similar forms of signal noise as respiration. Noise sources that result in baseline wandering in ECG signals include power line interference, electrode contact noise, and EMG. Respiration can also contribute to ECG baseline drift. Like ECG signals, baseline drift in respiration signals is in-band noise, meaning the frequency of the signal drift falls within the frequency range of the actual signal itself.

To investigate these issues, Afsar et al compared 7 techniques for baseline removal in ECG signals: cubic spline curve fitting, linear spline curve fitting, median filtering, finite impulse response high pass filtering, adaptive filtering, wavelet adaptive filtering, and empirical mode
decomposition [14]. For their application wavelet adaptive filtering worked best because their goal was to remove baseline drift while preserving the morphology of the ST wave. These seven approaches constitute the usual approaches to baseline removal. High pass filtering is not a viable solution for this application because the frequency range of the baseline drift overlaps with the frequency content of the signal. Wavelets are inappropriate for this application for the same reason.

In choosing the final method for baseline drift removal, a comparison was done between linear approximation, cubic spline approximation, an adaptive filter, a first derivative based approach, and a fifth approach described as a second derivative signal modeling approach.

E. Objectives

The purpose of this work was to compare four methods for baseline drift removal in preterm infant thermistor based respiratory signals. The first three methods selected all attempted to model the baseline drift in order to subtract it. These included a linear approximation, a cubic spline interpolated approximation, and a recurrent neural network approach mimicking an adaptive filter. The final method for comparison involved calculating the first and second derivatives of the signal in order to attenuate the baseline drift.
2. Baseline Removal Methods

Data was collected from 9 preterm infants during bottle feedings. This data was a subset of a larger study of preterm infant feeding (NIH R01NR05182, RH Pickler, PI). All respiratory data was collected using thermistors made by U.S. Sensor (model H1744). Figure 11 shows the thermistor and Figure 12 is a schematic of the thermistor. The thermistors were embedded in modified pediatric nasal cannula. The signal passed through a bridge circuit (see a simplified representation in Figure 13) was then differentially amplified through an instrumentation amplifier (Analog Devices, AD-524) then filtered through an active 2nd order low pass filter \( f_c = 10 \text{ Hz} \) before being digitized. The BIOPAC MP150 was used to sample the thermistor signals at a rate of 1000 samples/sec. Post processing was done using MATLAB (© Mathworks Ltm). The four methods were compared to a data expert’s findings. For this analysis one instance of data was used, file 01901.

Figure 11: Photograph of Thermistor [15]

Figure 12: Schematic of Thermistor [15]
Figure 13: Example Thermistor Bridge Circuit

Figure 14: Depiction of Sensor
A. Event Detection Algorithm

The same event detection algorithm was used to compare all the methods. The algorithm sets a threshold based on the statistical properties of the signal, and then zeros the signal below that level. All points where the signal crosses the threshold are treated as potential onset of breath locations. Maximums for each region where the signal crosses the threshold are calculated. These calculated points serve as the event markers, except for instances where the points are closer than 200 ms.

B. Linear Approximation

Linear approximation of baseline drift was chosen as a method for comparison due to its ease of implementation. The raw thermistor output was interpolated using a linear approximation that included downsampling to 2 Hz. Downsampling enabled a smoothing of the waveform that better approximated the baseline drift. Frequencies above 2 Hz started to mimic...
the true nasal airflow signal, which would result in dramatic signal loss. Once the linear approximation of baseline drift was calculated, it was subtracted from the original thermistor output signal, and the final result was visually examined to gage the efficacy of the methodology. The event detection algorithm was run using the subtracted signal as an input and points were matched to an expert’s opinion.

Figure 16 shows the linear approximation of the thermistor output signal. Unfortunately the linear interpolation did not closely approximate the signal drift in all instances (see Figure 17). The linearly interpolated signal was subtracted from the original thermistor output signal, resulting in a clear removal of the thermistor signal’s DC component (see Figure 18). However this approach was not able to eliminate the underlying signal drift (see Figure 19).

![Figure 16: Linear Approximation of Baseline Drift](image.png)
Figure 17: Discongruencies in the Baseline Approximation of the Linearly Interpolated Signal

Figure 18: Comparison of Thermistor Output to Subtracted Linear Interpolation
C. Cubic Spline Approximation

The cubic spline approximation of baseline drift was chosen as a method for comparison because its approximation is more accurate than the linear method due to its incorporation of every point of the signal. A cubic spline interpolation of the raw thermistor output signal was calculated. The resulting signal was then down sampled to 1 Hz. The sampling rate of the cubic spline signal was chosen to be 1 Hz in an attempt to only approximate the baseline wandering and exclude the actual respiratory signal. After the cubic spline was calculated, it was subtracted from the thermistor output signal, and the resulting waveform was visually examined for validity. The subtracted signal was then used as the input for the event detection algorithm, and the final output points were matched to those of an expert’s opinion.

Figure 20 shows the cubic spline approximation of the thermistor output signal. From this figure it is clear that this polynomial-based approach was a more accurate approximation.
method than the linear spline. Figure 21 shows how the subtraction of the cubic spline approximation from the original thermistor output signal eliminated the bulk of the thermistor signal’s DC components. A closer inspection, though, shows that the baseline drift is still present in the signal, although to a much lesser extent than with the linear approximation method (Figure 22).

![Figure 20: Cubic Spline Approximation of Baseline Drift](image)
Figure 21: Effect of Cubic Spline Subtraction on Thermistor Signal

Figure 22: Residual Baseline Drift After Cubic Spline Subtraction
D. Adaptive Filter (Elman Network) Approximation

An adaptive filter is a filter that changes its coefficients as a function of the input signal. It is self-adjusting and can use many different types of training algorithms. Figure 23 shows a standard arrangement for an adaptive filter. The input \( x[n] \) goes to both an unknown system \( H \) and to the finite impulse response (FIR) filter \( W \). The filter’s output \( y[n] \) is compared to the unknown system’s output \( d[n] \), which is the desired signal. An error is calculated \( e[n] \) and the coefficients of the FIR filter are adjusted accordingly.

![Diagram of an Adaptive Filter](image)

Figure 23: Diagram of an Adaptive Filter [16]

The most commonly used form of an adaptive filter uses the least mean-square algorithm. That approach was inappropriate for this set of data as it assumes the underlying process is stationary and requires that the solution space to be linearly separable. The adaptive filtering approach chosen to approximate the underlying baseline wander embedded in the thermistor output signal used the Elman neural network architecture. This was chosen because it is a recurrent neural network, which makes it suited to handle time series data, and because its architecture was developed for the purpose of amplitude detection. Recurrent neural networks store information in their hidden nodes that impact subsequent training epochs.
The goal of the network was to track the gross signal amplitude changes to approximate the baseline drift for subsequent removal. Two inputs went to a hidden layer of 10 nodes. The inputs were a 10 second sample of the thermistor output signal and an amplitude approximation signal that served as the network target. The 10 second data segment was chosen because MATLAB was unable to process longer segments of data. The network was trained with the data over 1000 epochs, and the final resulting weights were used to approximate the data.

The neural network did not reach convergence. Convergence was defined as occurring at the epoch after which the error rate stayed below 0.01. Figure 24 shows the mean squared error of the Elman network plotted by epoch number. The final error rate did not reach the target error rate of 0.01. Figure 25 shows the original data, the amplitude approximation signal that served as the network target, and the actual network output. From this figure it is clear that the neural network approach was not practical for the removal of signal drift. The output of the neural network could not be analyzed using the event detection algorithm because a final approximation of the baseline drift was never achieved, so it was not possible to subtract the network approximation from the original breath signal.
Figure 24: Mean Squared Error of the Elman Network Training

Figure 25: Comparison of the Thermistor Signal, Amplitude Approximation, and Neural Network Output
### E. Second Derivative Based Signal Modeling Approach

Breathing is a nonstationary process [17]. As such, breathing signals can be modeled as the sum of two sinusoids and a constant.

\[ A = A_1 \sin(\omega_1 t) + A_2 \sin(\omega_2 t) + C \]

The constant is the DC offset. One sinusoid is the actual breathing waveform, with a frequency of approximately 1Hz, and it is superimposed over the second sinusoid, of a much lower frequency, which is the baseline drift. When the first derivative of the signal is calculated it removes the DC offset.

\[ A' = A_1 \omega_1 \cos(\omega_1 t) + A_2 \omega_2 \cos(\omega_2 t) \]

The second derivative does not completely remove the baseline drift, but it attenuates the amplitude to near zero.

\[ A'' = -A_1 \omega_1^2 \cos(\omega_1 t) - A_2 \omega_2^2 \cos(\omega_2 t) \]

Griffiths et al first explored this model of nasal airflow in 2005 [9]. Figure 26 shows example outputs for this approach. From this figure it is clear that the DC component of the original nasal airflow signal is removed in the velocity calculation. It is also clear that the baseline drift attenuates to near zero with the calculation of the acceleration signal. For these reasons, the second derivative modeling approach was selected for the removal of baseline drift in the thermistor nasal airflow signals.
Figure 26: Comparison of Each Stage of the Algorithmic Flow

**F. Analysis of Accuracy of Second Derivative Signal Modeling Approach**

Figure 27 shows the algorithmic flow used. First the velocity signal was calculated from the original digitized thermistor output signal using a 20 point central difference method. The velocity signal was then smoothed using a 100 point rectangular window moving average technique. The same steps were repeated for the calculation and smoothing of the acceleration signal. The number of points chosen in both the derivative and smoothing techniques were empirically chosen. The resulting acceleration signal was filtered to remove any remnants of high frequency noise with a 10th order Butterworth low pass filter. This filter and order were
chosen out of the need prevent amplitude distortion while minimizing the amount of
introduced phase distortion. The filter cutoff frequency was 10 Hz, which was selected to
prevent the distortion of event transitions while leaving the bulk of the spectral content of the
signal (which is primarily from 0 to 2 Hz) unaffected. The filtered acceleration signal was then
used as the input to the event detection algorithm previously described. Positive peaks were
located as they mark the onset of inhalation while negative peaks mark the onset of exhalation.
The outputs were then compared to an expert’s opinion. A match was described as being within
400 ms of the expert detected point. The data files used to test the algorithm were chosen such
that each was free of any noise source not directly related to the signal acquisition process (free
of data collection anomalies).
Figure 27: Algorithmic Flow
3. Results

Figure 26 shows the signal outputs at each stage of analysis. It is clear that the velocity signal does not contain the signal offset that is contained in the original thermistor output signal. Furthermore, the acceleration signal has less baseline drift and resembles the original signal’s morphology more accurately, with only a slight phase shift.

Table 1 shows a comparison of three of the methods described. While the cubic spline approximation approach detected more points than the linear approximation method, it had a higher Type I error rate. Type I errors consisted of points detected by the expert that were not detected by the algorithm. The most accurate method is the second derivative method (Type I Error = 18%).

Table 2 shows the results for the analysis of accuracy of the second derivative method. The differentiated signal modeling approach combined with the described event detection algorithm yielded an average accuracy rate of 78%.
Figure 28: Comparison of Algorithmic Event Detection Using Second Derivative Method and Expert-Detected Points

Table 1: Comparison of Each Method’s Output to Expert’s Findings for File 01901

<table>
<thead>
<tr>
<th>Method</th>
<th>Expert’s # Points</th>
<th>Detected # Points</th>
<th>% Type I Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Interpolation</td>
<td>304</td>
<td>251</td>
<td>54%</td>
</tr>
<tr>
<td>Cubic Spline</td>
<td>304</td>
<td>277</td>
<td>59%</td>
</tr>
<tr>
<td>Second Derivative</td>
<td>304</td>
<td>308</td>
<td>18%</td>
</tr>
</tbody>
</table>

Table 2: Analysis of Second Derivative Method

<table>
<thead>
<tr>
<th>Subject</th>
<th>Expert’s # Points</th>
<th>Algorithm’s # Points</th>
<th>% Type I Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1205</td>
<td>233</td>
<td>277</td>
<td>4%</td>
</tr>
<tr>
<td>1599</td>
<td>179</td>
<td>187</td>
<td>16%</td>
</tr>
<tr>
<td>01901_alt</td>
<td>304</td>
<td>308</td>
<td>18%</td>
</tr>
<tr>
<td>2098</td>
<td>324</td>
<td>321</td>
<td>17%</td>
</tr>
<tr>
<td>2398</td>
<td>353</td>
<td>260</td>
<td>37%</td>
</tr>
<tr>
<td>2498</td>
<td>240</td>
<td>288</td>
<td>36%</td>
</tr>
<tr>
<td>2599</td>
<td>217</td>
<td>197</td>
<td>21%</td>
</tr>
<tr>
<td>02698_alt</td>
<td>247</td>
<td>240</td>
<td>39%</td>
</tr>
<tr>
<td>2798</td>
<td>320</td>
<td>258</td>
<td>27%</td>
</tr>
<tr>
<td>7112</td>
<td>299</td>
<td>370</td>
<td>8%</td>
</tr>
<tr>
<td>AVG</td>
<td>271.6</td>
<td>270.6</td>
<td>22%</td>
</tr>
</tbody>
</table>
4. Discussion

The purpose of this work was to compare the accuracy of four methods for baseline removal and to evaluate the effectiveness of the second derivative modeling approach in the detection of the onset of inhalation in nasal airflow signals. The results show that the second derivative modeling approach was far more accurate than the linear approximation or cubic spline approximation. The Elman network was never able to generate an approximation of baseline drift.

There are several factors to consider when examining preterm infant respiration signals obtained with thermistors during bottle feedings. One such factor is the heating of sensor surroundings from the temperature of the formula used during feeding. This can be a contributing factor to signal drift seen by the thermistor. Another factor to consider is the placement of the sensor on the infant. If the thermistor is not placed in close proximity to the infant’s nostril the acquired signal will be of very low amplitude and have a low signal to noise ratio. Sometimes infant movement during feeding causes the sensor to slip in relation to the nostril. Proper placement is depicted in Figure 15. The final major factor that affects signal quality before acquisition is the placement of the thermistor within the nasal cannula. If the sensing portion of the thermistor is too far inside the cannula, the sensor will have a low signal to noise ratio and low signal amplitude resulting from a decrease in the variations of the temperature. A portion of the sensing part of the thermistor could also end up contained within the hot glue, which would have a detrimental effect on the overall function of the sensor by insulating the sensor from variations in temperature, increasing thermal mass. If the thermistor is too far outside of the cannula, a lot of artifact can be introduced from excessive movement of
the sensor or from the sensor not being within the flow of airway currents. All of these factors contribute to the quality and consistency of the signal that is obtained during data acquisition.

While the double differentiation technique was the most effective method at removal of baseline drift, there are several weaknesses to this approach. One such weakness is when the original signal has a portion of low amplitude event occurrences and a portion of high amplitude even occurrences. Here the algorithm fails to detect events because they fall below the detection threshold. To compensate for this weakness, the number of events detected can be compared to an average preterm infant respiratory rate. If the value is significantly under a reasonable level, then it can be identified as potentially erroneous. The second derivative signal can be plotted, and a more appropriate threshold can be determined and implemented.

Another weakness of this approach is that there is no way to distinguish true apneas from instances of mouth breathing. Also, when the algorithm indicates the presence of an apneic episode, there is a chance that it could be that the amplitude of the signal was so low it passed below the algorithmic threshold, which can indicate shallow breathing and does not necessarily indicate a full cessation of breath. Both of these are due to the placement of the thermistors outside of the nasal cavity. While there are other ways to measure breath and respiration, this thermistor and nasal cannula technique is the least invasive and least cumbersome. As such it is best to address this weakness by simply being mindful of it during data analysis and interpretation.

Anecdotally it was observed that at times the double differentiation of the original signal made it possible to detect breath events that were hidden in the noise of the original signal, meaning at times this algorithmic approach was able to “salvage” otherwise unusable
data. Further evaluation of this approach would benefit from a quantification of this phenomenon. While this double differentiation modeling and algorithmic event detection approach has its downsides, overall it appears to be accurate enough to use for larger data sets.
6. References

2. F.L. Vice and I.H. Gewolb, “Respiratory patterns and strategies during feeding in preterm infants”,  
3. Costanzo
4. Feeding Disorders
6. A. BaHammam, “Comparison of nasal prong pressure and thermistor measurements for detecting  
8. A. Griffiths, J. Maul, A. Wilson, S. Stick, “Improved detection of obstructive events in childhood speel  
   apnoea with the use of the nasal cannula and the differentiated sum signal”, *J Sleep Res.*, vol. 14, pp.  
9. R. Farre, J.M. Montserrat, M. Rotger, E. Ballester, and D. Navajas, “Accuracy of thermistors and  
11. F. Series and I. Marc, “Nasal pressure recording in the diagnosis of sleep apnoea hypopnoea  
13. F.A. Afzar, M. Arif, and J. Yang, “Detection of ST segment deviation episodes in ECG using KLT with  