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Dynamic Model Inversion Techniques for Breath-by-Breath Measurement of Carbon Dioxide from Low Bandwidth Sensors

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Abstract— **Respiratory CO_2 measurement (capnography) is an important diagnosis tool that lacks inexpensive and wearable sensors. This paper develops techniques to enable use of inexpensive but slow CO_2 sensors for breath-by-breath tracking of CO_2 concentration. This is achieved by mathematically modeling the dynamic response and using model-inversion techniques to predict input CO_2 concentration from the slow-varying output. Experiments are designed to identify model-dynamics and extract relevant model-parameters for a solid-state room monitoring CO_2 sensor. A second-order model that accounts for flow through the sensor's filter and casing is found to be accurate in describing the sensor's slow response. The resulting estimate is compared with a standard-of-care respiratory CO_2 analyzer and shown to effectively track variation in breath-by-breath CO_2 concentration. This methodology is potentially useful for measuring fast-varying inputs to any slow sensor.**

I. Review of Capnography Sensors

RESPIRATORY carbon dioxide (CO_2) gas analysis or capnography, has become a critical part of a number of diagnostic tests and monitoring devices used clinically. For example, monitoring respiratory gases has now become current standard of care for patients receiving general anesthesia [1]. After anesthesia, respiration can be depressed because of anesthesetic agents or additionally administered drugs (namely opioids) used to control pain leading to a rise in CO_2 concentration (hypercapnia). Breath analysis involving monitoring of the exhaled CO_2 concentration is therefore used in anesthesia [2-4].

Integration of respiratory gas analysis with measures of breathing pattern (e.g., tidal volume, respiratory rate) and ventilation to obtain measures of oxygen consumption (VO_2) and carbon dioxide production (VCO_2), can provide powerful prognostic information in a number of diseases [5]. In the case of hypercapnia (excess CO_2 in blood), breath analysis requires measurement of concentration of CO_2. Measuring exhaled CO_2 has also been used to confirm the correct placement of an endotracheal tube in the trachea and has saved many lives [6]. Several other applications such as monitoring patient breathing during treatment of cardiac arrest, asthma, dyspnea, pediatric trauma etc have also been reported [7].

Current measurement systems for CO_2 gas analysis include infra-red analyzers and mass spectrometers. Bedside infra-red analyzers are used for respiratory CO_2 gas analysis in anesthesiology [8]. Mass spectrometers have always been considered the gold standard for respiratory gas analysis for a number of reasons, including fast response time, ability to measure dry gases, accuracy and stability of measures [5]. In addition they have the advantage of measuring multiple gases simultaneously. These systems however have fallen out of favor due primarily to cost and size, as well as the need for ongoing preventive maintenance. When cost and space are not an issue, they remain the premier system for respiratory gas analysis. Several modifications can be made to mass spectrometers to further reduce gas delays and enhance response times.

A major limitation of both bedside infrared analyzers and mass spectrometers is the fact that they are expensive, bulky, cannot be used for ambulatory applications and for remote dynamic applications. In addition, the constant sample draw, temperature changes and water vapor pressure result in additional complications in these systems that need to be overcome (e.g., special lines or chemicals to dry the gas prior to analysis), which often causes delays in analysis or reduced response times.

Thus there is a need for new technology that would overcome many of these current obstacles. In particular, there is a significant need for small portable CO_2 sensor units that can be attached to the patient and used for ambulatory clinical applications [9, 10]. A small wireless respiratory CO_2 analysis system would allow for continual ambulatory measures. Having the potential for continual or intermittent wireless feedback on respiratory CO_2 measures could provide unique and important feedback for monitoring health status in several patient groups and has the potential to reduce emergency room visits and reduce health care costs [11, 12].

Early embodiments [13, 14] of respiratory monitors for non-intubated patients have been limited to measurement of respiratory rate alone. A more recently developed infra-red probe (PhaseIn Medical Technologies, Inc.) may be used to measure CO_2 at the nose of the patient. While such probes are more convenient to use compared to the bedside analyzers, they are still far too bulky to be attached to the body of the patient. Hence, they cannot be used for ambulatory or home monitoring applications (such as sleep apnea), where a small untethered sensor unit that can be mounted on the nose of the patient would be invaluable.

II. Solid-State Technologies for CO_2 Sensing

Solid-state CO_2 sensors developed using responsive materials have the potential to be small, inexpensive and directly mountable beneath the nasal cavity, making them

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attractive for ambulatory monitoring. Several materials have been examined for realizing solid-state CO_2 sensors. Materials found responsive include polymers [15, 16], carbon nanotubes [17-19] and metal carbonates [20, 21]. However, most materials have been reported to be unacceptably sensitive to other respiratory variables (like temperature, humidity and other gases), making them inadequate for respiratory CO_2 analysis.

A relatively selective solid state sensing technology has been that of metal-carbonate electrolytic sensors. Electrolytic carbonate sensors possess sensitivity and selectivity suitable for respiratory monitoring. One embodiment [21] based on Li_2CO_3-$CaCO_3$ was shown to be particularly selective. This embodiment was later commercialized by Figaro Engineering, Japan [22].

However, such sensors show response times that are orders of magnitude higher (10's of seconds) than that required for respiratory monitoring (100ms). Hence they have been traditionally used for slow CO_2 monitoring applications like indoor air quality and greenhouse monitoring. However, it is possible to use such slow sensors for monitoring fast CO_2 concentration changes using a mathematical model of its time-response. This is shown for the first time in this paper using a Figaro electrolytic sensor.

The developed algorithm allows commercial electrolytic CO_2 sensors to be used for monitoring fast changes in respiratory CO_2 gas concentration. The estimation algorithm which could be easily implemented on a micro-controller or a base-computer is not expected to substantially add to the size and cost of electrolytic CO_2 sensors. Thus, this technique heralds the use of low-cost electrolytic CO_2 sensors for ambulatory respiratory monitoring.

The following section discusses algorithm development and signal processing techniques for estimation of fast varying CO_2 concentration input from a slow Figaro electrolytic sensor. Then, details of the experiments with the Figaro sensor are provided followed by experimental comparisons with an infra-red respiratory CO_2 analyzer. A robust second-order cascaded model is found to be sufficient for predicting respiratory CO2 input.

III. Model Inversion Using First Order Model

The development of an estimation algorithm requires a mathematical model of the slow sensor's dynamic response. Using a model, it would be possible to understand the relation between the actual input (respiratory CO_2 concentration) and the observed output from the sensor. In this work, the sensor is initially modeled as a first order transfer function of the form:

$$y(t) = x(t) - \tau \dot{y}(t) \qquad (1)$$

where y is voltage from the sensor, x is the respiratory CO_2 concentration and τ is the time constant. This model is chosen because the first order response closely resembles that of an electrolytic CO_2 sensor's response. Figure 1 shows the time response of a first order system ($\tau = 90$) and Figure 2 shows the observed response from a Figaro CO2 sensor. Since the sensor's response was similar to a first order system's response, the above model initially seems adequate.

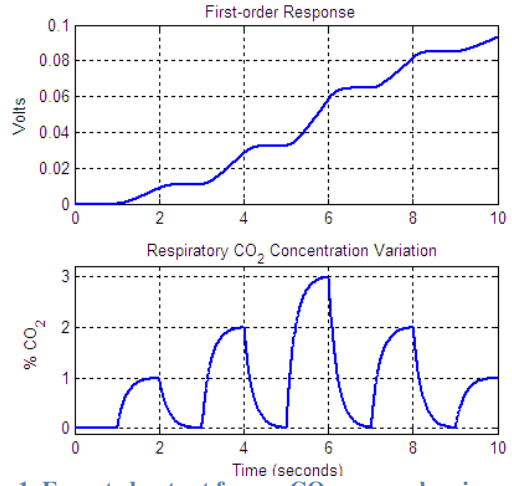

Figure 1. Expected output from a CO_2 sensor showing a first-order response to respiratory CO_2 input

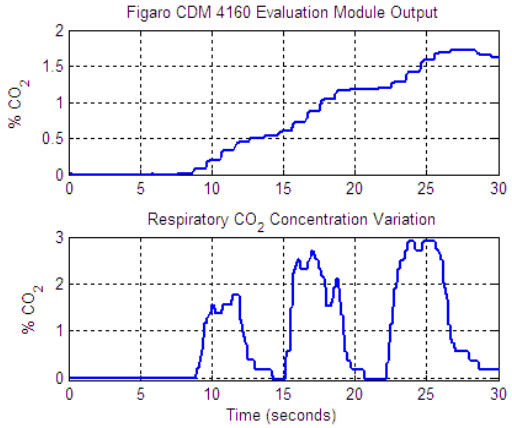

Figure 2. Observed response of Figaro CO_2 sensor to real breathing

An inverse first-order equation was then be used to predict the fast varying input provided the time constant τ of the system is known (the time constant itself can be determined by experiments). In this work, further signal processing was also used to remove the effect of noise and in the data.

A. *Estimation Algorithm*

Let the respiratory CO2 input and sensor output (as functions of time) be denoted by $x(t)$ and $y(t)$ respectively. Eq. 1 can be rewritten as:

$$y(t) + \tau \dot{y}(t) = x(t) \qquad (2)$$

Substituting $\dot{y}(t) = \frac{y[n] - y[n-1]}{\Delta t}$, Eq. 2 can be written in discrete-time domain as:

$$x[n] = y[n] + \tau . \frac{y[n] - y[n-1]}{\Delta t} \qquad (3)$$

where $x[n]$, $y[n]$, $y[n-1]$ denote present input, present output and output at previous time-step respectively.

τ and Δt are sensor's time constant and data acquisition system's sampling time respectively. Eq. 3 can be used to estimate the input $x[n]$ by measurement of the output $y[n]$ over time.

The above technique assumes that the sensor's time constant τ is known *apriori*. Time constant τ is defined as the time taken for the sensor's response to reach 63% of its final value. The time constant can be calculated by calibration experiments.

As Eqs. 2, 3 involve differentiation of a measured signal, high frequency measurement noise will be amplified greatly. Hence the estimate of the input $x[n]$ will be noisy. To reduce the effect of noise, the measured signal $y[n]$ is filtered through a low-pass filter before using Eq. 3. However, such filtering does not completely eliminate noise in the measurement. Hence, the input-estimate $x[n]$ is further filtered through a low-pass filter to remove noise and make the signal readable.

B. Results

The above procedure was used to estimate the breathing input to a Figaro CDM 4160 evaluation module. A calibrated NDIR capnograph (Nonin LifeSense with analog voltage output) was used to compare estimates with true respiratory CO_2 concentration. The capnograph drew breath samples using an internal pump through a 21" nasal pressure cannula (Medcare #1420002) which was stuck on the outer wall of the Figaro CO_2 sensor as shown in Figure 3. Note that delays due to transport through sampling tube are not compensated in this work as they do not affect comparison between estimated and measured CO_2 concentrations.

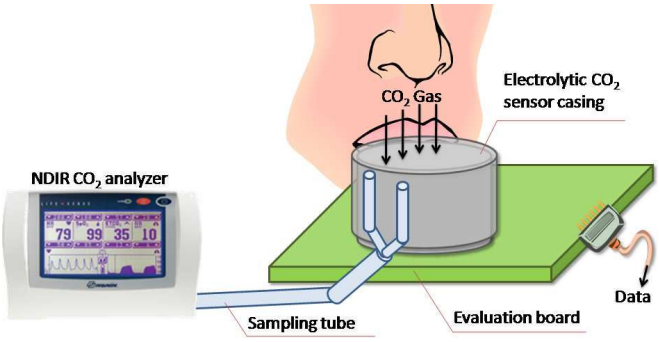

Figure 3. Schematic diagram of showing sampling tube stuck on Figaro CO_2 sensor's wall (not to scale)

Initial estimates (with τ = 17) using the first order model for the Figaro sensor resulted in drift in the estimate. This is shown in Figure 4. The drift observed in the estimate could not be corrected by altering the value of τ used in Eq. 3 indicating that the first-order model could not completely capture the dynamic response of the sensor.

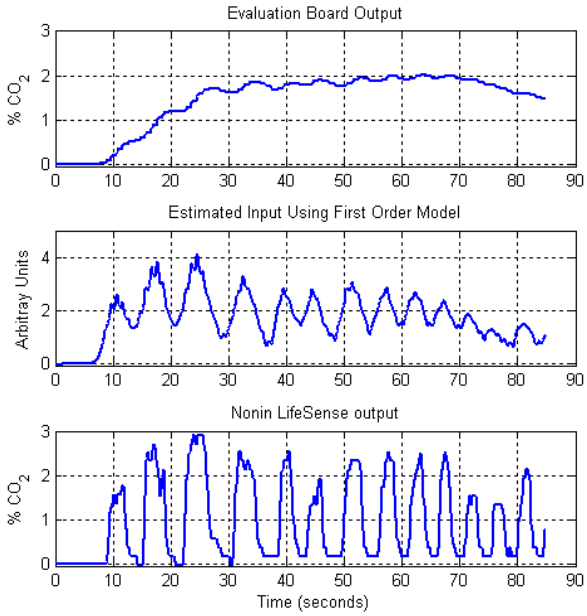

Figure 4. Drifting estimate using first order model for CO_2 sensor

IV. MODEL INVERSION USING SECOND ORDER MODEL

Since the first order model does not provide a completely accurate estimate of the capnogram, a more accurate model is developed to directly remove drift, while simultaneously correcting the shape of estimated input. The assumption behind the first order model was that the slow response was due to the inherent speed of the electrolytic sensor. The effect of the zeolite filter covering the sensor was ignored in the model. Zeolite filters are typically used to absorb certain interfering gas species that could corrupt the sensor's output. However, gas transit through such filters reduces the speed of response of the sensor. Thus zeolite filters enable robust sensing sacrificing speed of response.

The second order model is chosen as a cascade of two first order models:

$$y(t) = y_f(t) - \tau_s \dot{y}(t), \quad y_f(t) = x(t) - \tau_f \dot{y}_f(t)$$

where y_f is unmeasured CO_2 concentration of outflow from zeolite filter, τ_f and τ_s represent time constants for filter and sensor respectively. Following the derivation in the previous section,

$$y(t) + \left(\tau_f + \tau_s\right)\dot{y}(t) + \tau_f \tau_s \ddot{y}(t) = x(t) \qquad (4)$$

Substituting $\ddot{y}(t) = \dfrac{y[n] - 2y[n-1] + y[n-2]}{\Delta t^2}$, Eq. 4 can be written in discrete-time domain as:

$$x[n] = y[n] + \left(\tau_f + \tau_s\right).\frac{y[n] - y[n-1]}{\Delta t} + \tau_f \tau_s .\frac{y[n] - 2y[n-1] + y[n-2]}{\Delta t^2} \qquad (5)$$

Calibration experiments using the Nonin LifeSense CO_2 analyzer and Figaro CO_2 sensor were used to obtain values for τ_f, τ_s. MATLAB™ software's system identification toolbox was used to identify the time constants in the second

order model as $\tau_f = 15.13$ and $\tau_s = 1.44$. The software computes the best fit between the predicted data and measured data to calculate these time constants. Trial-and-error with model orders and time-constant values also indicated the correctness of the second order model and time constant values respectively. These time constants were used to estimate the input in other experiments.

Figure 5 shows the comparison between first and second order models in predicting the respiratory input due to a single breath. The error in estimating the input due to the first order model is clear from Figure 5.

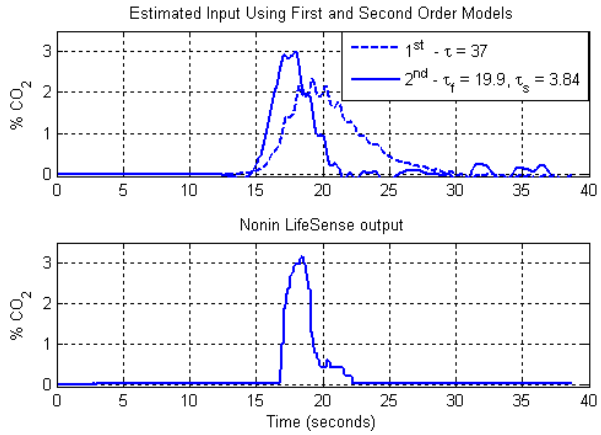

Figure 5. Comparison of estimated input using first and second order models for a single breath

Figure 6 shows the effect of using Eq. 5 in correcting the drift observed in Figure 4. It may be seen from Figure 6 that the estimation algorithm reliably tracks variation in peak CO_2 concentration in every breath with little drift.

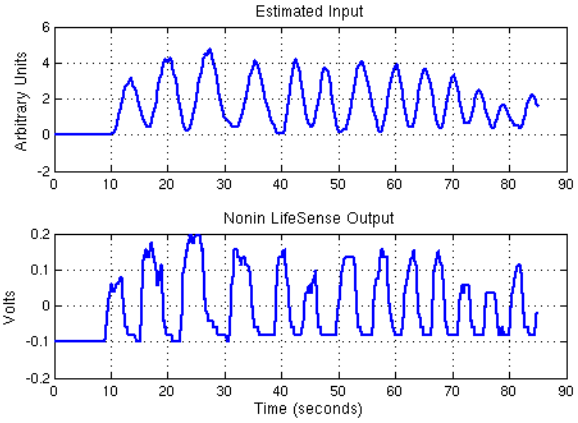

Figure 6. Drift-free estimate using second order model for CO_2 sensor

V. CONCLUSION

Results obtained show good correlation with measurements from standard-of-care NDIR respiratory CO_2 analyzers. The estimation algorithm reliably tracks the relative variation in peak CO_2 concentration with every breath. Future work will address improvements to predict the exact shape of capnogram.

The algorithms presented above are a first attempt to use signal processing to achieve high-speed gas sensing with slow CO_2 sensors. These modeling and measurement techniques allow use of any slow solid-state sensors for high-speed sensing. Thus, the developed method is potentially useful for a variety of sensing applications besides respiratory monitoring.

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