A Simple Model Implementation to Measure Breath by Breath the VO2 and VCO2 by the Indirect Calorimetry Technique

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Abstract — This paper proposes a discrete random time series modeling for the VO2 and VCO2 measurement in the Indirect Calorimetry Technique (ICT). Mathematical equations are developed in order to establish clear differences between the breath-by-breath and mixing chamber measurement based calorimeters. This simple model offers not only a physiological ICT definition approach but also defines the idea of VO2 and VCO2 short-term variability information for research. The preliminary results show a new physiological information when a computer oriented algorithm model implementation was applied to a data acquisition system in order to obtain the power spectrum analysis from a typical observation subject submitted to the clino-ortho maneuver.

I. INTRODUCTION

Oxygen consumption (VO2) and carbon dioxide production (VCO2) are measured by different techniques in order to compute the Resting Metabolic Rate (RMR), using the indirect calorimetry technique (ICT), in critical and ambulatory patients [1].

The current measurement practice in estimating the VO2 and VCO2 involves mainly “breath by breath” (BbB) and “mixing chamber” (MC) based instruments [2],[3]. In both cases, the measurement procedure is to perform a single 15 to 20 minute measurement test period, where a series patient conditions and equations are assumed to compute the RMR. This short time data window is extrapolated to 24 hr to provide an estimation value for daily resting energy losses and total energy expenditure calculations [1].

In addition, different studies have reported a very large inter-individual and intra-individual variability in the RMR between measurements with few hours of difference. For instance, normal volunteers and critical ill patients have been ICT tested showing 12.5% and 46.0 % of average variability, respectively [4]. Therefore, the implicit measurement model, under which most commercial instruments are designed, looks for the VO2 and VCO2 short-time average measurements as they were only random variables, even in BbB based calorimeters, in order to increase RMR measurement reliability and to diminish what it is considered to be variability. Hence, this commercial implicit model considers short-term variability as physiological irrelevant information, patient out of “steady state condition” or as instrument dependent noise [5],[11].

On the other hand, ICT measurement guidelines establish short-term “steady state” as a single 5-minute interval during which VO2 and VCO2 averages change by less than a variation coefficient (\( \frac{\Delta}{\bar{x}} \)) of ±5% in order to assure reasonable reliability and to expect a patient steady state measurement condition despite the fact that only 54% of most ambulatory patients under the ICT fulfill this requirement and to neglect, this probabilistic band criteria, patient’s physiological “reactivity” to the expired gas capture devices like face half masks and canopies [6], [7], [8]. Additionally, different ICT bench studies have been mainly devoted to show carefully the instruments performance (accuracy, precision, linearity, etc) without paying too much attention to the physiological issues together with the measurement model to explain differences between BbB and MC techniques [9]. This is probably because the metabolic dynamics studied by the ICT are not so well understood yet and due to the difficulty in comparing and interpreting similar results, which are related to the ample variety of instrument designs, that are not yet standardized [10], [11].

This work attempts to establish in the ICT a simple understanding model using the BbB measurement technique, that not only takes advantage of the state of the art instrumentation concepts and nomenclature but it also extends them in order to generate a new VO2 and VCO2 digital time series measurement technique, which is algorithmically easy to implement and to measure in the time and frequency domain.

II. METHODOLOGY

A. The Model

Figure 1 shows a schematic model, where VO2(t) and VCO2(t) are multiplied by the instant expired gas flow f(t) in terms of breath by breath events. This timing product produces a continuous sampling process that it is possible to model by the equations (1) and (2). Also, this model assumes that the VO2(t) and VCO2(t) are two variables that exist as a continuous random processes at the lung
blood alveoli supply level and, after their sampling procedure and an algorithm computation, are transformed into a discrete digital time random series VO2[n] and VCO2[n] at the mouth level.

\[ \frac{1}{V_T} \int_{-\infty}^{\infty} VO2(t) \cdot f(t) \cdot g(t - Dn) \cdot dt = VO2[n] \]

\[ \frac{1}{V_T} \int_{-\infty}^{\infty} VCO2(t) \cdot f(t) \cdot g(t - Dn) \cdot dt = VCO2[n] \]

Where:

\( V_T \) is the tidal volume, which is computed as \( \int_{0}^{res} f(t)dt \).

\( g(t - Dn) \) represents a continuous “gating” function that lasts only for the “Dn” instant flow time duration.

Equation (5) defines the nature of this function.

\[ g(t - Dn) = u(t - Dn) - u(t - D(n + 1)) ; n = 1,2,\ldots \text{etc} \] (5)

Therefore, VO2[n] and VCO2[n] represent a discrete time series generated by the breath by breath events. Equation (6) and (7) summarize these discrete series, where the weights VO2[Dn] and VCO2[Dn] depends on the integral values in equations (3) and (4), respectively, and are calculated in equations (13) and (14) for each breath.

\[ VO2[n] = \sum_{Dn=1}^{\infty} VO2[Dn] \cdot \delta[n - Dn] \] (6)

\[ VCO2[n] = \sum_{Dn=1}^{\infty} VCO2[Dn] \cdot \delta[n - Dn] \] (7)

Here, \( Dn = 1,2,\ldots \text{etc} \).

Observe that “Dn” has two different meanings at the same time in order to keep a simple notation and to combine digital with continuous domain analysis. This index serves to establish the variable breath by breath sequence using the subscript “n” as in (6) and (7), but the only “D” part stands for the instant flow continuous time duration for each breath as in (3), (4) and (5).

On the other hand, if one considers VO2[n] and VCO2[n] as stochastic processes, it is easy to see that it is possible for them to be decomposed into three statistical parts in order to understand the difference between “MC”
and “BbB” technique-based instruments. Equations (8) and (9) show what parameters are convenient to measure.

\[ \begin{align*}
    V'O_2[n] &= V'O_2 + vV'O_2[n] + r'[n] \\
    V'C'0_2[n] &= V'C'0_2 + vV'C'0_2[n] + r'z[n]
\end{align*} \]

Where:

1) \( \text{V'O}_2 \) and \( \text{V'C'}0_2 \) are the statistical averages that have to be interpreted as random variables, because their estimation values depend on the time window of breaths taking in account to compute these averages. The window size and the estimation algorithm is not well standardized among instrument manufactures.

2) \( vV'O_2[n] \) and \( vV'C'0_2[n] \) are the short-term variability that together with the intrinsic instrument noise \( (r'[n], r'z[n]) \) is considered as irrelevant information and it is not separated neither calculated but absorbed as a general measurement standard deviation \( (s) \) error. Here, the \( (\sum f(k)) \) variation coefficient \((\leq 10\%)\) is considered as a good figure to assure a “steady state” measurement condition.

3) Mixing chamber based instruments only compute averages, if one considers the MC as a low pass filter. Then, equations (10) and (11) show the MC effect over the stochastic processes time series \( (\text{V'O}_2[n], \text{V'C'}0_2[n]) \) as an expect value estimation calculation and the short-term variability does not correspond to \( \text{V'O}_2[n] \) and \( \text{V'C'}0_2[n] \).

\[ \begin{align*}
    E[\text{V'O}_2[n]] &= \text{V'O}_2 \\
    E[\text{V'C'}0_2[n]] &= \text{V'C'}0_2
\end{align*} \]

B. The instrument

We used an upgraded second-generation commercial calorimeter (EMS-50 model, Utah Medical Products Inc.).

With a new oxygen sensor (Oxigraf Inc.), an “Excel-MatLab” base data processing program and a superimposed pneumatic BbB circuit to the original MC instrument design [12].

The extra BbB measurement system was implemented using a commercial (TSI flowmeter) hot-wire instant flow transducer coupled to a half-face mask (3M Inc.) with two valves to capture only the expired gases. Figure 3 shows a block diagram sketch with the MC and BbB pneumatic circuits. The calibration quality was kept under control using different gas mixtures reference tanks (Ascott Inc & Lindell S.A.) in the physiological range \((0, 18, 21 \text{ and } 50\% \text{ for O}_2 \text{ fractions; similarly} 0, 3, 10, 5\% \text{ for CO}_2 \text{ fractions, all complemented in pairs with N}_2\)).

C. The measurement algorithm

Equations (12) and (13) show the discrete form implementation of the equations (3) and (4) for any single breath computation. Here, the integrals become discrete sums under the analog-digital process, where “k” stands for a running sampling index every 10 msec, and the continuous functions become discrete sequences in the “k” domain.

\[ \begin{align*}
    V'O_2[\text{D}n] &= \left( T \sum_{k=1}^{\text{D}n} f(k) \right) \cdot \left( F'I0_2[k] - F'E0_2[k] \right) \quad (12) \\
    V'C'0_2[\text{D}n] &= \left( T \sum_{k=1}^{\text{D}n} f(k) \right) \cdot F'E0_2[k] \quad (13)
\end{align*} \]

Then, “T” is the sampling 10 msec period and “Dn=1, 2,...” is an index to show the particular “breath” under processing, but in the sum limit should be interpreted as “k” sampling points duration.

This algorithm was implemented using Mathlab offline programming once digital flow and gas fractions data were obtain through out an Excel interface from the A/D converter. The time delay between instant flow and gas fraction products was compensated by a constant “k” data points equivalent to approximately 850 msec. The basic idea was to detect a flow threshold to assure that one breath was initiated, and then from that point on the product-sum was computed until “Dn” was detected as the end of the discrete instant flow end. Finally Dn point was used in order to place at \( \delta[n - \text{D}n] \) the “\( V'O_2[\text{D}n] \)” and “\( V'C'0_2[\text{D}n] \)” variable amplitudes.

III. RESULTS

The Figures 4 and 5 are examples of the data acquisition system and the \( \text{V'O}_2[n], \text{V'C'}0_2[n] \), discrete time series generation using the equations (12) and (13) for each breath computation. In addition, Figure 6 shows a power spectrum analysis, using the clinical clino-ortho maneuver in order to explore how useful could this time series random modeling approach be in order to analyze physiological experiments. The power spectrum was...
computed using the Welch algorithm after the time series were re-sampled in order to obtain a 0.5 Hz bandwidth.

![Graph showing continuous time gas fractions](image1)

**Fig. 4.** This graph shows an example of the continuous time gas fractions FE02(t), FECO2(t) and the “BbB” instant flow f(t) in the data acquisition system display.

![Graph showing random discrete time series](image2)

**Fig. 5.** This graph represents an example of the VO2[n] and VCO2[n] random discrete time generation during a clino-ortho physiological maneuver. Note that the delta sequence functions are placed just at the end of each breath flow cycle.

![Power spectrum analysis](image3)

**Fig. 6.** A power spectrum analysis of the VO2[n] and VCO2[n], obtained from a volunteer subject under the clino-ortho physiological maneuver, is shown. The frequency analysis bandwidth goes from zero to 0.5 Hertz, where it is observed “1/f” tendency in ortho and one relevant energy peak at 0.05 Hz in clino position, which disappears during the change position.

**IV. Conclusion**

These preliminary results show the ease to implement a computer algorithm in order to create a novel way to measure the VO2 and VCO2. The discrete random time series here proposed to measure the VO2(t) and VCO2(t) is not only more physiological, but also clarify differences between the “BbB” and MC instrument based techniques. In addition, this model creates a new analysis tool with possible application in physiology research as it is seen with the power spectrum analysis result at the time we implement the clino-ortho maneuver. Finally, this work encourage more research in order to define a new concept for the patient’s “steady state” condition, which may be more oriented to physiological information obtained through breath-by-breath ICT short-term variability analysis, as in (8) and (9).

**REFERENCES**


