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Design and modelling of a portable breath analyser for metabolic rate measurement.

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Abstract

Breath-by-breath levels of O_2 and CO_2 may be used to determine human metabolic rate which, in turn, is related to the problem of obesity. A sensor system has been designed to not only monitor O_2 and CO_2 in breath, but also temperature, relative humidity (RH), volumetric flow-rate, and trace levels of CO. Our system targets energy expenditure measurements to within a 1% tolerance. A data driven modelling approach has been adopted to characterise the gas sensors at gas concentrations found in inhaled air and exhaled breath. Data were collected for model fitting from experiments performed on an automated gas testing rig. Bi-exponential curves were fitted to the sensor data using partial least squares (PLS) regression. These fits show that the O_2 sensor functions close to the target accuracy, with a 95% confidence interval, whereas the CO_2 sensor performs less well (70%). Development of a microcontroller interface combined with work on new low-power CMOS sensors will eventually lead to a miniature low-cost system for mobile phone application.

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Keywords: breath; metabolic-rate; calorimeter; modelling; low-cost; CMOS; smartphone.

1. Introduction

Breath analysis offers a non-invasive insight into the body function, with applications such as the disease screening and detection and providing information on physical fitness. In this paper, we present a prototype indirect calorimeter developed to determine the metabolic rate of a subject through differential measurements of CO_2 and O_2 levels of air

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inhaled into and exhaled out of the lungs. A flow sensor is used to detect the direction and rate of airflow to enable the volume of gas exchange taking place during a subject's breathing to be calculated. Energy expenditure (EE) can be calculated from volumes of O_2 consumed and CO_2 produced. It is hoped that, on a minute by minute basis, a handheld device will be able to calculate instantaneous EE values and be capable of extrapolating several measurements throughout a day to produce 24 hour metabolic rate estimation.

Sampling breath directly poses conditions which require robust gas sensors, to endure saturated gas potentially contaminated with a large range of gases and compounds. To verify that the sensors incorporated in the gas testing system function sufficiently in controlled laboratory conditions (with known temperature, humidity and gas mixture), experiments were performed to demonstrate their characteristics. The gas sensor responses are modelled, the corresponding response times calculated using these models, and the device repeatability and accuracy explored.

1.1. Background

Whole body calorimetry is considered to be the gold standard for metabolic rate determination through measurements of CO_2 production and O_2 consumption [1]. However, respiratory room experiments require the subject to remain enclosed inside a chamber, with no access to medical care, for a considerable period of time (24 hour measurements are common). Such a setting is not suitable either for routine use in the community or for acutely ill patients in hospital. A human subject's total EE is composed of the energy required by the functions necessary to sustain life (respiratory etc.), the thermal effects of food and the energy consumed by physical activity. Knowledge of metabolic rate can help assess a subject's metabolic requirements and their fuel utilisation, all of which are important factors relating to weight variation and obesity investigations [2-3]. In intensive care units (ICUs) patients' nutritional needs are often approximated based on their medical condition, height, weight and age. However patients are susceptible to malnutrition [4], and the empirical mathematical model equations used to estimate metabolic rate are liable to introduce errors when either unsuitable for a particular case or when incorrectly applied. Patient recovery times may therefore benefit from more accurate determination of metabolic rate.

The target for our prototype device measuring a subject's EE was set at 1% tolerance. Analysis of data collected from the University Hospitals Coventry & Warwickshire (UHCW) Whole Body Calorimeter Unit demonstrated that O_2 and CO_2 concentrations need to be measured to an accuracy of 0.52% and 1.2%, respectively. To meet this requirement, an electrochemical O_2 sensor (Alphasense O2G2) and non-dispersive infrared (NDIR) CO_2 (Gas Sensing Solutions SPRINTIR 0-5%) sensor were selected for their promising specifications and affordability. These sensors are known to be sensitive to temperature and humidity [5-6]; therefore a GE ChipCap2 sensor was fitted to compensate for these parameters. To detect trace levels of CO contained in breath an Applied Sensor AS-MLC CO sensor is included the test chamber and Sensirion SFM3000 flow meter to calculate exhaled volume.

1.2. Methodology

Exhaled breath is almost completely saturated (*ca*. 100% RH) and is at a higher temperature (~36°c) than normal ambient conditions, thus components in any device designed to measure breath need to be able to function in this abnormal environment. In order to characterise the performance of each sensor, synthetic laboratory gases (and water vapour) were mixed to levels similar to those expected in exhaled breath. Testing the device with exhaled breath from human volunteers to test intra-individual variability is ongoing.

A block diagram of the prototype system is shown in Fig. 1 (a) which was designed for the testing of low cost gas sensors, together with a photograph of the innovative Perspex chamber housing, Fig. 1 (b), fitted with the sensors and relevant circuit boards. The chamber was connected to a gas testing rig, capable of providing controlled levels of O_2, CO_2, CO and RH via four mass flow controllers (Alicat MC-5SLPM). Analogue gas sensor voltage responses were recorded via a LabVIEW (2013) interface connected to a National Instruments 6341 USB data acquisition unit. Digital outputs from the CO_2 and flow sensors were logged using an Arduino Uno microcontroller. Ongoing work targets a standalone system to record all sensor outputs using only a microcontroller, without the requirement for a computer. The O_2 and CO_2 sensors were tested using pulses of each gas, while maintaining one at a set concentration. A section of a test routine is shown in Fig. 1 (c), where the O_2 level was pulsed between 20 and 16%, while the CO_2 concentration was kept constant, initially at 2% and then 3% (baseline of 21% O_2 zero air).To examine the range of O_2 and CO_2 gas

concentrations found in breath, the levels were varied from between 21-16% and 0-5% respectively. A voltage difference feature was extracted from each sensor's output response to a step change in gas concentration. The change in output from baseline to one minute after the introduction of the gas concentration step was extracted across three repetitions performed for each mixture. The results for each sensor were randomly split into 50% training and 50% test vectors. A PLS regression model was implemented using MatLab software (R2013b), to categorise each sensor response. A CI was produced to validate whether each sensor was capable of meeting the target 1% EE measurement.

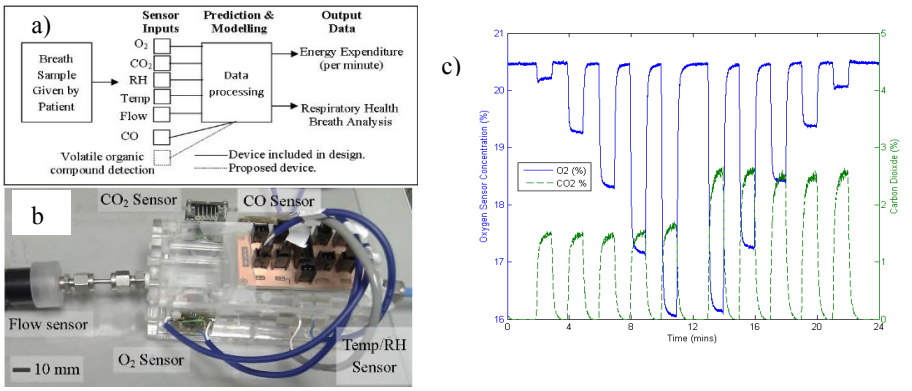

Fig. 1. (a) System level block diagram; (b) Photograph of the sensor chamber, ~132 mm length, 23 ml dead volume, connected to gas testing rig; (c) Section of test patterns used to generate the PLS regression model of the O_2 and CO_2 sensors.

2. Results and Discussion

Assuming the occurrence of a two stage reaction, bi-exponential curves were fitted to the O_2 sensor responses to each gas concentration step change. A 20 s window was selected to fit each curve to the sensor response. The curve fitted, Fig. 2 (a), shows a very close fit to the sensor response (R^2 =0.999); the t_{90} response time was calculated as 9.5 s from the bi-exponential fit. A similar curve fitting procedure was repeated for the CO_2 sensor, shown in Fig. 2 (b), where a bi-exponential curve was fitted to the response with R^2 = 0.998. The response time of the CO_2 sensor is slower with a t_{90} time of 14.1 s. In the current configuration, neither sensor responds within a sufficient time to perform breath-by-breath calorimetry. Human respiratory rate is typically ~12 breaths per minute [7], with a breath-to-breath interval of ~5 s. It is hoped that the system will be adapted further, using a chamber with lower dead volume, thus reducing mixing time in the chamber, along with investigation of methods to decrease sensor response time, will enable the sensors to respond rapidly enough to capture an exhalation. The sensor response is otherwise adequate for gas analysis of this concentration range; the outputs do not contain spurious noise or cross-sensitivity problems. The sensors were tested for sensitivity to CO and RH where neither device was adversely affected.

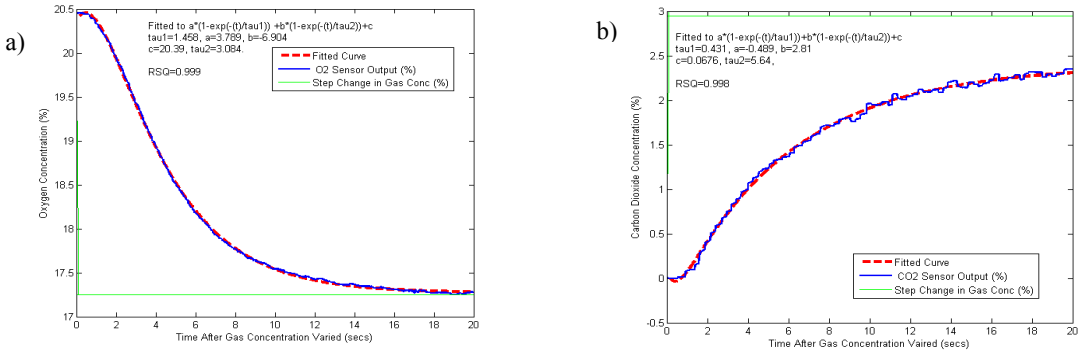

Fig. 2. (a) First 20s window from O_2 sensor response showing raw sensor output, bi-exponential fitted curve and step change in O_2 concentration; (b) First 20s window from CO_2 sensor response to step gas concentration variance, with raw, fitted curve and input step change plotted.

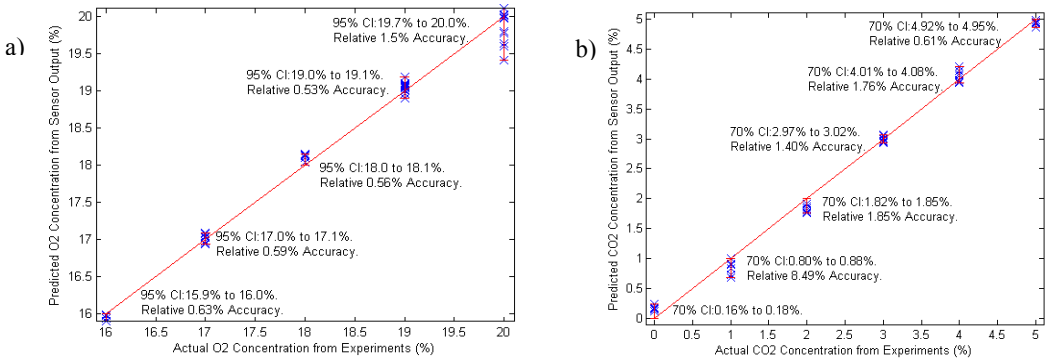

Fig. 3. (a) Model output for O_2 sensor including 95% CI calculations to assess performance, demonstrating the sensor is operating close to desired target 0.52% accuracy; (b) Model output for CO_2 sensor, target relative accuracy of 1.20%, 70% CI demonstrates poor performance.

O_2 and CO_2 concentrations were varied in 1% steps cylindrically, to simulate the cyclical nature of breathing. The PLS model outputs for the O_2 and CO_2 sensors are shown in Figs. 3 (a) and (b), respectively. The O_2 sensor is shown to produce high accuracy, with a 95% CI that the sensor output will be close to the desired 0.52% target accuracy, to guarantee EE measurements accuracy to within ±1%. The repeatability of the O_2 measurements is acceptable, however results at 20% O_2 level have a greater variation of 0.3%, compared to the 0.1% accuracy shown at lower concentrations. The CO_2 sensor results demonstrate poorer performance, needing a 70% CI to come close to the desired 1.20% relative accuracy. The spread of these results is lower (mean 0.06%), however given the lower range of CO_2 of interest, the sensor's accuracy is inferior.

3. Conclusions

An innovative modelling approach has been developed to test low cost gas sensors for use in a portable metabolic rate breath analysis unit. The current unit contains sensors for O_2, CO_2, CO, flow, temperature and RH. The O_2 and CO_2 sensors have been found to respond too slowly to perform breath-by-breath analysis of metabolic rate, although further work redesigning an improved sensor chamber aims to remedy this issue. The electrochemical O_2 sensor, used to measure concentrations of O_2 from 16-21%, produces sufficiently accurate results in a laboratory setting to measure EE to within a 1% tolerance. Current work involves trialing the system with human participants. The NDIR CO_2 sensor has a slow response time of 14.1 s, given the nature of the measurement principle, and further work aims to improve this aspect. The current configuration can only be used as a benchmark for the trialing of sensors and chamber designs, when considering breath-by-breath measurements. The aim is that this system will ultimately allow us to monitor breath gas composition and identify sensors that can predict metabolic rate.

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