Early Prediction of Hypoxia Based on Vitals Analysis and Predictive Analytics

Vahram Mouradian, Afarin Famili, Mahdieh Ashiani
Sensogram Technologies Inc.
Plano, Texas, USA
emails: {vahram, afarin, mahdieh}@sensogram.com

Alexandra Kozhemiakina
Sensogram Technologies Inc.
Kiev, Ukraine
email: alexandra@sensogram.com

***Abstract* — This study investigates the SensoSCAN device for both its health monitoring properties and prediction of different diseases by vital sign analysis. The study's objective is to develop a probabilistic model for predicting the presence of hypoxia using correlation chains to assess patients' vital signs gathered by the SensoSCAN. Vital signs, including heart rate, oxygen saturation, activity level, and systolic and diastolic blood pressure, are used to monitor patients' health conditions. Our functional system helps predict hypoxia in its early stages, when distinctive symptoms are absent and patients may not be aware of the presence of the disease. Analysis is made using dependencies in correlation matrix, constructed correlation chains, and predictive analytics. This study utilizes the hypothesis that hypoxia is an effect of consecutive process of activity where the increase in heart rate and respiration rate correlate with a decrease in oxygen saturation. The ultimate goal is to use mathematical Markov processes and build Markov chains, where elevated heart rate and respiration rate and depressed oxygen saturation are caused by higher activity levels. Alternatively, Markov chains are constituted considering other vitals (either heart rate, respiration rate or oxygen saturation) as independent variables. This system will ultimately assist doctors in assessing patients' health by defining the main dependencies between human vitals.**

Keywords-Vitals; hypoxia; SensoSCAN; correlation analysis; predictive modeling.

I. INTRODUCTION

A. Introduction to Hypoxia

Oxygen is essential for the development and growth of multi-cellular organisms. Many sophisticated biological mechanisms that involve capturing, binding, and transporting of oxygen maintain our cell and tissue homeostasis [1]. Two terms are used for oxygen deficiency: hypoxia and hypoxemia. Hypoxemia is a frequent cause of hypoxia. They are interrelated as both terms are states of oxygen deficiency; hypoxemia is a condition when there is a significant drop in blood oxygenation and arterial oxygen tension is below normal, while hypoxia is oxygen deficiency on the cellular or tissue level. The lack of treatment of hypoxemia can lead to hypoxia [2][3]. Types of hypoxia include: hypoxic hypoxia (oxygen deficiency in the lungs from high altitude or decreased oxygen saturation (SPO_2) in the air) anemic hypoxia (inability of the blood to accept oxygen in suitable volume), stagnant hypoxia (inability of cells to accept or use oxygen molecules), and histotoxic hypoxia (inability of cells to use oxygen [3][4]). Hypoxemia and/or hypoxia can result in severe changes in cellular metabolism. In the case of oxygen insufficiency, normal metabolism turns to anaerobic metabolism that produces fewer molecules of energy (adenosine triphosphate). Products of this type of metabolism can destroy cell membranes and lead to cell death and organ failure [3][5]. Clinical assessment of oxygen is usually invasive, and a challenging task to tackle. Patients with cardiac and respiratory illnesses, and patients who smoke, consume alcohol, or coffee are in the risk zone. Early recognition, prediction, prevention, and treatment of hypoxemia is very important for patients as the disease can result in decreasing tissue oxygen consumption and severe physiological symptoms as organs begin to fail. Nevertheless, the prediction should be made to prevent many adverse situations [3][4]. Vitals monitoring can help in prediction of the early stages of hypoxia; decreased oxygenation results in abnormalities that include tachycardia (heart rate more than 100 beats per minute (bpm)), tachypnea, (respiratory rate more than twenty-four breaths per minute (brpm)) and high blood pressure. Bradycardia and hypotension are the result of severe hypoxia [3]. The most logical technique for recognition of hypoxia is reading the percentage of hemoglobin that is saturated with oxygen. Normal oxygen saturation is greater than 95%, whereas 90% and below is connected with hypoxemia. The interval between 90% and 95% is considered to be an asymptomatic first stage of the disease that causes confusion. A patient may not be aware of the presence of the disease. Critical stage of the disease, where SPO_2 is 70% or less, may result in brain damage and death. Patients are almost incapacitated, lose consciousness, and stop breathing; their tissues are not provided with an adequate amount of oxygen, resulting in widespread tissue necrosis and organ damage that may not be fully reversible [3][4].

B. Remote Monitoring Systems and Wearable Devices

The traditional hospital treatment model keeps patients in hospital beds attached to smart monitoring systems for health assessment. In modern healthcare, wireless sensors and smart technologies make it possible to monitor patients' health parameters under remote oversight of a doctor and can give the ability to effectively monitor health. The accurate and early prediction of clinical events is an important part of remote health-monitoring. Continuous remote health monitoring being established is crucial as it can reduce the staggering cost of observations as wearable sensors are available at a very low cost. Such systems also

 ISBN: 978-1-61208-659-0

give the ability to save patient waiting time, and solve the problem with the limited capacity of hospitals. In addition, there is a possibility to control patients' health at any time, from any place [6]. Unfortunately, most remote wearable prediction systems work only on one vital parameter (such as a pulse oximeter that measures a person's SPO_2). As a result, a device that monitors multiple vitals simultaneously can more accurately predict a clinical condition than one that relies on one vital statistic alone)

C. General Information about SensoSCAN

Living tissue is a series of sub-tissues with different concatenations of absorbing optical segments. Each time a pressure pulse reaches the illuminated segment, an increase of the local blood volume occurs, supplements the local absorption, and decreases the light intensity. This model is based on measuring light absorption changes and it is the main model of measuring the blood flow and different vitals in SensoSCAN.

SensoSCAN is a non-invasive wireless wearable mobile device that allows real-time, continuous, remote monitoring and analysis of vital signs. The device works based on an assessment technique, which provides a waveform illustration of pulsatile blood flow. Light is more strongly absorbed by blood than the surrounding tissues, so that the changes in blood flow can be detected by sensor as changes in the intensity of light and provide information on the cardiovascular system of a patient. Advantages of this method include easy set-up, simple and widespread use, low cost, and the ability to take measurements without direct skin contact. The system consists of both photodiode and dual LED emitter as SensoSCAN requires a bi-wavelength light source for vitals measuring. Both red and infrared wavelengths are used as light sources because in this way differences between oxyhemoglobin (HbO_2) and reduced hemoglobin (Hb) with different absorption wavelengths can be assessed for oxygen saturation measurements. Photodiode (PD PIN-8.0-CSL) is used in combination with the dual emitter (DLED-660/905-CSL-3 (a 660nm (red) LED and a companion IR LED with 905 nm)). The device works in conjunction with iOS and Android smartphones and tablets to monitor, share and analyze the data. The captured data is transmitted via Bluetooth Low Energy (BLE) to the smartphone or tablet, which display the parameters. The SensoSCAN application also allows the user to send the data to a dedicated secured cloud system that is accessible via the SensoSCAN web portal.

The system setup is illustrated in Figure 1. The SensoSCAN Monitoring System is intended for use by clinicians and medically qualified personnel to simultaneously monitor multiple vital signs.

SensoSCAN is capable of non-invasive measurement of Respiration Rate (RR), Heart Rate (HR), Systolic and Diastolic Blood Pressure (Systolic BP, Diastolic BP) and Oxygen Saturation of Arterial Hemoglobin (SPO_2), Pulse Rate (PR), and skin Temperature (TEMP) in hospital-based facilities. Vitals are computed based on assessing different

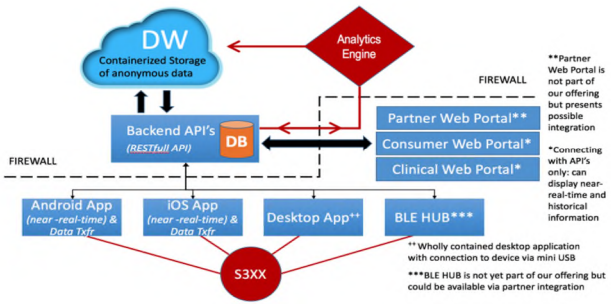

Figure 1. SensoSCAN Measurement System

features of patients' blood flow (e.g., pulse amplitudes, forms, frequency and analyzing derivatives of the signal etc.). As a result, there is a complex assessment of patients' blood flow, cardiovascular and breathing systems. All these vitals can be used to detect different clinical events and diseases. Using the existing correlations between the vital parameters and their dependencies can help predict severe conditions in their early stages. SensoSCAN is on its final stage of development and becoming a commercially available device. Currently, the device is used for in-house clinical testing, data acquisition and algorithm development.

In the rest of this paper, Section II describes the data acquisition process and the utilized statistical techniques to assess clinical conditions. Section III includes the achieved preliminary results from the subject pool introduced in Section II. Section IV concludes the results at hand. Finally, Section V discusses the shortcomings of the current analysis and our planned path forward.

II. MATERIALS AND METHODS

A. Experimental Design

- Vital Changes Induced by Activity

Four healthy subjects with mean age 25 years (age range 23-26), with a mean heart rate of 72 bpm were recruited. SensoSCAN was used for continuous vitals monitoring. Subjects were advised to be at steady state for 5 minutes, followed by a 10-minute interval activity (while keeping the sensor still on their finger), and the last 5 minutes at rest. Data acquisition took around 20 minutes for each subject.

- Vital Changes by Lowering the Amount of Oxygen

Experiments were run on 10 subjects at a clinical lab in Louisville, CO after approval from the Institutional Review Board (IRB). Test subjects provided their written consent to participate in the study and had the right to leave at any time. The study was conducted by clinical staff in the clinical lab environment where subjects lay reclined. Sensors were placed on subject's finger to collect vitals data. Subjects were given medical grade mixtures of oxygen and nitrogen to induce various hypoxic levels in them. SpO2 levels were brought down to about 70% by inducing more nitrogen via a breathing mask.

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B. Vitals Pairwise Correlation

Future dangerous clinical conditions could be predicted by examining the correlation between vital parameters. To this end, Pearson Correlation Coefficient was examined between the pairs of vitals, aiming at predicting a clinical condition such as hypoxia. We computed the Pearson Correlation Coefficient (1) between vital pairs using [7]:

$$r_{xy} = \frac{cov(x,y)}{\sqrt{var(x).var(y)}}, (1)$$

where x and y are the two variables between which Correlation Coefficient (e.g., the two variables could be HR and RR) is computed. Cov(x,y) is sample covariance of the two variables, while var(x) and var(y) are sample variance of variables x and y respectively. The Pearson Correlation measures the strength and direction of linear relationship between two variables. A higher, more positive correlation indicates a strong, direct linear relationship between two variables, while a more negative Pearson Correlation represents the strong, inverse linear association between the two variables. In order to prove the statistical significance of the correlations, the p-value associated with each score is also computed.

C. Correlation Chains in Predicting Hypoxia

The goal is to predict hypoxia from the existing correlations between the vitals. HR, RR, and SPO2 are the most relevant vitals recorded by SensoSCAN in predicting respiratory disease. Elevated HR and RR, accompanied by depressed SPO2 levels are expected in patients suffering from hypoxia. As a result, in order to pre-diagnose hypoxia, correlation chains were generated based on the correlations between the three aforementioned vitals.

III. PRELIMINARY RESULTS

A. Vital Changes Induced by Activity

Pearson Correlation Coefficients between the vital pairs were computed and stored them in a 6 × 6 correlation matrix (Figure 2). Each cell of the correlation matrix indicates the strength of the association between respective vital pairs. The cell color indicates the strength and direction of the association between two parameters. Dark blue indicates the strong, positive correlation between vital pairs. The strong, inverse association between the vital pairs is further indicated with lighter colors (e.g., yellow indicates the strongest inverse correlation between the corresponding variables). TABLE I includes the numerical values of the scores associated with each color-coded cell of the adjacency matrix. As shown in this table, subject's heart beats faster and she breathes faster. This is indicated by the relatively strong, positive Pearson Correlation with magnitude 0.60 ($p < 0.01$) between HR and RR. The inverse, strong Correlation between SPO2 and either HR (-0.63, $p < 0.01$) and RR (-0.49, $p < 0.01$) is also observed in the presence of the interval activity.

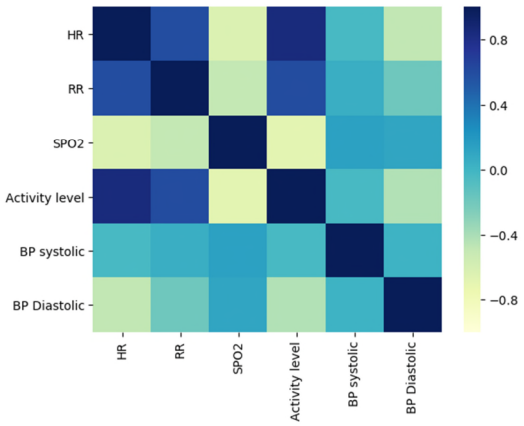

Figure 2. Correlation matrix containing vital pairs Pearson Correlation Coefficients

Considering the strongest correlations and setting a threshold correlation score of 0.5 (the probability due to chance in bivariate analysis), correlation chains between these vitals were constructed. The chain in Figure 3A is generated based on the correlation matrix in Figure 2. The pairwise associations between these vitals (SPO2, HR and RR) is indicative of hypoxia (Figure 3A), while signs of hypoxia are absent in the subject shown in Figure 3B as one of the correlation scores in the correlation chain is below the specified threshold and is not considered significant.

B. Vital Changes Induced by Lowering Oxygen Levels

Correlation matrices (between HR, RR and SPO2) were generated for experiments performed at the clinical lab. TABLE II (the following page) indicates the pairwise correlation results in a subject. As observed, SPO2 has a strong, inverse association with HR ($r = -0.78$, $p < 0.01$); meaning HR increases as the amount of oxygen applied in the mask decreases. This holds true for a weaker inverse correlation between SPO2 and RR ($r = -0.41$, $p < 0.01$), while HR and RR are positively correlated ($r = 0.56$, $p < 0.01$).

C. Predicting Hypoxia from Vital Chain Correlations

Upon reducing and elevating oxygen levels via the breathing mask at the clinical lab, correlations between HR, RR, and SPO2 indicated the presence of hypoxia. The provided correlation chain in Figure 4 shows the resulting chain with the specified correlation scores in one of the participants. Out of 10 subjects participating in this study, 4 happened to be diagnosed with hypoxia based on the developed algorithm.

IV. CONCLUSION AND FUTURE WORK

This work shows a correlation engine capable of predicting hypoxia based on pairwise correlations between vitals. Integration of this engine in SensoSCAN provides health care professionals with a tool, measuring continuous-valued vitals data, which can help them make more educated decisions while diagnosing the patients and advance home-based remote monitoring systems.

 ISBN: 978-1-61208-659-0

TABLE I. PEARSON CORRELATION COEFFICIENT SCORES BETWEEN SIX VITAL PAIRS

	HR	RR	SPO2	Activity	SBP	DBP
HR	1.00	0.60	-0.63	0.85	-0.54	-0.57
RR	0.60	1.00	-0.49	0.61	-0.46	-0.47
SPO2	-0.63	-0.49	1.00	-0.68	0.74	0.75
Activity	0.85	0.61	-0.68	1.00	-0.64	-0.67
SBP	-0.54	-0.46	0.74	-0.64	1.00	0.98
DBP	-0.57	-0.47	0.75	-0.67	0.98	1.00

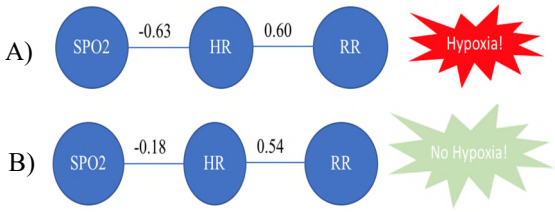

Figure 3. Generated correlation chains indicating the presence (A) and absence (B) of hypoxia

A shortcoming of this method was the limited number of resources due to the invasiveness of the method (as oxygen levels were decreased by inducing more nitrogen via the breathing mask). As a part of the ongoing work, more subjects from varying age groups will be recruited in order to better validate the algorithm. Furthermore, the correlation engine design is ultimately aimed at developing dynamic machine learning algorithms such as Hidden Markov Models [8], taking advantage of Markov chains features to develop probabilistic models that are capable of diagnosing not only hypoxia, but other dangerous clinical conditions such as chronic obstructive pulmonary disease (COPD) and diseases related to the cardiovascular system. The model will ultimately be deployed in the device for remote-monitoring. Prototyping and experimental evaluation will further be implemented in the system in order to generate real-time estimation of chronic diseases with a remarkable accuracy. This is a work in progress and the validity of the hypothesis in diagnosing dangerous clinical conditions by continuous vitals monitoring is under scrutiny.

TABLE II. PEARSON'S CORRELATION COEFFICIENT SCORES BETWEEN PAIRS OF HR, RR AND SPO2

	HR	RR	SpO2
HR	1.00	0.56	-0.78
RR	0.56	1.00	-0.41
SpO2	-0.78	-0.41	1.00

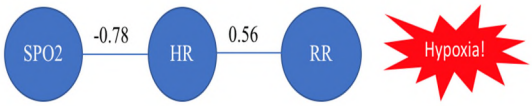

Figure 4. Generated correlation chains indicating the presence of hypoxia based on vitals chains

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 ISBN: 978-1-61208-659-0