Predicting Transitions in Oxygen Saturation Using Phone Sensors

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Abstract

Introduction: Widespread availability of mobile devices is revolutionizing health monitoring. Smartphones are ubiquitous, but it is unknown what vital signs can be monitored with medical quality. Oxygen saturation is a standard measure of health status. We have shown phone sensors can accurately measure walking patterns. **Subjects and Methods:** *Twenty cardiopulmonary patients performed 6-min walk tests in pulmonary rehabilitation at a regional hospital. They wore pulse oximeters and carried smartphones running our MoveSense software, which continuously recorded saturation and motion. Continuous saturation defined categories corresponding to status levels, including transitions. Continuous motion was used to compute spatiotemporal gait parameters from sensor data. Our existing gait model was then trained with these data and used to predict transitions in oxygen saturation. For walking variation, 10-s windows are units for classifying into status categories.* **Results:** *Oxygen saturation clustered into three categories, corresponding to pulmonary function Global Initiative for Chronic Obstructive Lung Disease (GOLD) 1 and GOLD 2, with a Transition category where saturation varied around the mean rather than remaining steady with low standard deviation. This category indicates patients who are not clinically stable. The gait model predicted status during each measured window of free walking, with 100% accuracy for the 20 subjects, based on majority voting.*

Conclusions: Continuous recording of oxygen saturation can predict cardiopulmonary status, including patients in transition between status levels. Gait models using phone sensors can accurately predict these saturation categories from walking motion. This suggests medical devices for predicting clinical stability from passive monitoring using carried smartphones.

Key words: gait analysis, oxygen saturation, pulse oximeter, clinical stability, smartphone application, health monitoring, chronic disease assessment

Introduction

A revolution in health monitoring is coming, due to widespread mobile devices. Individual measurement can generate population cohorts of similar patients with similar status, so treatments can be effectively and efficiently targeted toward all groups.[1] Mobile phones are nearly ubiquitous in the United States, with the Pew Internet Project showing 91% ownership in May 2013, including 56% with smartphones. These numbers are higher in younger persons, but even seniors over 65 years of age have 76% penetration of mobile phones.[2] Because millions of patients are already carrying phones, the opportunity appears for passive monitoring without adherence difficulties. We therefore seek medically valid vital signs that can be accurately monitored with mobile phones.

Here we consider the most important composite sign, oxygen saturation (SpO_2), as measured by pulse oximeters. We show clinically that continuously monitoring cardiopulmonary patients using pulse oximeters produces values that naturally partition into status categories, including transitions between levels. We show computationally that continuously monitoring such patients using phone sensors can accurately predict such categories. That is, using only sensors embedded within smartphones, a trained model can predict saturation of the patient internally from motion of the patient externally. These results have great potential to impact healthcare across chronic conditions and multiple diseases.

For chronic heart and lung conditions, walk tests are widely used to assess the severity of the disease, including measures with accelerometer sensors.[3,4] The 6-Min Walk Test (6MWT) is a standard assessment[5] for chronic obstructive pulmonary disease (COPD) and congestive heart failure. This tests shortness of breath, while patients walk for 6 min back and forth over a fixed-length walkway. Normal gait, or walking pattern, requires that many systems, including strength, sensation, and coordination, function in an integrated fashion, so abnormal gait is a diagnostic of many conditions.[6] Previously, we used the 6MWT to show gait parameters can be measured with smartphones carried by chronic disease patients, as sole input to a trained model that accurately predicts pulmonary function.[7]

To perform walk tests with chronic disease patients, medical safety requires the test be performed while the patients are wearing a pulse oximeter.[8] This is a standard medical device typically worn on the finger, which measures heart rate and SpO_2. The latter is an overall measure of cardiopulmonary fitness, with blood oxygen level as a composite of the two primary organ systems. Spot checks of SpO_2 are standard clinical practice, as providing a single number for patient status.[9] However, it is unusual to analyze continuous saturation for patterns within categories rather than threshold of desaturation.[10]

We show that cardiopulmonary patients can be placed into status categories based on continuous curves of SpO_2. During walk tests, gait parameters are recorded from sensors in phones carried by patients. The gait model is used to predict the saturation categories. Correlation between gait parameters and oxygen saturation is intuitively appealing, due to correlation between gait speed and oxygen desaturation in walk tests.[11] Because oxygen saturation is often considered the fifth vital sign,[12,13] predicting saturation categories using carried phones would impact general medicine and many specialties.

Subjects and Methods

We conducted experimental measurements on 28 senior patients in the Pulmonary Rehabilitation Clinic at Carle Foundation Hospital, Urbana, IL. The study was approved under Institutional Review Board (IRB) approval number 497221. Subjects must be in the age range of 40–89 years and have chronic disease records, including a pulmonary function test (PFT). A smartphone (Droid™ 4 Mini; Motorola, Chicago, IL) in a fanny pack was placed at the lower back (L3) position of tested subjects. Each subject completed a full 6MWT under the supervision of nurses.[5]

MOVESENSE SOFTWARE

For these experiments, we developed MoveSense,[14] a sensing application based on the Android™ (Google,

Mountain View, CA) operating system. MoveSense records walking data from smartphone sensors, such as accelerometers, gyroscopes, and magnetometers, at a guaranteed sampling rate (60 Hz). MoveSense is also an extensible platform to integrate functions such as step counting, speed calculation, and health status prediction from data analysis on remote servers. In addition to phone sensors, MoveSense can record sensor data from other devices via wireless connects.

In this study, each subject is required to wear a Nonin® (Plymouth, MN) Onyx® II model 9560 pulse oximeter during the entire test. Their SpO_2 values are recorded through a Bluetooth® (Bluetooth SIG, Kirkland, WA) connection between the pulse oximeter and smart phone. Thus, there are continuous recordings for saturation and motion transmitted to the analysis server, enabling analysis of the entire curve for SpO_2 during active walking. This is the first such analysis of the resultant patterns for saturation categories, as previous clinical studies considered only desaturation occurrences with ambulatory patients having pulmonary disease.[15,16]

SUBJECT SELECTION

PFTs are performed with a spirometer in clinical conditions to measure severity level of pulmonary diseases. In obstructive diseases, such as COPD, the ratio of forced expiratory volume in 1 s (FEV1) and forced vital capacity is used as an effective indicator. The FEV1% predicted is a normalized version of FEV1%, which is defined as the ratio of the patient's FEV1% divided by the average FEV1% in the population within the same demographic range. The Global Initiative for Chronic Obstructive Lung Disease (GOLD) defines a standard for COPD severity levels based on the predicted FEV1% values.[17] There are four stages representing levels: mild, moderate, severe, and very severe.

In this analysis, we focus on ambulatory patients who are the most mobile as the best candidates for health monitors in daily living. This means we focused on GOLD 1 (FEV1% ≥80%) and GOLD 2 (FEV1% 50–79%). So we eliminated the samples with FEV1% <50%, with 2 subjects in this GOLD 3 (FEV1% 30–49%) category. We also eliminated 2 subjects who did not complete the walk test and 2 more for whom the pulse oximeter did not record.

Finally, we eliminated 2 subjects whose medical conditions caused the pulmonary function for validation to have changed significantly, so that the PFT no longer reflected the function being measured by the 6MWT, due to time delay between tests. The first had a diagnosis of bronchiectasis, a lung condition where function changes within short periods. The second had

Table 1. Demographic Information of Tested Subjects		
	GOLD 1	GOLD 2
Total number (number female)	14 (8)	6 (3)
Age (years) [median (minimum–maximum)]	64.5 (43–81)	70.5 (54–80)
Height (cm) [mean (minimum–maximum)]	169.09 (147.32–187.96)	170.60 (157.48–182.88)
Weight (kg) [mean (minimum–maximum)]	83.27 (49.44–119.75)	86.25 (54.43–124.28)
GOLD, Global Initiative for Chronic Obstructive Lung Disease.		

change of medication between PFT and 6MWT, with our model correctly showing a marked increase in function. All subjects were permitted to use their inhalers before testing, but she changed from albuterol (for asthma) to tiotropium (for COPD).

Of the initial 28 patients tested, this left 20 patients to analyze. Regarding health status, there were 14 with GOLD 1 and 6 with GOLD 2 status, consisting of 11 females and 9 males.

The demographics used for adjusting the raw values are age, sex, height, and weight, as shown in *Table 1*. We calculated p values for each demographic feature by Student's t test between GOLD 1 and GOLD 2 samples. The t test result shows all p values are >0.05, which indicates within the 95% confidence interval, so there is no obvious correlation between demographic information and GOLD stages in this sample set. For this specific population subset, demographic features do not affect GOLD stages significantly.

Results

CORRELATION BETWEEN OXYGEN SATURATION PATTERN AND GOLD STATUS LEVEL

In our study, there were three different oxygen saturation patterns: (1) the SpO_2 value of the subject starts above 93% and remains stable; (2) the SpO_2 value of the subject starts above 93% and then varies around 93%; and (3) the SpO_2 value of the subject starts below 93% and remains stable. Patterns 1 and 3 obviously correspond to GOLD 1 and GOLD 2, whereas pattern 2 is a transition status in between GOLD 1 and GOLD 2. We label the Transition group as GOLD 1T, indicating that it is between the GOLD 1 and GOLD 2 groups. If we had had enough patients tested with GOLD 3, then there would have been GOLD 2T, between GOLD 2 and GOLD 3.

To demonstrate validity, we used Student's t tests to analyze SpO_2 values between GOLD 1 and the Transition group ($p < 0.001$), plus be-

tween the Transition group and GOLD 2 ($p < 0.001$). We compare the SpO_2 patterns of the three groups by considering the mean SpO_2 of each group over 10-s windows at 5-s intervals, yielding 71 sample points for the entire 6MWT. As shown in *Figure 1*, the three different SpO_2 patterns are clearly distinguished.

By observing the SpO_2 variations during 6MWT, we explored correlation between SpO_2 and GOLD levels. Generally, an SpO_2 pattern for GOLD 1 will yield higher SpO_2 values during 6MWT. However, by manual observation, there are several subjects observed as a "transition" group between GOLD 1 and GOLD 2.

We create a novel heuristic model to represent the categorization of the three different groups: GOLD 1, GOLD 2, and Transition group GOLD 1T, in between the first two groups. For the GOLD 1 group, the SpO_2 value will remain above the overall mean, and for the GOLD 2 group the SpO_2 will be below the overall mean, with the SpO_2 value of the Transition group varying in between. Our heuristic model captures these differences between each group and thus can predict health status, including transitions.

With the heuristic model, we calculate the mean and standard deviation (SD). The result is shown in *Figure 2*, with the subjects displayed in mean order for each category. Mean and SD are independent, as subjects at the boundaries between GOLD and Transition demonstrate in *Figure 2*. The mean of SpO_2 corresponds to patients' GOLD status, and the SD corresponds to their clinical stability. The 20 subjects naturally
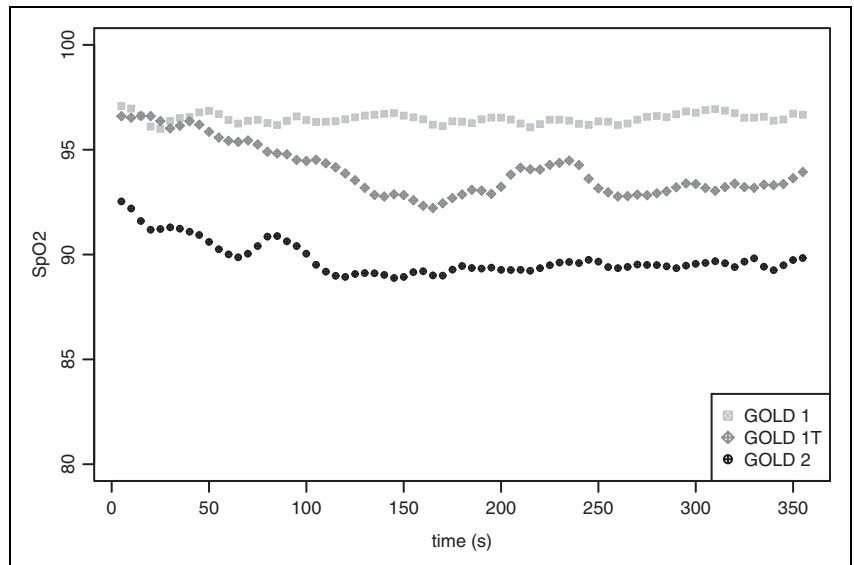
Fig. 1. Mean oxygen saturation (SpO_2) for Global Initiative for Chronic Obstructive Lung Disease (GOLD) 1, Transition (GOLD 1T), and GOLD 2 by 5-s time intervals in the 6-Min Walk Test.
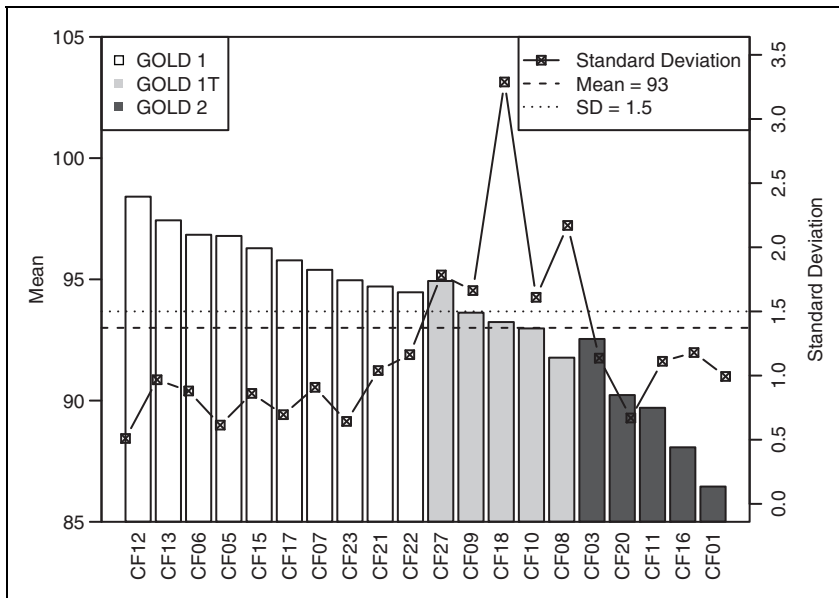
Fig. 2. Mean and standard deviation (SD) of oxygen saturation for each subject.

partition, corresponding to clinically stable (SD < 1.5) or clinically unstable (SD > 1.5).

The categorization can then be used to label the subjects, with the left category corresponding to GOLD 1 (10 subjects), the middle category corresponding to the Transition group (5 subjects), and the right category corresponding to GOLD 2 (5 subjects). The subjects in the Transition group vary in actual status from GOLD 1 on the left to GOLD 2 on the right; the first 4 subjects have FEV1% > 80%, whereas the last (CF08) has FEV1% < 80%. The mechanism of this model for each patient is to check the SD of their SpO_2 values to decide if they are in stable groups (SD < 1.5) or transition groups (SD > 1.5). If the patient is categorized into the stable group, then we look at the mean of the SpO_2 value to decide whether the patient is in stable GOLD 1 (mean > 93%) or stable GOLD 2 (mean < 93%). This is why the boundary patients have higher mean values than the lowest of the previous category (CF22 and CF08), as their SD places them into GOLD 1T and GOLD 2, for the boundary patients CF27 and CF03.

COMPUTED WALKING PATTERNS PREDICT OXYGEN SATURATION PATTERNS

Now that the saturation categories are established from the pulse oximeter, we show that these categories can be predicted from a gait model using phone sensors as the inputs. Our hypothesis is that during 6MWT, walking pattern and SpO_2 patterns are correlated. We previously developed the gait model and used it to predict pulmonary function[7] and walk distance.[14]

Spatiotemporal gait parameters[18] are used as model input, with eight parameters in both the time and frequency domains used to represent phone motion and corresponding body motion. The mean and SD of the raw acceleration are chosen as two primary parameters, with two other general parameters (mean crossing rate and Shannon entropy) to describe variation of acceleration. We also choose peak frequency, root mean square, autocorrelation coefficient, and coefficient of variance, as additional features.[19]

Support vector machine (SVM) is an efficient state-of-the-art machine learning technique that maps high-dimensional samples into a hyperplane followed by classification.[20] The acceleration is split into 10-s sliding windows with a 5-s interval. The input contains three parts: (1) demographic information, including age, sex, height, and weight; (2) cadence; and (3) spatiotemporal gait parameters. We apply the Fisher's linear kernel for optimizing the support vectors, while the insensitive factor is 0.1, and the tolerance of termination is 0.001.

We trained a classification model predicting three categories (GOLD 1, GOLD 1T, and GOLD 2) from walking patterns, applying the feature selection approach and SVM. The 10-fold cross-validation is applied to evaluate the model. Then we collect all prediction results for each subject and perform majority voting to obtain the status of this subject. For example, considering all samples for a subject, if most windows of walking are predicted as GOLD 1, the status of this subject is predicted as GOLD 1. This medical assumption is cardiopulmonary patients are usually walking at the pace related to their status.

The validation of classification model is shown in *Table 2*. The overall prediction accuracy is 89.58%. The prediction accuracy for GOLD 1 is 87.96%, and the prediction accuracy for GOLD 2 is 92.99%, while the prediction accuracy for the GOLD 1T Transition group is 89.88%. When voting is applied to all samples of a subject, the result shows all subjects are correctly classified into three category groups, which means accuracy is 100%, or perfect prediction. Thus accuracy increases from 90% to 100% if the short periods of catching one's breath to manage respiration during walking are dominated by normal periods within testing.

Discussion

Oxygen saturation is perhaps the most important vital sign in clinical use.[12] It is closely correlated with clinical outcomes

Table 2. Validation of Classification Model for Oxygen Saturation

PREDICTED STATUS	PREDICTION (%) FOR ACTUAL STATUS		
	GOLD 1	GOLD 1T	GOLD 2
GOLD 1	**87.96**	6.48	5.55
GOLD 1T	7.73	**89.88**	2.38
GOLD 2	5.79	1.22	**92.99**

GOLD, Global Initiative for Chronic Obstructive Lung Disease.

for health status and thus is diagnostic as a warning sign for many conditions.[21] Although motion sensors are not directly measuring heart rate or lung function, motion is correlated to these for cardiopulmonary patients. Predicting saturation patterns from carried phones is a breakthrough, showing that gait speed (a proposed sixth vital sign[22]) can predict oxygen saturation (a proposed fifth vital sign[13]).

Our results reveal a new aspect of SpO_2, from analyzing curves of continuous measures. The saturation for the 20 patients clusters naturally into three categories, based on the mean when clinically stable and SD when clinically unstable, as shown in *Figure 2*. The saturation categories corresponded to a higher status (GOLD 1) with steady values above 93% and a lower status (GOLD 2) with steady values below 93%, plus a transition category status (GOLD 1T) with varying values around 93%, in between these two steady levels.

There were another 2 patients whose values would fit into categories GOLD 2T or GOLD 3, but we eliminated them for modeling, due to small sample size with such status. More subjects would enable five-way categories, as with athletes running for 10 min on treadmills.[23] When there are more categories, the thresholds for mean and SD may be different. In general, the thresholds need to be set to define categories with the greatest discriminatory power and the fewest patient outliers. Through a new collaboration with NorthShore University HealthSystem in Evanston, IL, we are recording saturation and motion for a much larger training set for chronic patients with cardiopulmonary disease.

Our results also demonstrate that our gait model can accurately predict oxygen saturation. That is, motion can predict saturation for broad categories. This is a novel computational prediction from a novel clinical observation. We trained a support vector machine to match SpO_2 categories, from 6MWTs on 20 chronic patients under IRB approval in the hospital clinic. The gait model had perfect prediction of saturation patterns, after voting was applied to classify by the majority of sampled windows. The voting is necessary because the patients change patterns while walking, for example,

going slower when they become short of breath before returning to their usual pace at their current status.

The perfect prediction of saturation category leads to a broader impact for adult medicine. *Table 2* shows the category accuracy is about 90% for the samples of 10-s windows, but 100% for each patient overall with majority voting. If transition patterns can be separated cleanly from status patterns, then change in status can be automatically detected. Thus, passive monitors from carried phones can continuously detect when a patient is within a transition category between status levels. Such transition detection can provide an accurate monitor, alerting that status has changed so that treatments may need to change.

Because SpO_2 status changes slowly, smartphones carried during daily activities can sample frequently enough to record sensor data to accurately predict saturation category, only when the patient is moving similarly to walk tests. Such carrying will require adjusting for phone positions other than L3, including pants and coat pockets and hand and shoulder bags. We have done significant preliminary work towards such activity recognition and position adjustment.

This study with oxygen saturation demonstrates new clinical paradigms. When body measures can be continuously recorded, then analyzing curves for patterns can produce new clinical observations. With saturation, automatically detecting the transition category was straightforward, once we knew to look for this observation. Due to device limitations, most vital signs have been monitored with thresholds, ignoring the curves. Observing trends enables future predictions, as shown here. So we are now studying transition categories of health status for other vital signs, such as heart rate and blood pressure.

Mobile phones can measure health status at stable levels and during transition stages. Passive monitors from phone sensors can predict clinical stability from oxygen saturation. Because our system can support such prediction, it has great potential for health monitoring outside of clinical settings. Patient status for oxygen saturation can be continuously monitored using personal smartphones, and medical alerts can be generated when personal motions into transition categories are detected. Predicting transitions in saturation categories may catalyze a major advance in clinical monitoring for population health.

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Disclosure Statement

No competing financial interests exist.

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