Development of an Automated 30 Second Chair Stand Test Using Smartwatch Application

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Abstract—**This paper presents development of the smartwatch application for automation of the standard 30 Second Chair Stand Test (30SCST). 30SCST is primarily used to test leg strength and endurance, but also speed and mobility and assess risk of falls. We use inertial signals on smartwatch to detect and count stands during the test. The application notifies the user to start and stop the test using vibration on the smartwatch. Synchronization of notifications and signal acquisition allows assessment of user's response time during the test. Our application monitors baseline heart rate before the test, heart rate increase during the test, and heart rate recovery after the test that might allow assessment of cardiovascular fitness of the user. The application is developed using Wear OS and tested on two smartwatch platforms: Fossil G4 and Polar M600. Pilot test included 12 subjects, six male and six female (mean age 39.1, S.D. 19 years). Overall accuracy of detection of the number of standups is 98.8%. Smartwatch application can be used for automated testing in clinical setups as well as for self-monitoring at home.**

I. Introduction

Exponential increase of new sensors and systems supporting wearable monitoring and Internet of Things (IoT) provides new opportunities to improve health monitoring and quality of living as a part of mHealth systems [1]. Remote monitoring allows chronic disease management and support for older adults living alone in their homes. Recent surveys indicate that more than 90% of older adults want to stay in their own homes as long as possible [2]. Remote monitoring facilitates support for informal caregivers [3] or remote health care services [4]. Technological developments support independence, autonomy, and connections with informal caregivers and social network, also known as Aging in Place (AiP) [2], [3]. Remote monitoring technology for chronic disease management and AiP is becoming a reality for many, regardless of income and mobility level.

Integration of ambient intelligence and wearable monitoring allows unobtrusive, continuous monitoring of activity of daily living in assisted ambient living environment [5]. Wearable sensors include wristband fitness trackers or smartwatches, smart pill bottles and other compliance devices, and ambient sensors, such as pressure sensors and passive infrared motion sensors embedded in walls, ceilings, beds, and floors [6]. The combination of wearable inertial sensors and/or ambient sensors can support monitoring of user's posture, activity, and gait that can be used to detect falls or evaluate fall risk.

Standard mobility tests, such as Stopping Elderly Accidents, Deaths, and Injuries (STEADI) Tool Kit recommended by the United States Centers for Disease Control and Prevention (CDC) [7], are typically administered only in physician's offices and performed by manual counting or stopwatch time measurement. STEADI toolkit includes the Timed-up-Go (TUG), the 30-second Chair Stand (30SCS) test, and the Four-stage Balance (FSB) test. These assessments use simple measures of time to complete a chair-stand, walk for 10 feet, turn, return 10 feet, and sit down in the chair (TUG), the number of stands from a chair in 30 seconds (30SCST), and the number of seconds a person can hold a position in four different standing positions (FSB). A provider making these measurements needs only a stopwatch, chair, and space to safely conduct the assessment. Even though the tests are simple to administer, the measurements miss subtle changes that might be important. For example, if an older adult completed 12 chair stands in 30 seconds with the standard tests at two different times, a decrease in time for those 12 chair stands from 29.8 seconds to 27 seconds would be unnoticed. However, the speed of the chair stands would have increased almost 10%. This change could be assessed using technology with automated data capture and analysis. We created a mobile tool suite to automate tests from the STEADI tool kit using a smartphone [8] that has been used as a part of our mHealth system for more than five years [9].

In this paper, we present preliminary results from implementation of 30SCST test on a smartwatch. A smartwatch has several advantages as an implementation platform: a) a smartwatch is always on the user or close to the user, unlike a smartphone, b) a smartwatch can monitor heart rate in response to exercise, and c) notifications on a smartwatch are more effective than on a smartphone. Therefore, smartwatches are increasingly used for remote health monitoring, although significant research and larger scale studies are necessary to determine their acceptability and effectiveness in specific applications [10]. However, inertial sensors on the smartwatch during 30SCST are not aligned with body planes in our previously developed smartphone application [8], which requires application specific signal processing algorithms as described in this paper.

Heart rate monitoring on existing smartwatches is robust enough for some applications, and even allows short term analysis of heart rate variability [11]. The latest versions of the smartwatch, such as Apple Watch 4, also include ECG amplifier that allows collection of both ECG and PPG; therefore, values of pulse rate, heart rate, pulse transmit time (PTT), and assessment of blood pressure could be accurately derived.

Sit to stand transition as a form of exercise can be used to determine aerobic threshold in young, healthy individuals [12]. However, the proposed method is applicable only to young and healthy subjects with no joint problems. We believe the 30SCST can be used to assess the state of fitness of the user, using heart rate increase during the test and heart rate recovery after the test. The time-constant of postexercise heart rate recovery obtained by fitting heart rate decay curve by a first-order exponential fitting has been used to assess cardiac autonomic recovery after endurance exercise [13].

Our ultimate goal is to support *automation of mobility tests on smartwatches and facilitate self-monitoring and personalized guidance*. We believe that this approach would stimulate proactive approach and focus and wellness, and provide early indication of reduced mobility, deterioration of overall health, and behavioral changes.

The automated collection of data and storage in an integrated system would create massive data collections that can be used for Big Data modeling to better understand the mechanisms of changes of mobility of older adults. Wearable technology, such as smartwatches, presents a viable method for automating functional assessment tests that can collect and transmit precise data to a cloud-based system for data processing and analysis.

In this paper, we discuss system implementation, theory of operation, and signal processing. Preliminary results from the pilot test are also presented.

II. METHODS

A. *Smartwatch-based 30SCS Test*

The 30SCS test measures the number of complete standups a person can perform during a 30 s interval [14]. An alternative test is "five repetition sit-to-stand test (FRSTST)" commonly used for subject that can not complete a 30 s test. The test assesses strength and endurance of lower extremities, but it can also measure speed, balance, and mobility [15]. Age, body weight, and stature also influence FRSTST performance and should be considered [16].

The test is conducted using a straight back chair without arm rests, and a stopwatch. The patient is sitting in the middle of the chair with feet flat on the floor, hands placed on opposite shoulders and crossed at the wrists, as shown in Fig. 1.

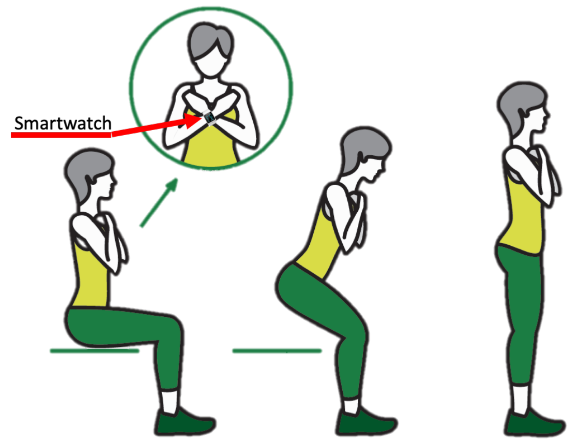

Figure 1. Smartwatch-based 30SCS test

On the command "Start" the patient rises to a full standing position and then sits back down holding arms against his/her chest. If the total number of chair stands is below average, the subject is at risk of falls [14]. For example, "below average" performance for age group 85-89 is "less than eight" chair stands for both genders. The standard test provides only the number of completed stands, while automated tests provide a number of additional parameters [8].

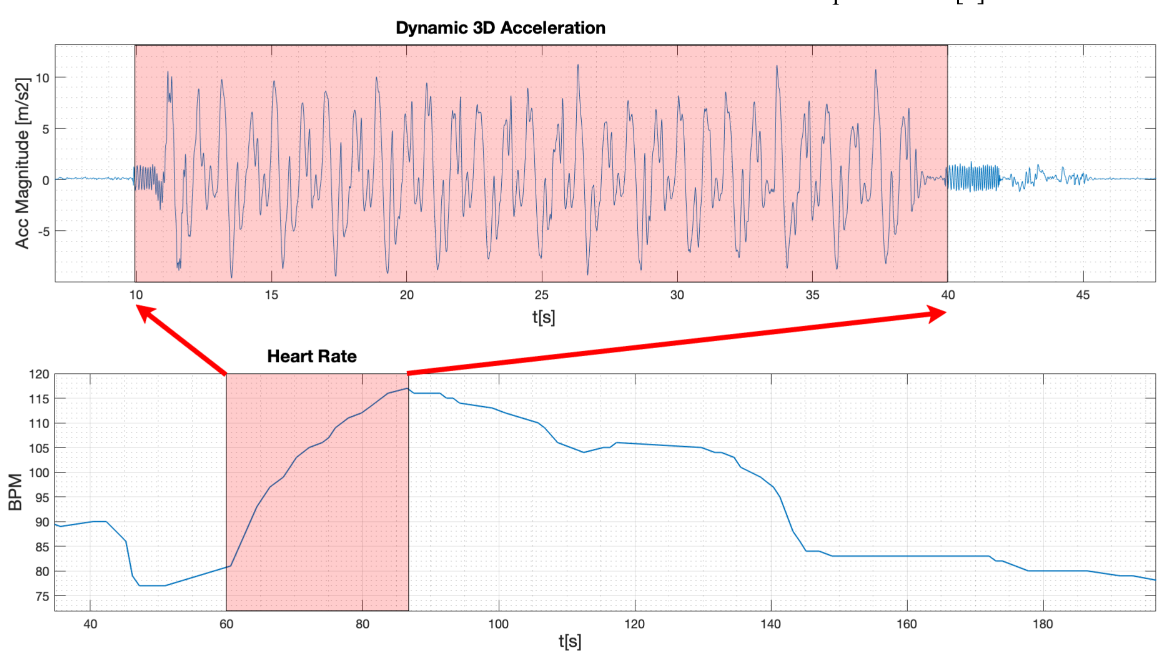

Figure 2. Change of dynamic acceleration and heart rate during 30SCS test

We implemented a smartwatch application for Android Wear OS operating system. We tested the application on two smartwatch platforms: Fossil Gen 4 and Polar M600. The smartwatch application collects inertial signals (3 axis of acceleration and 3 gyroscope signals) sampled at Fs=100 Hz, and heart rate provided as events in Wear OS. Dynamic acceleration is calculated as AC component of 3D vector magnitude of all components of the acceleration.

In our initial application we calculate average 3D acceleration during quiet periods (1g or 9.81 m/s^2) as A_{rest}, and subtract it from the 3D acceleration during test using equation (1), although high pass filter can be used for complete elimination of the DC offset in A_d.

$$A_d = \sqrt{X^2 + Y^2 + Z^2} - A_{rest} \left[{}^{m}/_{s^2}\right] \qquad (1)$$

Change of A_d and HR during 30SCS test is presented in Fig. 2. The upper plot represents A_d only during the test (10-40 s), while the lower plot also depicts heart rate before the test (baseline heart rate) and after the test (heart rate recovery).

In order to determine reliability of heart rate monitoring on smartwatch during exercise, we ran a pilot test with synchronized monitoring of heart rate using Polar smartwatch and a 3-lead ECG using Nexfin/BMEYE noninvasive cardiovascular monitor. Nexfin provides precise time stamps of each heart beat and RR intervals that are used to calculate equivalent heart rate on each heart beat.

Heart rate from smartwatch was available once per second with resolution of 1 beat per minute (BPM). Fig. 3 represents heart rate from the smartwatch and ECG monitor during exercise and recovery. Each circle represents heart rate at the moment when it was provided by the smartwatch. Missed readings can be identified as longer periods without measurements. It can be seen that the smartwatch averages measurements over a time window; therefore, heart rate from the smartwatch accurately represents average heart rate of the user during moderate changes of the heart rate, and delayed heart rate average during rapid change of the exercise (e.g. sudden change of heart rate at the beginning of the exercise). Therefore, smartwatch provides accurate measurement of the heart rate during baseline monitoring and recovery, and precise change of heart rate during exercise. Smartwatch provides slower rate of heart rate change during rapid change of the heart rate; for example, heart rate changed at the beginning of the exercise from 75 BPM to 95 BPM in 1.42 seconds at t=60 s in Fig. 3. Smartwatch measurements responded with lower rate of change, but accurately represented heart rate during exercise starting from t=70 s, limited only by the resolution of the smartwatch measurements.

Application protocol is executed as follows:

1. Application starts when command “Start” is pressed on the smartwatch.
2. After 50s smartwatch vibrates to notify user to cross hands on chest, as required for the standard test
3. At 60s smartwatch vibration notifies user to start 30SCS test
4. After 30s smartwatch vibration notifies user to stop the test, sit and relax after exercise
5. Application continues to collect data for three more minutes and record pattern of recovery of heart rate.

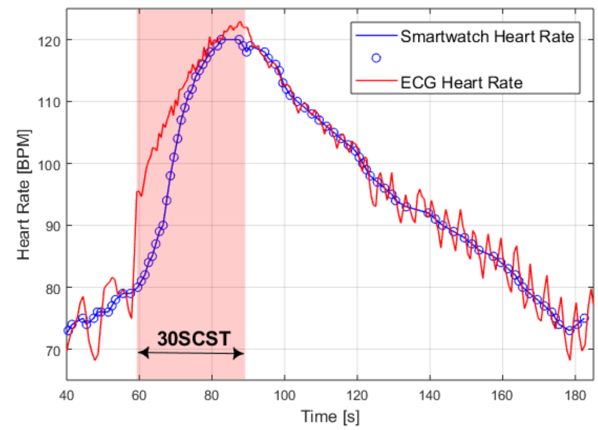

Figure 3. Heart rate during 30SCS test and recovery detected by the smartwatch and ECG.

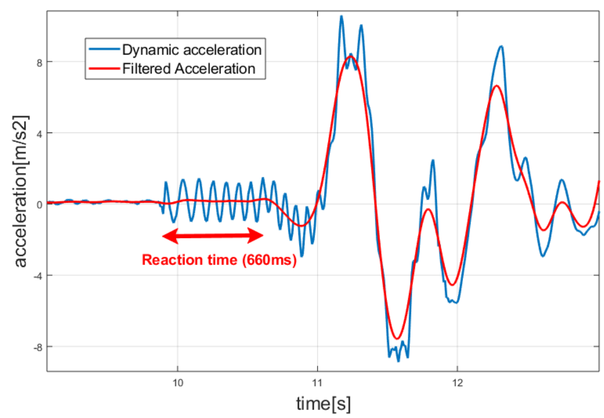

Figure 4. Measurement of reaction time after vibration used as notification.

Heart rate is recorded for the entire duration of the test (4.5 minutes/270 seconds). The first 60s are used to determine heart rate baseline (HRB), or resting heart rate. Accelerometer signals are recorded only 10 s before the test and 10 s after the test; that is the reason why acceleration and heart rate have different time axes in Fig. 2. Actual test corresponds to time 10-40s in upper plot (acceleration), and 60-90s in lower plot (heart rate). Test period is highlighted in red color.

It is important to notice small oscillation at the beginning and the end of the test that represents smartwatch vibration used as notification. That signal allows us to clearly determine start and end of the test, but also determine reaction time of the user as time interval between the start of the vibration band the beginning of the motion. Details of the processing are explained in the next section. According to our protocol, we can measure two reaction times: motion of hands to the chest after first vibration, and start of standup after second vibration.

B. Signal Processing

The application records both accelerometer and gyroscope signals. However, quality of recorded accelerometer signal allowed us to use only dynamic acceleration to detect stand events, as can be seen in Fig. 2. Dynamic acceleration signal is first filtered using a low pass FIR filter (N=20, Fc=2Hz). Raw and filtered signals (shifted to compensate processing latency) are presented in Fig. 3. Reaction time can be measured from the beginning of the vibration in the raw signal to start of motion in the filtered signal.

C. Experiment

We tested the application using 12 subjects (6 male and 6 female), ages from 20 to 75 years. Mean age of subjects was 39.1 years (S.D. 19 years). All subjects were able to complete the test in 30s.

III. Results

Summary of the Experimental results is presented in Table I. We used two watches (Fossil and Polar). Percentage of time when HR was detected correctly is presented as *pHR*. Average percentage of correct detection for Fossil was 39.2% and for Polar 64%, probably because of the better Polar optical sensor with six LEDs. Overall detection is sufficient to represent physiological response to exercise for all subjects, particularly subjects using Polar watch as shown in Fig. 3.

Number of standups counted manually is presented as *Nman* and the result of the analysis is presented as *Nsw.* Our software missed one standup event for two subjects with total accuracy of 98.8%. Current version of the software did not implement CDC recommendation to consider completed stand "if the patient is over halfway to a standing position when 30 seconds have elapsed" that will be implement in the next version using total distance in each stand calculated using inertial signals.

TABLE I. Experimental Results

Subject	Watch	pHR [%]	Sex	Age	Nman	Nsw
S1	Fossil	38.5	F	50	10	10
S2	Polar	61.9	F	21	10	10
S3	Polar	62.4	F	20	12	11
S4	Fossil	39.2	F	55	8	8
S5	Fossil	30.4	M	58	12	12
S6	Fossil	42.2	M	59	18	18
S7	Fossil	33.8	F	75	8	8
S8	Polar	63.9	M	28	17	16
S9	Fossil	41.3	M	22	15	15
S10	Polar	68.4	F	25	11	11
S11	Fossil	48.9	M	28	18	18
S12	Polar	63.6	M	28	22	22

IV. Discussion and Conclusion

Automation of mobility assessment procedures provides new biomarkers that can be used to better assess mobility of users. Preliminary results presented in this paper demonstrate possible use of smartwatch applications to assess user's mobility using 30SCST test and possible use of heart rate measurements on the smartwatch to assess fitness level of the user.

Our preliminary results indicate significant differences in accuracy of heart rate monitoring between smartwatches, caused by the differences in the quality of the PPG sensor. Typically, smartwatches designed for fitness applications feature more robust heart rate monitoring. Therefore, it is recommended to evaluate the performance of heart rate monitoring on specific smartwatches before clinical deployment.

Future work includes development of more robust signal processing procedures suitable for slower motion of older adults and assessment of the fitness level based on the personalized change of heart rate during the test and intensity of the exercise.

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