USING THE BLACKBERRY TO ASSESS MOBILITY FOR REHABILITATION

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ABSTRACT

A Wearable Mobility Monitoring System (WMMS) could be a valuable device for rehabilitation decision-making. This paper presents preliminary research on a proof-of-concept system that uses the BlackBerry 9550 as a self-contained WMMS platform. Integrated triaxial accelerometer, GPS, and timing data were processed to identify mobility changes-of-state between standing, walking, sitting, lying, stairs, ramps, riding an elevator, and car riding. This pilot project provides insight into new algorithms and features that can be used to recognize changes-of-state in real-time. Following feature extraction from the sensor data, a decision tree was used to distinguish the change-of-state. In the complete system, real-time change-of-state identification will trigger video capture for improved mobility context analysis. Five trials were collected from one subject while he completed a continuous circuit that incorporated all target mobility tasks. Average sensitivity was 100.00 % and specificity was 86.73 % for walking on level ground and ramps. Sensitivity was 100.00 % and specificity was 98.86 % for stair navigation. These results support continued evaluation of the new WMMS for mobility monitoring.

INTRODUCTION

BlackBerry Smartphones could provide an ideal platform for ubiquitous assessment of how people with disabilities move outside the healthcare clinic. We have previously shown that synchronized sensors in a “Smart-holster”, combined with Smartphone GPS and camera images, can be used in a WMMS [1]. New BlackBerry devices that integrate accelerometers and video capture provide an opportunity for mobility assessment using only integrated sensors.

Other researchers have developed wearable video systems with sensors, such as GPS, ECG and accelerometers, to record information on location, movement, and context [2], [3], [4]. Our project evaluated the BlackBerry Storm2 9550 as a WMMS. Previous preliminary work confirmed accelerometer capabilities, video capture capabilities, and potential activity / change-of-state identification algorithms for moving, standing, sitting, and lying down [1].

In this study, video was captured while changes-of-state were identified. Change-of-state is the act of changing necessary characteristics from one physical activity behavior to another. Combining activity change-of-state and video information, the mobility context can be identified. This contextual information, combined with improved activity classification, will lead to better rehabilitation decision-making.

METHODS

<u>System Architecture</u>

A data logging application was developed using Eclipse 3.5, BlackBerry Java SDK 5.0, and BlackBerry OS 5.0. Acceleration, GPS location, and video were collected at the phone’s maximum sampling frequency. During multimedia capture, acceleration sampling frequency is 8 Hz.

Using the Blackberry 9550-Storm2, all data were simultaneously collected with the phone positioned in a passive holster (Figure 1).

Following data transfer to a computer, MATLAB was used to extract features from the 3-axis accelerometer data and a decision tree was used to identity changes-of-state (Figure 2). Excel was used for all statistical analyses.

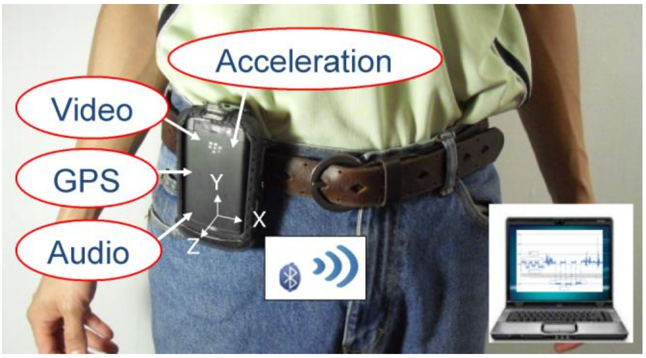

Figure 1: Smartphone and sensor orientation, placed on the right side of front pelvis.

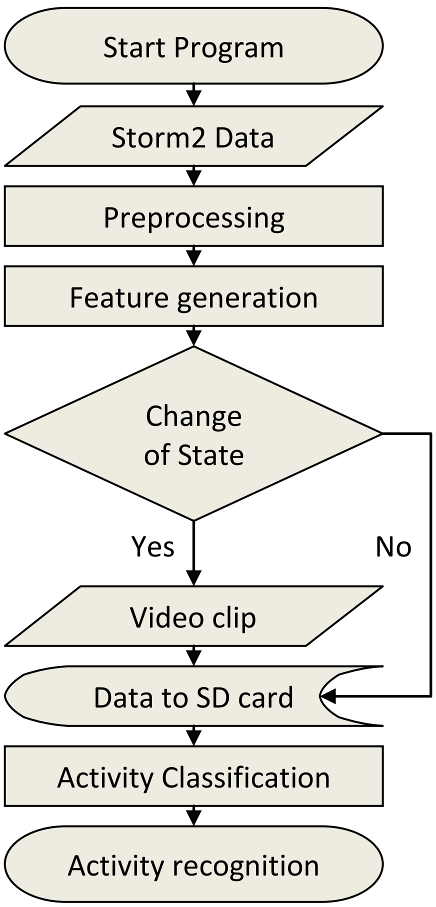

Figure 2: WMMS algorithm.

Features Calculations

From the 3-axis accelerometer data, certain features were calculated that were sensitive to changes in mobility status.

The standard deviation of the Y acceleration (STD Y) is used to define static or dynamic movement states. In Equation 1,

$$\sigma_y = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - m)^2} \tag{1}$$

σ_y is STD Y, y_i is the Y-acceleration value, *m* is the mean Y-acceleration, and *N* is the data window size.

The Y-accelerometer range (Range Y) is defined in Equation 2 and used for stair and ramp identification. When possible, range is used instead of standard deviation to reduce computational load and improve real-time capabilities. $MaxY, MinY$ are the maximum and minimum values within the data window.

$$RangeY = (MaxY - MinY) \tag{2}$$

Sum of range (SR) distinguishes between walking, going upstairs, and going downstairs. From Equation 3, Range X, Y, and Z are the range values from the three acceleration axes.

$$SR = RangeX + RangeY + RangeZ \tag{3}$$

Signal Magnitude Area of SR (SMA-of-SR) is the sum of all SR values within the data window (Equation 4). Since the time interval is a constant, this becomes an efficient estimation of the SR integral.

$$SMA-of-SR = \sum_{i=1}^{N} SR_i \tag{4}$$

DiffSR is the difference in SR values between the current (SR2) and previous (SR1) windows. DiffSR helps to recognize mobility changes over time (Equation 5).

$$DiffSR = (SR2 - SR1) \tag{5}$$

Rxz has a similar task, identifying mobility changes, but acts within the data window (Equation 6).

$$Rxz = (Rx + Rz) \tag{6}$$

Where Rx is the range X, and Rz is the range Z.

SGPSspeed is the sum of the GPS speeds within a 20 second data window (Equation 7). The larger data window is used to decrease false positives when a car stops at a stop sign or traffic light.

$$SGPSspeed = \sum_{i=1}^{N} GPSspeed \tag{7}$$

Change-of-state / Classification

The decision tree (Figure 3) uses pre-set thresholds for feature analysis. The ten previously defined features are combined to recognize static, dynamic, riding an elevator, walking, stairs, ramps, and car riding states. Double thresholds are required to reduce false-positives when transitioning between states. To identify a change-of-state, classification values are summed and compared with summation results from the previous three data windows. Visual video clip assessment improves activity classification accuracy. Three second video clips are adequate to recognize the activity and context.

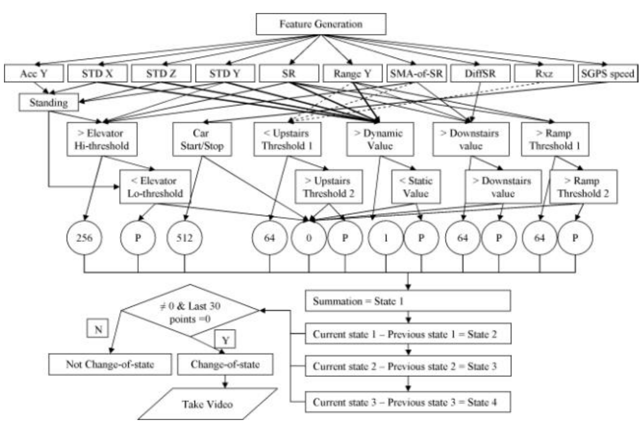

Figure 3: State determination algorithm with change of state judgment. "P" = previous output number.

Test Procedure

One able-bodied subject performed a series of movements continuously: sitting, standing, lying, and walking, climbing stairs, walking on ramps, riding an elevator, and start/end car ride. Five trials were captured for each activity. Each set of activities were performed with accelerometer and video recording. Each activity took approximately 10 seconds to complete.

The Storm2 9550 accelerometer sampling rate, with BlackBerry video control running, averaged 8.25 Hz (STD=0.49) [5]. Accelerometer sampling stops during video recording. Therefore, a continuous cycle of three seconds of video capture followed by ten seconds without video was used for this study. In practice, video will only be captured after a change-of-state.

RESULTS

The SR curve has a similar shape as the STD Y curve, but the SR values are several times larger than the STD Y values. This difference enhances the activity classification in Figure 4. Further, STD Y produces more false negatives than SR. "St" means standing, and "W" means walking.

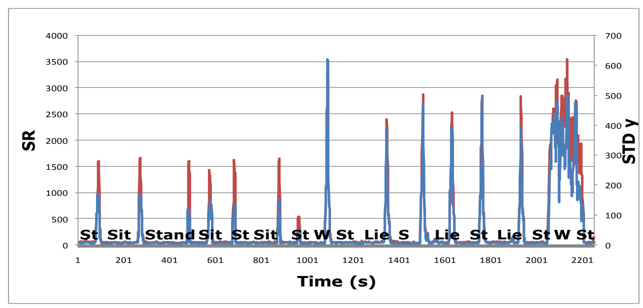

Figure 4: Comparison of STD Y and SR.

The comparison of SMA and SMA-of-SR is shown in Figure 5. SMA-of-SR can identify more spikes than SMA, which was one of features in the previous WMMS [1]. From 129 to 171 seconds, SMA-of-SR can recognize walking for a short period, but the SMA cannot, as seen in Figure 5. Further, comparison of Figure 4 and Figure 5 in SMA-of-SR and SR, the SMA curve is smoother than the SR curve.

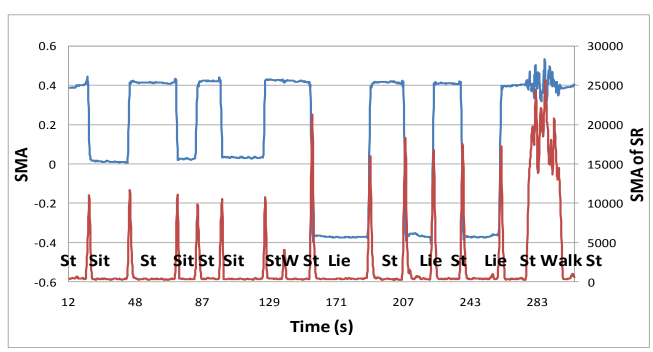

Figure 5: Comparison of SMA and SMA-of-SR.

The results of activity classification when using the accelerometer features and video clips are shown in Table 1. Walking produced more false positives than other activities.

Table 1: Accelerometer and video results. Se = sensitivity, Sp = specificity, TP = true positive, FN = false negative, FP = false positive, TN = true negative.

Change of State	TP	FN	FP	TN	Se %	Sp %
Stand-to-sit	18	0	0		100	100
Sit-to-stand	20	0	0		100	100
Stand-to-lie	15	0	0		100	100
lie-to-stand	15	0	0		100	100
Walk-to-stand	69	0	0		100	100
Taking elevator	6	0	1	36	100	97
Walking on level ground	112	0	26	162	100	86
Going ramps	22	0	1	15	100	94
Going upstairs	25	0	0		100	100
Going downstairs	25	0	1	18	100	95
Start of car ride	5	0	1	76	100	99
End of car ride	5	0	1	76	100	99

CONCLUSION

The 3-axis accelerometer, GPS, and video in the Blackberry 9550 provided important tools for wearable mobility monitoring. A challenge for WMM implementation will be the relatively low accelerometer sampling rate with BlackBerry OS 5. At less than 10 Hz, fewer accelerometer signal processing options are possible. In addition, the loss of accelerometer data during video recording limits the practical video clip duration.

By combining and weighting the range, sum, and covariance statistics, good activity classification was possible for standing, sitting, and lying. Sensitivity and specificity outcomes were high for all activities except walking specificity (86%). Higher accelerometer sampling frequencies (above 20Hz, and ideally 50 Hz) could help to reduce walking false positives and help to classify walking –related activities correctly (level ground, inclines, stairs, etc.). Further research on methods to set appropriate thresholds for the individual could also help to decrease false positives.

This study demonstrated the potential of the BlackBerry integrated sensor and multimedia approach for a WMMS. However, additional research is required to increase the accelerometer sampling rate on the Smartphone and/or to add additional sensors for activity state identification.

ACKNOWLEDGEMENTS

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