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CHANGE-OF-STATE DETERMINATION TO RECOGNIZE MOBILITY ACTIVITIES USING A BLACKBERRY SMARTPHONE

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***Abstract*—A Wearable Mobility Monitoring System (WMMS) can be a useful tool for rehabilitation decision-making. This paper presents preliminary design and evaluation of a WMMS proof-of-concept system. Software was developed for the BlackBerry 9550, using the integrated three axes accelerometer, GPS, video camera, and timer to identify mobility changes-of-state (CoS) between static activities, walking-related activities, taking an elevator, bathroom activities, working in the kitchen, and meal preparation (five able-bodied subjects). This pilot project provides insight into new algorithms and features that recognize CoS and activities in real-time. Following features extraction from the sensor data, two decision trees were used to distinguish the CoS and activities. Real-time CoS identification triggered BlackBerry video recording for improved mobility context analysis during post-processing.**

I. INTRODUCTION

Smartphone platforms provide an ideal interface for mobility assessment in the community (home, school, shopping, etc.). A previous project showed that synchronized sensors in a "Smart-holster", combined with BlackBerry GPS and pictures, were useful as a WMMS [4]. New BlackBerry devices that integrate an accelerometer and video camera provide an opportunity for mobility analysis using only integrated sensors.

Other researchers have developed wearable video systems with sensors to record GPS, ECG, video clips, and/or acceleration [1], [2], [3]. Further, some researchers used cell phone platforms to recognize multi-activities by accelerometer only [6], [8]. The research in this paper used the BlackBerry Storm2 as a WMMS. Previous preliminary work confirmed that the BlackBerry WMMS, using acceleration and pictures, could identify walking movements, standing, sitting, and lying down [5].

This study evaluated the sensitivity and specificity of the new BlackBerry WMMS, which only used internal sensors and cell phone video, for identifying mobility activities for able-bodied individuals.

II. METHODS

A. System Architecture

Raw data including accelerations, GPS location, and video were collected at the maximum sampling frequency (8 Hz), for multimedia recording and 20 Hz without video capture (Fig. 1).

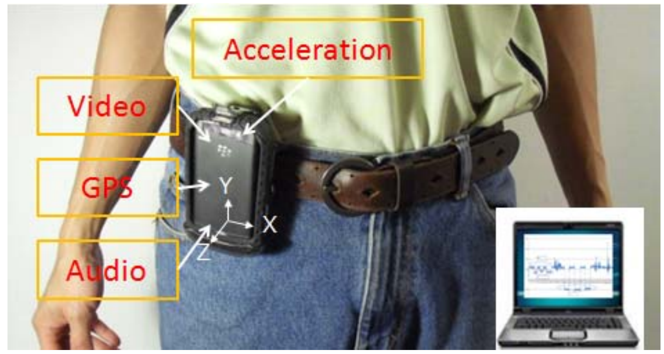

Fig. 1. Smartphone and holster's location.

B. Application Development

An application was developed for BlackBerry OS 5 using Eclipse, BlackBerry SDK, and BlackBerry Desktop Manager. Testing was performed with a BlackBerry 9550 Smartphone.

Accelerations, GPS location, and video were collected at the phone's maximum sampling frequency. The accelerations sampling rate was 8 Hz, since multimedia capture was active [5]. The GPS Location Listener was updated each second to get longitude, latitude, altitude, heading, and speed, when in an outdoor environment. System output included time, raw sensor data, activity features, and digital video.

After saving the sensor data to a 16 Gb SD card, one-second data windows were extracted and processed to detect CoS.

As shown in Fig. 2, features were identified from the accelerations. The features that were sensitive to changes in mobility status included acceleration Y, standard deviation (STD) (eq. 1) in X to Z accelerations, range of Y (Range-Y) (eq. 2), sum of ranges (SR) (eq. 3), Signal Magnitude Area (SMA) of sum of ranges (eq. 4), difference of range (DiffSR) (eq. 5), range of X and Z (Rxz) (eq. 6). These features were entered into a decision tree (Fig. 3) to determine if a CoS occurred. Single or double thresholds, with threshold values modifiable in the setup menu, were used to identify CoS. Status values were also calculated for each feature. These status values were imported into a second decision tree for activity classification (Fig. 4).

When a change was recognized, the video API was started to record a three second video clip.

$$STD-Y=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i-m)^2} \quad (1)$$

$$Range-Y=(MaxY-MinY) \quad (2)$$

$$SR=(Range-X+Range-Y+Range-Z) \quad (3)$$

$$SMA-SR=\sum_{i=1}^{N}SR_i \quad (4)$$

$$DiffSR=(SR2-SR1) \quad (5)$$

$$Rxz=(Range-X+Range-Z) \quad (6)$$

m = mean Y-acceleration, y_i= individual acceleration value, N = data window size, SR2 = current sum of ranges, SR1 = previous sum of ranges, R_X = range X, R_Z = range Z.

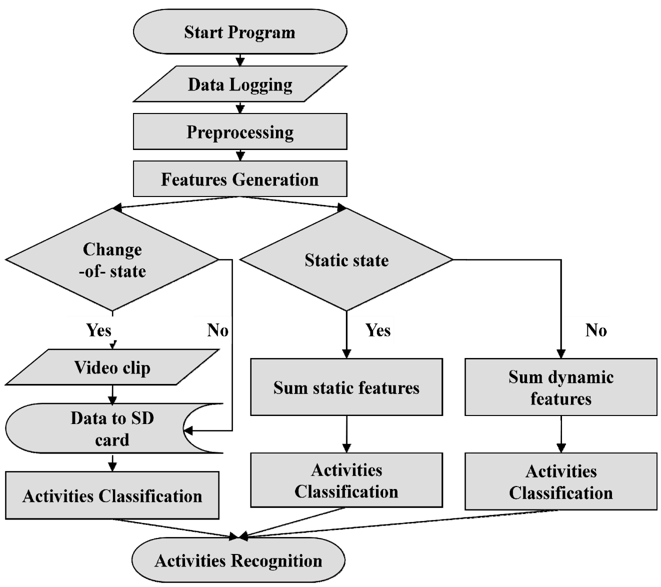

Fig. 2. WMMS algorithm.

C. *Change-of-state / Classification*

The state algorithm (Fig. 3) uses pre-set thresholds for features analysis. The features introduced in the previous section are combined to recognize a static state, taking an elevator, walking-related movements, and small movements such as meal preparation, hygienic activities or working in the kitchen. The judgment includes CoS and maintaining the same state (MS). True responses show that the boxes connect with numbers including "1", "64", "256", "2048", and "0". The red arrows, which are false responses, link to "P. False positives are reduced by using double thresholds and multi-feature combinations. To trigger video capture, classification values are summed and compared with summation results from the previous three data windows.

D. *Activity Classification*

The decision tree for potential activities (Fig. 4) uses the same features and thresholds to classify eight activities; sitting, standing, lying, riding an elevator, small stand-movements, small sit-movements, small lie-movements, and walking. The method only uses accelerations to distinguish activities. Transitional states between mobility activities are not classified.

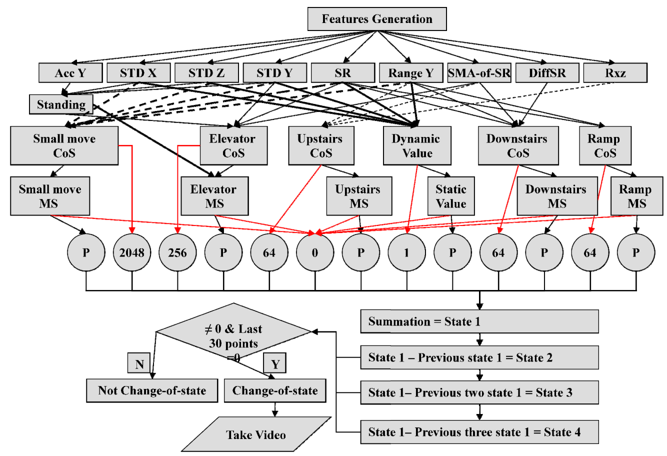

Fig. 3. State determination algorithm with CoS and MS judgment. "P" = previous output number.

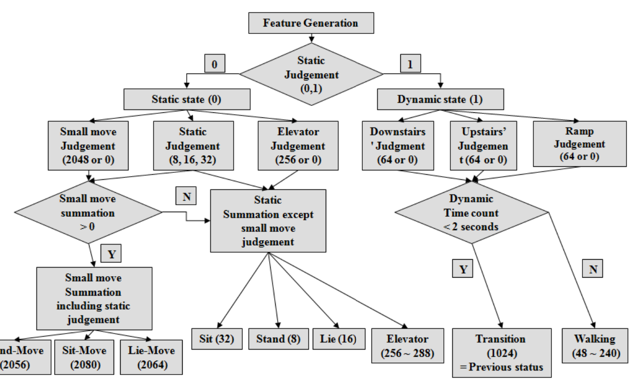

Fig. 4. Activities recognition from accelerometer data.

E. *Test Procedure*

Five able-bodied subjects, who wore a BlackBerry 9950 on the right front pelvis, performed a continuous sequence of pre-determined movements/activities. Car ride test, which required GPS features, was only set in the self-test **Error! Reference source not found.** because of safety consideration and the accuracy of car ride (100%). Three trials were captured for each sequence. All movements were recorded by a digital camcorder, with timing from the video record used as the gold standard for comparison. Each activity in the sequence took approximately 10 to 20 seconds to complete. The average accelerometer sampling rate was 8.25 Hz (STD=0.49) with BlackBerry video control running [5]. Acceleration data collection stops during video recording. Video clips are only captured after a CoS occurs.

Data were imported from the SD card into Microsoft Excel for statistical analysis.

III. RESULTS

Sum of ranges was more sensitive than the STD-Y for distinguishing mobility states (Fig. 5).

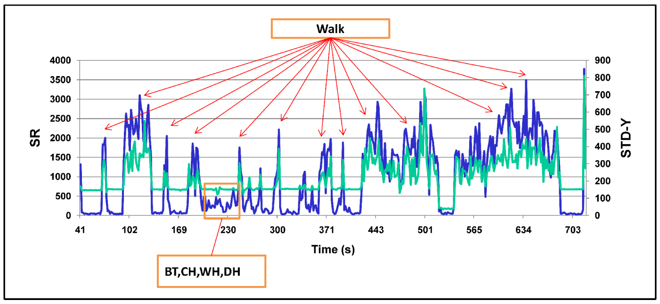

Fig. 5. Sum of ranges to distinguish walking and static states. BT =brushing teeth, CH=combing hair, WH=washing hands, and DH=drying hands .

The extracted features can also help to recognize small movements; such as, brushing teeth (BT), combing hair (CH), washing hands (WH), drying hands (DH), moving dishes (MD), moving a kettle (MK), toasting bread (TB), preparing a meal (PM), and washing dishes (WD), as shown in Fig. 6. A combination of Static Status and SR were used to identify these small movements. Discrete small movements are easily distinguished; however, CoS can be missed for a continuous series of small movements. For example, brushing teeth and then combing hair.

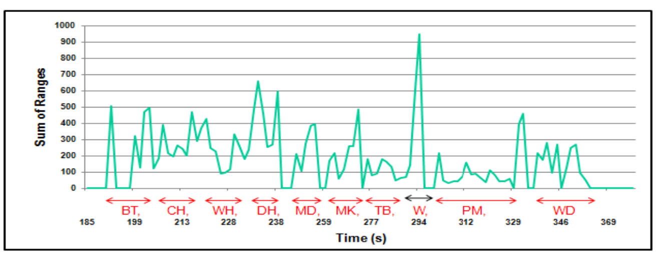

Fig. 6. Sum of Ranges and static judgement to distinguish small movements.

The SMA of sum of ranges curves was smoother than the sum of ranges curves. The smooth SMA of sum of ranges (SMA-SR) curve easily defined thresholds to classify climbing stairs and walking (Fig. 7).

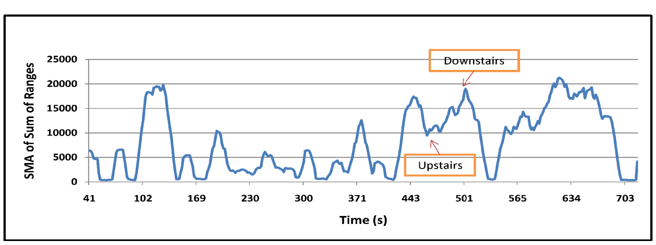

Fig. 7. SMA-SR to distinguish climbing stairs and walking.

For CoS identification using accelerometer data, sensitivity between sitting, standing, lying, and taking an elevator activities were between 93 and 100% (TABLE I). Walking-related CoS, such as stairs and ramp, has 60 to 83% sensitivity. Sensitivity related to CoS between walking and small movements (i.e., brushing teeth, etc.) were between 40 and 93%. The results were poorer for CoS involving a continuous series of small movements (TABLE I) because acceleration features are similar between these activities.

The number of false positives was less than 12% for all measures, with half the measures reporting less that 5% false positives. Walking produced false positive in CoS identification for 324 out of 2700 cases (12%) (TABLE II).

TABLE I
SENSITIVITY OF COS IDENTIFICATION

Changes-of-State	TP	FN	SE
Stand ↔ Walk	67	0	100.00%
Walk ↔ Lie	30	0	100.00%
Walk ↔ Elevator	57	1	98.28%
Sit ↔ Walk	29	1	96.67%
Walk ↔ Stairs	44	16	73.33%
Walk ↔ Ramp	20	10	66.67%
Toast bread → Walk	14	1	93.33%
Prepare a meal → Walk	14	1	93.33%
Dry hands → Walk	13	2	86.67%
Wash dishes → Walk	13	2	86.67%
Walk → Brush teeth	12	3	80.00%
Dishes → Move a kettle	11	4	73.33%
Walk → Prepare a meal	11	4	73.33%
Move kettle → Toast bread	8	7	53.33%
Walk → Wash dishes	7	8	46.67%
Walk → Move dishes	6	9	40.00%
Wash hands → Dry hands	4	11	26.67%
Brush teeth → Comb hair	2	13	13.33%
Comb hair → Wash hands	2	13	13.33%

SE = sensitivity, TP = true positive, FN = false negative.

TABLE II
SPECIFICITY OF COS IDENTIFICATION

Changes-of-State	FP	TN	SP
Lie	0	266	100.00%
Sit	1	238	99.58%
Dry hands	1	76	98.70%
Move dishes	2	60	96.77%

Take an elevator	27	576	95.52%
Comb hair	7	140	95.24%
Toast bread	5	91	94.79%
Wash dishes	8	164	95.35%
Wash hands	6	98	94.23%
Ramp	8	115	93.50%
Brush teeth	13	145	91.77%
Prepare a meal	23	200	89.69%
Stairs	34	319	90.37%
Walk	324	2376	88.00%
Move a kettle	12	90	88.24%

SP = specificity, FP = false positive, TN = true negative.

Better activities classification results were achieved when using both acceleration features and video clips, as compared to using the accelerometer only (TABLE III), with the exception of sitting. Acceleration-only had 4% greater sensitivity than acceleration-and-video for sitting because one CoS was missed, which resulted in no associated video data.

TABLE III
COMPARISON OF ACTIVITY CLASSIFICATION IN ACCELEROMETER ONLY AND ACCELEROMETER WITH VIDEO CLIPS RESULTS

	Acc. Only		Acc. + Video	
Activity	**SE(%)**	**SP %)**	**SE(%)**	**SP(%)**
Lie	96	100	100	100
Elevator	2	100	100	100
Stand	98	99	100	100
Walk	95	92	96	93
Dining activity	0	100	94	100
Sit	96	99	92	100
Stairs	45	73	86	99
Bathroom act.	0	100	84	100
Kitchen activity	0	100	70	100
Ramp	22	98	50	100
Move a kettle	0	100	37	100
Wash dishes	0	100	32	100
Toast bread	0	100	31	100
Prepare a meal	0	100	21	100
Dry hands	0	100	15	100
Move dishes	0	100	7	100
Wash hands	0	100	5	100
Brush teeth	0	100	0	100
Comb hair	0	100	0	100

Acc. = acceleration

IV. Conclusion

The relatively low accelerometer sampling rate with BlackBerry OS 5 is a challenge for WMMS activities classification. At less than 10 Hz, fewer accelerometer signal processing options are available and the loss of accelerometer data during video recording limits the ability to detect CoS within the video recording period. However, by combining and weighting the range, sum, and covariance statistics, good activities classification was possible for standing, sitting, lying, preparing a meal, and brushing teeth. Walking, climbing stairs, and riding an elevator had high sensitivity, but the specificity of CoS identification and activities classification could be improved by adding additional sensors or increasing the accelerometer sampling rate. The classification of other small movement activities requires further research to increase sensitivity and specificity. Higher accelerometer sampling frequencies (above 20Hz, and ideally above 50 Hz) could help reduce walking false positives and help to classify walking–related activities correctly (level ground, inclines, stairs, etc.). Further research on calibration methods to set appropriate thresholds for each individual could also help decrease false positives.

Acknowledgements

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