RESEARCH ARTICLE

Combining low sampling frequency smartphone sensors and video for a Wearable Mobility Monitoring System [version 1; peer review: 1 approved, 1 approved with reservations]

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Abstract

A proof-of-concept Wearable Mobility Monitoring System (WMMS) was developed to identify daily activities and provide environmental context, using integrated BlackBerry Smartphone low sensor and video data. Integrated accelerometer data were used to identify mobility changes-of-state (CoS) in real-time, trigger BlackBerry video capture at each CoS, and save activity outcomes on the Smartphone. System evaluation involved collecting WMMS output and (separate) camcorder video under realistic conditions for five able-bodied subjects. The subjects each performed a consecutive series of mobility tasks; including, walking, sitting, lying, stairs, ramps, elevator, bathroom activities, kitchen activities, dining activities and outdoor walking. Activity, timing and contextual information were obtained from the camcorder for comparison. Sensitivity results for sensor-based CoS identification were 97-100% for standing, sitting, lying and taking an elevator; 67-73% for walking-related CoS (stairs, ramps); 40-93% between walking and small movements (brushing teeth, etc.); and below 27% for daily living activities. False positives occurred in less than 12% of all activities, with less than 5% false positives for half the measures. Better classification results were achieved when using both acceleration features and Smartphone integrated video for all activities except sitting. The evaluation demonstrated that the WMMS algorithm and BlackBerry platform were effective for detecting mobility activities, even with low sampling rate sensors. The combined sensor and video analysis enhanced mobility task identification and contextual information.

Keywords

Wearable, activity monitoring, mobility, change of state, smartphone, accelerometer, video

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Introduction

Understanding how people move within their daily lives is important for healthcare decision-making. Typically, a person's mobility status is self-reported in the clinic, thereby introducing error and increasing the potential for biased information. Functional scales can be administered to help gain an understanding of a person's mobility status¹⁻⁴. However, these tests do not measure how a person moves when leaving the clinic. A quantitative method of characterizing mobility in the community would provide valid and useful information for healthcare providers and researchers.

Wearable systems have been developed to evaluate mobility in any environment or location. These portable systems are worn on the body and collect mobility information within the home and community. Examples include accelerometer-based systems⁵⁻⁸ portable electromyographs (EMG)⁹, and foot pressure devices¹⁰. Some wearable systems can be used for long-term and low effort monitoring.

Smartphones provide an ideal interface for mobility assessment in the community since they are small, light, easily worn, and

easy to use for most consumers. These phones are multitasking, computing platforms that can incorporate accelerometers, GPS, video camera, light sensors, temperature sensors, gyroscopes, and magnetometers^{11,12}.

As shown in Table 1, cell phones have been used to recognize multiple activities by analyzing the phone's accelerometer or external sensor data. However, most systems only used the phone as a wireless data transfer device, not as a wearable computing platform. These systems used an external computer for analysis of the data.

Wearable video-sensor systems have also been developed to log digital memories. Video, GPS, electrocardiogram, and acceleration were used to record location and context of a person's daily life¹⁶⁻¹⁸. These Lifelogs had several limitations, including information retrieval, synchronization, light quality, low visual resolution, artifacts, and automatic annotation.

A previous project showed that sensors located in a "smart-holster" could be combined with a BlackBerry Smartphone to provide

Table 1. Studies that use a tri-axial accelerometer for mobility monitoring.

Author	Location	Phone based	Features	Freq (Hz)	Accuracy	Activities	Method
He ⁷	Pocket	N	Discrete cosine transform, Principal Component Analysis	100	97%	Still, walk, run, jump	Support vector machine
Wang ⁶	Waist	N	Linear sum, duration, mean, median, STD, zero-crossing count, correlation, spectrum amplitude: mean ratio, empirical mode decomposition	50	91%	Walk up and down slope	Gaussian mixture model
Hache ⁵	Waist	N	STD-Y, magnitude area, skewness Y, inclination angle	50	88%	Stand, sit, lie, walk, stairs, ramp, elevator	Hierarchical decision tree
Khan ⁸	Chest	N	Autoregressive coefficients, signal magnitude area, tilt angle to 3D feature plot	20	98%	Sit, stand, lie, walk, stairs, run	Artificial neural net, hierarchical LDA Features
Kwapisz ¹³	Front pant pocket	Y	Average, STD, average absolute difference, average resultant acceleration, signal magnitude area, time between peaks, and binned distribution	20	50% stairs, others 91 ~ 95%	Walk, jog, walk on stairs, sit, and stand	Multilayer perceptron
Shumei ¹⁴	Waist	Y	Change, max, min, and velocity	1	81.9% for motion, 83.7% for motionless	Walk, posture transition, gentle motion, stand, sit, lie	Hierarchical classification with multiclass SVM
Ganti ¹⁵	Waist	Y	Energy expenditure, body angle, 3D acceleration skewness, acceleration entropy	7	Eat, meeting (14%); drive, watch TV, aerobic (82%); desk work (50%); hygiene, cook (99%)	Sit, stand, aerobic, brush teeth, work, lie	Hidden Markov Model
Wu ¹⁹	Waist	Y	STD-X, STD-Y, STD-Z, mean-Y, sum of ranges, range-Y, signal magnitude area's sum of ranges, difference of sum of ranges, range-XZ, sum of GPS speed, and GPS speed.	8	100% for static activities, 98% for walking, 66 ~ 77% for stairs, 33% for ramp.	Stand, sit, lie, walk, going stairs, going ramp, elevator, an, car ride	Hierarchical decision tree

¹Location = sensor location on the person

²Freq = data acquisition frequency

image-assisted mobility assessment⁵. An external accelerometer, temperature sensor, humidity sensor, light sensor, and Bluetooth were integrated into the Smartphone holster. Software was written for the BlackBerry 9000, which had an embedded camera and GPS. A hierarchical decision tree combined with a double threshold algorithm classified signals to recognize changes-of-state (CoS) and activities. The BlackBerry then automatically took a digital picture at each CoS. This preliminary work confirmed that a wearable mobility monitoring system (WMMS) could use acceleration and pictures to identify walking movements, standing, sitting, and lying down, and additionally provide context for these activities.

Subsequent research¹⁹ used the BlackBerry 9550 Smartphone, with an integrated accelerometer, and revised algorithms to detect changes of state (CoS) and classify activities of daily living. The low sampling rate of the BlackBerry 9550 required some of the algorithms for the first WMMS to be revised. Having all sensors and computing power within the Smartphone provides a broadly accessible platform for wearable activity monitoring. A single subject case study resulted in an average sensitivity of 89.7% and the specificity of 99.5% for walking-related activities, sensitivity of 72.2% for stair navigation, and sensitivity of 33.3% for ramp recognition. Ramp results were poorer since accelerations for ramp gait were similar for walking gait.

Since it was demonstrated that new BlackBerry Smartphones can identify CoS in real-time¹⁹, and Smartphone video capture is available on these devices, a preliminary evaluation of the usefulness of wearable video for improving activity classification and context identification is needed. The present study builds on this prior work and presents a proof-of-concept evaluation of a new BlackBerry-based WMMS that uses internal sensors and cell phone video to identify a range of mobility and daily living activities by using the CoS to trigger the acquisition of short video clips. A proof-of-concept evaluation is a necessary step before a large scale evaluation with people with disabilities. This study is the first to integrate sensor and (non-automated) video analysis for wearable mobility monitoring.

Materials and methods

WMMS system

The prototype WMMS was developed for BlackBerry OS 5.0 on the Storm2 9550 Smartphone. The WMMS used the BlackBerry's integrated accelerometer (3-axis, $\pm 2g$), GPS, camera, and SD memory card for mobility data collection. The 3.15 MP camera had a maximum video resolution of 480x352 pixels and a video frame rate of 30 frames per second²⁰. During video capture, no accelerometer or GPS data were available. With video control active, the accelerometer sampling rate was approximately 8 Hz²¹. For the WMMS, GPS data were sampled at 1 Hz, but GPS data were not used in the algorithm presented in this paper. The WMMS was worn in a holster on the right, front pelvis.

The new WMMS software developed in²², sampled time, acceleration, and GPS location and then saved the raw data to a 16Gb SD-card. Accelerations were processed to calibrate the axis orientation, using the gravity rotation method⁴. The processed acceleration was input into a feature extraction algorithm¹⁹ for analysis

within 1-second data windows. Following feature extraction, the features were analyzed in a decision tree to determine if a CoS had occurred. If a CoS was identified, a three-second video clip was captured. A second decision tree was used to categorize the activity¹⁹. Time, features, and activity classification were saved to an output file on the SD card.

Accelerometer features

Acceleration features were identified that were sensitive to changes in mobility status¹⁹. These included mean Y-axis acceleration, standard deviation (STD) in X,Y,Z axes (1), Y-axis range (Range_Y) (2), Sum of Ranges (SR) (3), Signal Magnitude Area (SMA) of SR (4), difference of Sum of Ranges (DiffSR) (5), and range of X and Z (Rxx) (6). The inclination angle (7) could distinguish sitting, lying, and standing for the classification of static activities. While the GPS provides useful location information, GPS was not required in this study because accelerometer-based recognition of vehicle riding showed good results¹⁹.

$$STD_Y = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - m_y)^2} \quad (1)$$

$$Range_Y = (MaxY - MinY) \quad (2)$$

$$SR = (Range_X + Range_Y + Range_Z) \quad (3)$$

$$SMA_SR = \sum_{i=1}^N SR_i \quad (4)$$

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

$$Rxx = (Range_X + Range_Z) \quad (6)$$

$$Inclination \ Angle = \arctan\left(\frac{m_z}{m_y}\right) (^{\circ}) \quad (7)$$

In equations (1) to (7), m_y is the mean Y-acceleration, y_i is the individual acceleration value, N is the samples per data window, SR2 is the sum of ranges in current window, SR1 is the sum of ranges in previous window, and finally m_z is the mean Z-acceleration.

Change of state/classification

The CoS algorithm described in¹⁹ used pre-set thresholds for feature analysis. Each feature was independently analyzed using single or double-thresholds and scored as true or false. These Boolean values were combined to recognize the activities reported in¹⁹ (static state, taking an elevator, walking-related movements) and also to identify changes of state for small movements during activities of daily living (ADL) (meals, hygienic activities, working in the kitchen). CoS classification ran in real-time to enable accurate Smartphone video recording.

Activity classification

The decision tree for activity classification, described in¹⁹, used the same features and thresholds as the CoS algorithm to classify eight activities: sitting, standing, lying, riding an elevator, small stand-movements, small sit-movements, small lie-movements, and walking. The small movement categories included ADL and movements while sitting and standing. Following data collection, the video

clips were manually reviewed by a human operator to help classify activities. Clips were played back on a BlackBerry 9700 phone. Video and audio were available for qualitative assessment of the current activity.

Test procedure

A convenience sample of five able-bodied subjects (four males and one female, age: 35.2 ± 8.72 years, height: 174.58 ± 10.75 cm, weight: 66.46 ± 9.7 kg) were recruited from the Ottawa Hospital Rehabilitation Center (TOHRC, Ottawa, Canada) for the proof-of-concept evaluation. A form that included informed consent, information sheet, and media agreement was obtained for each subject. Ethical approval for the study was obtained from the Office of Research Ethics and Integrity, University of Ottawa, File Number: A08-12-01. Subjects who had injuries or gait deficits were excluded.

Data collection took place within the TOHRC (hallways, elevator, one bedroom apartment, stairs, Rehabilitation Technology Laboratory) and outside on a paved pathway. Participants wore the WMMS on their right-front waist, in a regular BlackBerry holster attached to a belt, with the camera pointing forward. No additional instructions were given for WMMS positioning. The participants were asked to follow a predetermined path and perform a series of mobility tasks, including, standing, walking, sitting, riding an elevator, brushing teeth, combing hair, washing hands, drying hands, setting dishes, filling the kettle with water, toasting bread, a simulated meal at a dining table, washing dishes, walking on stairs, lying on

a bed, walking on a ramp, and walking outdoors. Each activity in the sequence took approximately 10 to 20 seconds to complete. Each trial had 41 changes of state. Three trials were captured on the Smartphone and on a digital video camcorder.

Activity timing was obtained from the camcorder recording for comparison with the WMMS output. Start and end points of each trial were identified by shaking the Smartphone for 2 seconds. The camcorder also provided contextual information for analysis.

Data were imported from the Smartphone SD card into Microsoft Excel for statistical analysis. The Smartphone video clips were reviewed by two independent evaluators to qualitatively classify activities and assess video quality. The evaluators had access to the WMMS activity classification results during video classification.

Results

The results were analyzed in terms of CoS and activity classification. For CoS identification at the transition point between activities (Table 2), sensitivities for standing, sitting, lying, and taking an elevator were between 97% and 100%. Walking-related CoS, such as stairs and ramps, had 67% to 73% sensitivity. Sensitivity³ related to CoS between walking and small movements, such as brushing teeth, were between 40% and 93%. The CoS results for daily living activities were poorer (below 27%) since the continuous series of small movements produced similar acceleration features.

Table 2. CoS sensitivity during the transition between activities.

Changes of State		Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Sensitivity %
		TP	FN	TP	FN	TP	FN	TP	FN	TP	FN	
Static	Stand ↔ Walk	14	0	15	0	13	0	10	0	15	0	100.00
	Lie ↔ Walk	6	0	6	0	6	0	6	0	6	0	100.00
	Elevator ↔ Walk	12	0	11	0	12	0	11	0	11	1	98.30
	Sit ↔ Walk	6	0	6	0	5	1	6	0	6	0	96.70
Walking	Walk ↔ Stairs	8	4	11	1	8	4	12	0	5	7	73.30
	Walk ↔ Ramp	2	4	4	2	4	2	6	0	4	2	66.70
Daily living with walking	Toast bread → Walk	3	0	3	0	2	1	3	0	3	0	93.30
	Dry hands → Walk	3	0	2	1	2	1	3	0	3	0	83.30
	Prepare meal ↔ Walk	5	1	5	1	5	1	6	0	4	2	86.70
	Wash dishes ↔ Walk	4	2	4	2	4	2	5	1	3	3	66.70
	Walk → Brush teeth	3	0	2	1	2	1	3	0	2	1	80.00
	Dishes → Kettle	3	0	2	1	1	2	2	1	3	0	73.30
	Kettle → Toast	3	0	0	3	2	1	0	3	3	0	73.30
	Walk → Set dishes	2	1	2	1	1	2	1	2	0	3	40.00
Daily living	Wash → Dry hands	0	3	0	3	2	1	1	2	1	2	26.70
	Brush teeth → Comb hair	0	3	0	3	1	2	0	3	1	2	13.30
	Comb hair → Wash hands	0	3	0	3	1	2	1	2	0	3	13.30

¹TP = average true positives

²FN = average false negatives

Table 3 shows the specificity⁵ results for activity classification using the CoS algorithm¹⁹. These classifications are compared between data windows for CoS identification. The number of false positives was less than 12% for all measures, with half the measures reporting less than 5% false positives. Walking produced the most false positives, identifying a walking-CoS when no CoS occurred, for 324 out of 2700 cases (12%). Large standard deviations were found for some measures due to timing differences (i.e., people who walked slower took more time and had more data points for analysis, leading to more true negatives).

Better activity classification results were achieved when using both acceleration features and video clips for all activities except sitting, as compared to using the accelerometer only (Table 4). Acceleration-only analysis with the activity classification algorithm¹⁹ had a greater sensitivity than acceleration-and-video for sitting because one CoS was missed in one trial, resulting in no associated video data. Using the accelerometer only, none of the ADLs were identified; however, no false positives were reported, resulting in a high specificity.

Since accelerometer data were unavailable during video recording, no acceleration could be recorded for a minimum of 2.9 seconds after a CoS was identified. For example, if a person sits in a chair, stands up, and sits down again within 4 seconds (3 seconds of video capture and 1-second data window), the CoS will not be detected or identified. However, digital video would be available during this period for activity classification, enabling the evaluator to see the additional movements during post-processing. The average

accelerometer sampling frequency was 7.88 ± 1.39 Hz. Video analyses became difficult in some circumstances, in particular when video images were dark.

The BlackBerry 9550 included a light sensor, but the sensor output was unavailable with Java API 5.0. Light intensity level could be beneficial for recognizing indoor and outdoor environments.

As shown in Figure 1, the extracted features were used to recognize small movements, identified using a combination of SR and STD_Y. Discrete small movements were easily distinguished; however, a CoS could be missed for a continuous series of small movements that has similar accelerometer features. For example, brushing teeth and then combing hair.

The sum of ranges was more sensitive than the STD_Y for distinguishing mobility states (Figure 2). Further, the SMA-SR curves were smoother than the sum of ranges curves. Smooth SMA-SR curves were better at defining classification thresholds for climbing stairs and walking.

Recording a video was a valuable medium for evaluating mobility activities since audio information was available and multiple-images could be used in the analysis (Table 5). The sense of motion also provided useful information for categorizing the activity and context.

Activity recognition for static and walking states was confirmed by video-clip evaluation. Occasionally, the video showed a moving-hand during walking, as the arm swung during locomotion. Since

Table 3. Activity classification specificity.

Changes of state	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Specificity %
	FP	TN	FP	TN	FP	TN	FP	TN	FP	TN	
Lie	0	57	0	48	0	40	0	41	0	80	100
Sit	1	61	0	47	0	34	0	23	0	73	99.6
Dry hands	0	15	1	12	0	17	0	15	0	17	98.7
Stand	0	137	5	171	8	147	5	65	1	297	97.7
Move dishes	0	22	1	14	0	9	1	9	0	6	96.8
Take an elevator	7	89	6	101	5	107	9	99	0	180	95.5
Wash dishes	3	37	1	28	1	27	0	48	3	24	95.4
Comb hair	0	28	1	38	2	28	1	23	3	23	95.2
Toast bread	3	31	0	11	0	15	1	22	1	12	94.8
Wash hands	0	20	2	36	1	12	1	13	2	17	94.2
Ramp	1	29	3	19	0	40	3	12	1	15	93.5
Brush teeth	2	34	4	36	3	32	1	25	3	18	91.8
Stairs	3	61	12	42	5	98	10	57	4	61	90.4
Prepare a meal	4	53	3	30	7	48	4	35	5	34	89.7
Move a kettle	1	24	2	14	5	24	4	17	0	11	88.2
Walk	74	499	75	563	84	667	55	434	36	213	88
Meal setup-Walk	3	0	3	0	3	0	3	0	2	1	93.3

¹FP = average false positives

²TN = average true negatives

Table 4. Activity classification sensitivity and specificity for accelerometer only and accelerometer with Smartphone video.

	Activity	Acc. Only		Reviewer 1		Reviewer 2	
		SE (%)	SP (%)	Acc. + Video		Acc. + Video	
				SE (%)	SP (%)	SE (%)	SP (%)
Static	Lie	96	100	100	100	100	100
	Stand	98	99	100	100	98	100
	Sit	96	99	92	100	79	100
	Elevator	2	100	100	100	92	100
Walking-related	Walk	95	92	96	93	95	93
	Stairs	45	73	86	99	64	99
	Ramp	22	98	50	100	37	100
Daily Living	Dining activity	0	100	94	100	75	100
	Bathroom activity	0	100	84	100	75	100
	Kitchen activity	0	100	70	100	63	100
	Move a kettle	0	100	37	100	37	100
	Wash dishes	0	100	32	100	32	100
	Make toast	0	100	31	100	31	100
	Meal setup	0	100	21	100	1	100
	Dry hands	0	100	15	100	1	100
	Wash hands	0	100	5	100	31	100
	Move dishes	0	100	7	100	0	100
	Brush teeth	0	100	0	100	0	100
	Comb hair	0	100	0	100	0	100

¹Acc. = accelerometer²SE = sensitivity³SP = specificity **Figure 1.** Sum of Ranges to distinguish small movements: 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).

Figure 2. Top: Sum of ranges (SR) and STD_Y to distinguish walking and static states (BT=brushing teeth, CH=combing hair, WH=washing hands, and DH=drying hands). Bottom: SMA-SR to identify climbing stairs and walking.

the phone was located on the right waist, the video usually showed more of the right side than the left. For ramp navigation, the Smartphone video was not able to show the ramp, however, the video did allow the evaluator to determine if the person was ascending or descending. Similarly, the video was unable to show the stairs when descending, but the downward movement and sound of the footfalls on the stairs allowed the evaluator to categorize the stair descent activity.

The elevator CoS was usually triggered by a transition from walking to standing, rather than from elevator movement. The activity was classified using the video by seeing the elevator door or the inside of the elevator in the video-clip. The elevator inside was unclear and dark, but the elevator sound was clearly defined. Further, the

bathroom, kitchen, and dining room areas were clearly identified from video analysis.

Small movements, such as brushing teeth, combing hair and moving plates could not be identified because these activities were out of the Smartphone video field. Some clips could clearly identify moving a kettle, toasting bread, meal preparation, and washing dishes (Figure 3). Furthermore, drying hands and meal preparation needed continuous video images to identify the activities (i.e., single images would not be useful). Moreover, the video-based activity classification was hampered for people with shorter lower bodies when a tabletop or kitchen counter obstructed the phone. For example, moving a kettle and toasting bread were not visible in the video field for these shorter participants.

Table 5. Video-clip analysis.

Activity	Context	Shaking images	Image direction	Sound
Stand	Wall, ground	N	Forward	Quiet
Sit	Ceiling, wall	N	Forward, upward	Quiet
Lie	Ceiling	N	Upward	Quiet
Ride an elevator	Elevator	N	Forward	Elevator
Walk on level ground	Ground	Y	Forward	Walking
Climb upstairs	Stairs, hand rail	Y	Forward, upward	Climbing stairs
Climb downstairs	Wall	Y	Forward, downward	Climbing stairs
Up ramp	Wall, ceiling, hand rail	Y	Forward, upward	Walking
Down ramp	Wall, ceiling, hand rail	Y	Forward, downward	Walking
Brush teeth	Washbasin	Y	Forward	Flushing
Comb hair	Washbasin	N	Forward	Quiet
Wash hands	Washbasin	Y	Downward	Flushing
Dry hands	Towel rack, towel	Y	Forward	Quiet
Set dishes	Table	Y	Forward	Dish collisions
Move kettle	Kettle, kitchen background	Y	Forward	Quiet or filling water
Toast bread	Toaster, Table	N	Forward	Quiet
Meal setup	Table	N	Forward & upward	Quiet or filling water
Wash dishes	Sink, dishes	Y	Forward	Washing, flushing, dish collisions

Dataset 1. Data for combination of smartphone sensors and video for a wearable mobility monitoring system

The Raw-acceleration-file contains the raw accelerations as output by the BlackBerry smartphone during all trials. The Raw-data-files (subjects 1-2-3-4-5) contain the signal features calculated from the accelerations plus the 'real status' of the subject (what they were doing at that instant) during each sample of each trial. The real status is required to verify the accuracy of the wearable mobility monitoring system (WMMS) prediction.

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Discussion

This study demonstrated that BlackBerry accelerometer signal analysis and cell phone video assessment can be combined to identify many mobility activities and the context of these activities. Since a readily available Smartphone was worn in a typical manner, at the waist in a holster, and no external sensors or hardware was required, the WMMS could be easily implemented in the community.

The ability to appropriately identify a CoS is critical for a WMMS that uses video, with accurate and real-time CoS identification needed to trigger the acquisition of video clips at the appropriate time to enable post-processing. The WMMS successfully recognized CoS for both static and walking activities. By taking the initial activity classification from the sensor data and refining the classification decision using the BlackBerry video, superior activity recognition results were obtained.

Static activity (sitting, standing, lying) classification accuracy improved from outcomes in the literature (below 94.6%,^{5,13,23}) to 97.3%. The results would have been 100% except one CoS was missed during a walk-to-sit CoS of one of the trials. More thorough biomechanical analysis is required to identify the movement pattern that created this outlying error. Standing and lying down were recognized with 100% accuracy.

The WMMS produced better sensitivity results for walking than the previous Smartphone-smart-holster system⁵. While various studies in the literature had better walking accuracy (above 96%^{7,23}), these

Figure 3. Images from BlackBerry video for small movements: **a)** kitchen cabinet and oven, **b)** bathroom sink, **c)** dining table and meals, **d)** moving a kettle, **e)** toasting bread, **f)** meal preparation, **g)** washing dishes, **h)** towel and towel rack, **i)** drying hands.

studies only distinguished differences between very distinct mobility states, such as running, jumping, and no-movement. Accuracy of these systems would likely reduce if they were categorizing similar activities, such as running on level ground and running up an incline.

Stair navigation identification improved from 60% in the literature^{5,13} to 75% with the new WMMS. However, the result did not reach the 95% target. Acceleration-based categorization remains difficult for stairs since the signal patterns between walking on level ground and stairs are similar, and the stair slope may not greatly change accelerations at the waist for able-bodied people.

CoS identification for ramp walking was enhanced from 43.3% for the previous system⁵ to 66% because the new WMMS used a specific ramp judgment within the decision tree. Ramp classification also improved from 16.6%⁵ to 43.5%. Accelerometer signals from able-bodied people do not always change when moving from level ground to an incline, however, accelerometer signals from people with mobility disabilities may be sufficiently distinct to enable consistent ramp CoS triggering. During ramp descent, classification errors may occur if a walking CoS is triggered before the person finishes descent and the waist-mounted video does not show the ramp bottom. An altitude sensor may help detect changes in body vertical position during ramp and stair navigation, thereby providing more accurate CoS triggering and sensor-based classification.

Specificity is also important for a WMMS that incorporates video since identifying a CoS when no change actually occurs (i.e. a false positive) results in inappropriate video capture that affects storage capacity, battery life, and increases the workload for video post-processing. Most prior research did not report specificity or false positive results^{13–15}. For the two studies that reported false positives, the maximum false positive rate was above 12% for walking-related activities^{5,24}. Improved threshold calibration methods that are specific to the individual may help to decrease false positives and false negatives.

The BlackBerry device was able to process the features and algorithms in real-time and save outcome data for each 1-second window. Most mobility research used cell phones to collect raw data and then analyzed features and algorithms offline^{13–15,25}. For the new WMMS, threshold settings, decision trees, feature extraction and timing were executed on the Smartphone in real time.

The combination of accelerometer and video camera was superior to using the accelerometer data alone to provide mobility information for activities of daily living. Bathroom, kitchen, and dining room activities were recognized by videos in 63% to 94% of the cases. Although the combination of accelerometer and video could not consistently identify small ADL movements, this method had better accuracy than the accelerometer only, which could not categorize any of these ADLs. Further, CoS for small movements could

not be clearly identified. A higher accelerometer sampling rate may allow for more complex signal analysis that could improve small movement CoS identification. Additional features, such as signal magnitude area, skewness⁵, energy, correlation²⁶, and kurtosis²⁷, might help to recognize the small movement CoS, but these features need greater sampling rates and/or greater accelerometer range.

The video was better than still images for refining activity classification and recognizing context, such as flooring type, bathroom/kitchen, and outdoors. From previous research⁵, still images had limitations in dark areas such as elevators, but video clips with audio were helpful for identifying an elevator and other states. Since videos had continuous images to distinguish upward and downward movement, these clips were useful for stairs and ramp navigation. Although video cameras could potentially recognize small ADL movements, the waist-mounted Smartphone location limited the camera to activities occurring about waist height.

While BlackBerry video proved useful, the current implementation requires human time to review and classify the activities. Manual video assessment could be used for research and specific clinical applications; however, automated video analysis would make the system more efficient and promote widespread use of video data for activity classification. Further research into automated video analysis is required to achieve this goal.

Conclusions

Building on previous work that demonstrated the BlackBerry's ability to identify changes of state in real-time, a new WMMS was presented that uses only the Smartphone's accelerometer and video for unsupervised and ubiquitous mobility analysis for research and healthcare applications. This study was the first to integrate sensor and video analysis for wearable mobility monitoring. This sampling rate for the phone sensors was lower than used in previous studies, demonstrating that a standalone WMMS can be implemented even for older-hardware phones. This standalone WMMS was designed for independent community ambulation and has minimal space requirements and setup time. Furthermore, the context of a person's mobility activities can be identified, including the environment in which mobility takes place.

While monitoring mobility, the new system saves raw sensor data and features. The raw data could be analyzed by other researchers or used in post-processing to improve activity classification. Novel multi-feature algorithms were developed to recognize activities under lower accelerometer sampling rates and range. By combining and weighting sum, range, and covariance statistics, the WMMS was able to recognize standing, sitting, lying, riding an elevator, walking on level ground, ramps, stairs, and ADL (washing hands, drying hands, setting dishes, moving a kettle, toasting bread, preparing a meal, and washing dishes). Static activities, walking on level ground, walking on stairs, walking on a ramp, and riding an

elevator had higher sensitivities than previous studies, but the overall CoS identification and activity classification performance could be improved by further research.

Adding additional sensors, increasing the accelerometer sampling rate/sensitivity, and adding new user-specific threshold calibration methods can be considered in future work. The classification of other small movement ADL activities also requires further research to increase sensitivity and specificity. While evaluation with able-bodied participants was warranted for this proof-of-concept study, further evaluation research with various patient populations is required before this WMMS can be accepted for use by people with mobility disabilities.

Consent

Informed written consent to publish the results of this study was obtained from each participant.

Data availability

F1000Research: Dataset 1. Data for combination of smartphone sensors and video for a wearable mobility monitoring system, [10.5256/f1000research.4790.d32538](https://doi.org/10.5256/f1000research.4790.d32538)²⁸

Author contributions

EL conceived the WMMS. HW, EL and NB designed and developed the WMMS and its evaluation protocol. HW wrote the WMMS code, performed the data collection and analysis. HW, EL and NB and wrote the manuscript.

Competing interests

No competing interests were disclosed.

Grant information

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The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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Alan Godfrey

Institute of Neuroscience, Newcastle University, UK, Newcastle, UK

This study investigates the use of a smart phone as a wearable mobility monitoring system. However, it is of moderate quality and there are a number of issues that warrant attention for the reader. The study could have been simplified, shortened and presented in a more clear and concise manner. Instead it is often vague and illogical in most parts, and introduces concepts/methods that are unsuitable.

In brief:

The title should make reference to the fact that it is a feasibility / proof of concept study. Throughout the manuscript several unsubstantiated claims are made without any real justification.

Introduction:

The authors remark that several video-sensor systems have been used in the past, with various limitations. While this study uses a smart phone as the system, the same limitations were encountered with no insight as to how those limitations may be overcome to progress this type of monitoring.

Materials and Methods:

This section is poorly written. For example the authors introduce GPS and later say it wasn't used. Therefore the text can be misleading in parts and could have been reduced and made concise and easier to read.

A flow diagram of the data processing and activity recognition used from previous work would have been useful to explain the flow.

Accelerometer features:

Use of the inclination angle distinguished sitting from standing - this is true for their slim (66kg) young adults - how successful do the authors think the method will be for older and/or heavier

subjects? How did the authors define sitting, i.e. what was the trunk angle? Would the method work if the participants were sat upright with a trunk orientation similar to standing?

Test procedure:

The evaluators were not blinded during video analysis. This is not discussed as a (major) limitation: bias (favoring correct classification) may have been introduced during classification. Some of the activities performed by the participants seems a bit arbitrary in what is basically a feasibility study. With a device worn on the hip, its not feasible to detect brushing teeth or combing hair (as shown by poor sensitivity values) nor is it worthwhile, at this stage. (brushing occurred outside video field - discussion). It would have been more suitable to concentrate on physical capability tasks relating to whole body movement.

Results:

"Better classification results were achieved when using acceleration and video" - of course as video was manually analysed.

Periods of video capture hinders accelerometer logging - how is this system likely to be useful in the example of a postural transition? For example: this limits the use within pathology and more specifically falls, where most falls can occur during sitting to standing transition. Use of the acceleration data is key to detecting a transition and subsequent fall.

It appears that the accelerometer data could distinguish very little of the activities with manual video observations proving key and the only suitable means to distinguish tasks.

Discussion:

In a few instances the authors refer to "sounds" - perhaps this might be a better tool to help distinguish activities in an automated system?

Competing Interests: No competing interests were disclosed.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 28 Feb 2015

Natalie Baddour, University of Ottawa, Ottawa, Canada

Thank you for taking the time to read the manuscript. In response to comments:

- The abstract and introduction both make reference to the fact that this is a proof-of-concept study.
- We have uploaded a new version of the manuscript removing the reference to the GPS in materials and methods.
- The new version of the manuscript also includes a figure of the high-level overview of the WMMS algorithm.
- Although it was requested by reviewer #2, we have not included the figure of the

decision tree used in the WMMS algorithm in the new version of the manuscript. Such a figure would not be meaningful without explanation, which would greatly lengthen the manuscript. The details of the algorithm are given in reference #19, the focus of which was the algorithm. The focus of this manuscript was on the evaluation of the algorithm.

- Correspondingly, the circuit used to evaluate the algorithm was designed to include activities from "real life" such as hair-combing and teeth-brushing. The intent was not for the a waist-worn WMMS system to identify these activities but rather to see how the WMMS algorithm would perform once these everyday (small movement) activities were included. We felt that this would be a more realistic test of the proof-of-concept WMMS, rather than investigating the performance of the algorithm with only a limited set of activities.
- The comment about the use of the inclination angle to distinguish sitting from standing likely causing problems with older or heavier adults is quite astute. This was, in fact, our experience and an algorithm to correct for the larger girth of some waists has been developed and incorporated into subsequent versions of the WMMS. M. Tundo, E. Lemaire, N. Baddour, Correcting Smartphone Orientation for Accelerometer-Based Analysis, *Proceedings of the IEEE International Symposium on Medical Measurements and Application*, Gatineau, Canada, May 2013. [dx.doi.org/10.1109/MeMeA.2013.6549706](https://doi.org/10.1109/MeMeA.2013.6549706).

Competing Interests: The authors declare that they have no competing interests.

Reviewer Report 24 October 2014

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Paul McCullagh

Computer Science Research Institute, University of Ulster, Newtownabbey, UK

The paper: "Combining low sampling frequency smartphone sensors and video for a Wearable Mobility Monitoring System", examines the feasibility of combining the accelerometry and video, available in a commercial smart phone for classifying activities of living in the home.

As can be anticipate some activities are easy to classify; others with movement overlap are more difficult. Data are provided which can allow the work to be progressed by other researchers. Whilst the individual elements of the work are not novel (accelerometry for activity monitoring and video for life logs and reminiscence), the combination and the superior performance of the sensor modalities provide a useful contribution.

Abstract:

This provides good orientation for the reader and cites the headline results. The sensitivity of 27% for daily living activities is low and show the challenge of higher level classification. Overall activity and mobility (changes of state, CoS) may however be more relevant features anyway (in a subsequent referral). The sample number (N=5) is small and is described as a convenience sample, for this initial feasibility study.

Material and methods:

The WMMS system is based on a Blackberry OS5.0. There is no mention as to whether this can be easily implemented on other smart phones (Android and IOS). Accelerometer sampling rate of 8Hz is appropriate but may miss faster transitions. The feature extraction algorithm and decision tress rely on cited literature. These are key components of the activity classification used for CoS detection. The use of thresholds usually makes it difficult to generalize to the wider population (male/female, height, weight etc.) for accelerometry.

Results:

- *"Better activity classification results were achieved when using both acceleration features and video clips for all activities except sitting, as compared to using the accelerometer only"* This is the crux of the paper and the results underpin this. Of course this is a relative measure. It's difficult to determine what would be a clinically useful measure.
- The figures are useful and inform the reader as to the difficulty of differential classification between some of these activities.
- There is some useful reflection on the use of video. The time required to manually classify the video is a limiting feature.

Conclusions:

The conclusions are realistic and pave the way for further research questions. In particular it may be possible to improve the classification algorithms and the publication of the data sets is advantageous.

The Blackberry has a restricted market and the evolution of smartphone hardware and software continues to advance rapidly. Porting of the algorithms to other operating systems and provision source code would enable further refinement of the approach.

There is little comment on the acceptability of the device, particularly with regard to privacy issues. These are not apparent in simulated environments but would occur if such a device is to be deployed, particularly in a multi-person home environment.

Competing Interests: No competing interests were disclosed.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Author Response 31 Oct 2014

Natalie Baddour, University of Ottawa, Ottawa, Canada

Thank you for a thorough and thoughtful review. Work on the WMMS continues on an

ongoing basis; we have developed the WMMS for the BlackBerry Z10, which has an average sampling rate of 50Hz. However, based on the work in this paper, it is interesting to note that reasonable results can be obtained even with a much lower sampling rate. The WMMS with the Z10 has been evaluated with larger populations and we are working on writing up those results.

We are also currently working on porting the WMMS algorithms to android, with an eye to developing them for the iOS in the near future also.

Thank you once again for taking the time to write a thoughtful and thorough review.

Competing Interests: No competing interests were disclosed.

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