Identifying the Number and Location of Body Worn Sensors to Accurately Classify Walking, Transferring and Sedentary Activities

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***Abstract*—In order to perform fall risk assessments using wearable inertial sensors in older adults in their natural settings where falls are likely to occur, a first step is to automatically segment and classify sensor signals of human movements into the known 'activities of interest'. Sensor data from such activities can later be used through quantitative and qualitative analysis for differentiating fallers from non-fallers. In this study, ten young adults participated in experimental trials involving several variations of walking, transferring and sedentary activities. Data from tri-axial accelerometers and gyroscopes were used to classify the aforementioned three categories using a multiclass support vector machine algorithm. Our results showed 100% accuracy in distinguishing walking, transferring and sedentary activities using data from a three-sensor combination of sternum and both ankles.**

I. Introduction

Falls are a significant cause of injury in older adults. Over 90% of hip and wrist injuries, and mortality with more than 20% of injury related deaths are attributed to falls in this population. Falls in older adults often lead to loss of confidence in their ability to carry out activities of daily living (ADLs), and being less active can negatively affect their health and independence and further increase their risk for more falls. Therefore, identification of fall risk factors in the early stage is important for the healthcare providers in order to develop effective fall prevention strategies.

Walking, transferring (sitting down, lowering, rising etc.) and standing quietly are the most common activities at the time of fall in older adults [1]. Quantitative and qualitative analysis of these mobility tasks have shown the association with risk for falls [2]. Traditional fall risk assessment tools like Tinetti Gait and Balance Tool, Berg Balance Scale and Timed Up and Go Test also involve functional assessment of similar mobility. Such fall risk assessment tools, commonly used in hospital and clinical settings, are often found limited in their sensitivity to predict patients who will or will not fall [3, 4]. The low sensitivity could be because the results of these clinical tests depend on the subjective judgment and experience of the therapists, as well as on the fact that these tests involve measuring patients' physical functions in rigorously defined activities while being supervised in a somewhat artificial laboratory environment. Wearable inertial sensors (e.g., accelerometers and gyroscopes), on the other hand, present promising technology that can not only provide objective information about normal daily activities of older adults in their natural environment where falls are likely to occur, but can also reduce the need for a supervising healthcare professional and specialist laboratory equipment.

As a first step towards the development of such systems, the goal of the current study was to develop a wearable sensor system, and a related data classification algorithm, for accurately classifying ADLs into walking, transferring and sedentary categories. We addressed this goal by conducting laboratory experiments with young subjects who carried out a range of ADLs which were commonly observed in older adults residing in care homes. From acquired sensor data, several time and frequency domain features were extracted and subsequently reduced to a smaller set by using correlation based feature selection method. Finally, Support Vector Machines (SVM) algorithm was used to determine the classification accuracy of individual sensors (at sternum, waist, left wrist and right wrist), as well as in combinations with the sensors placed at both ankles.

II. Methods

A. Participants

Ten healthy young individuals (8 of whom were men), ranging in age between 22 and 32 years (mean = 27.9 years, SD = 3.1 years) were recruited to participate in this study. All participants were students and staff members at Simon Fraser University. The experiment protocol was approved by the Research Ethics Committee at Simon Fraser University and all participants provided informed written consent.

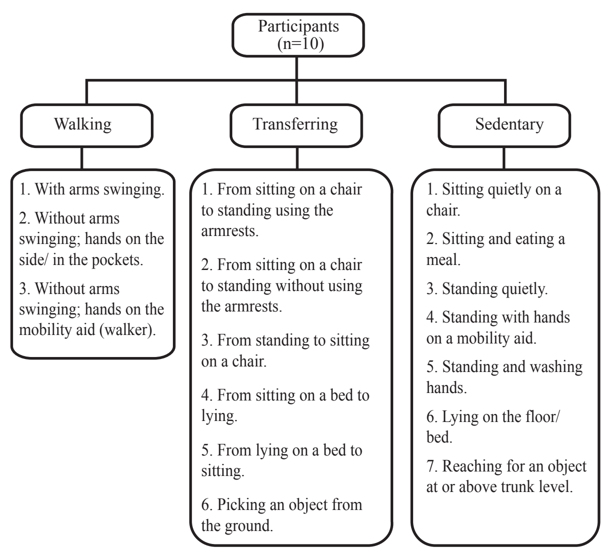

Figure 1. Experiment protocol, indicating walking, transferring and sedentary trials simulated by each participant.

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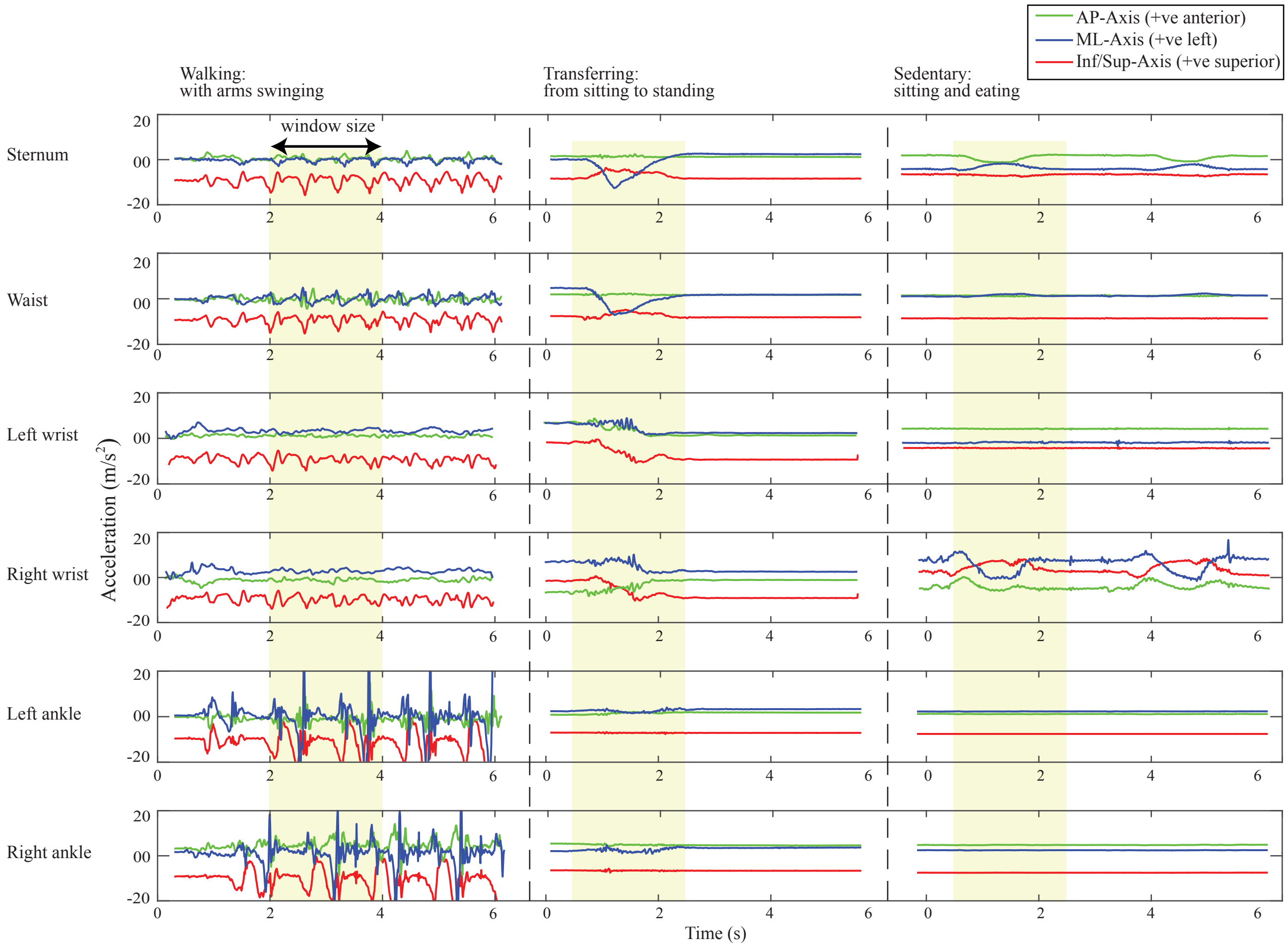

Figure 2. Acceleration traces from a typical participant in walking, transferring and sedentary trials. Features were calculated within a 2 seconds time window (yellow shading) for each of the anteroposterior (AP), mediolateral (ML), and inferior-superior (Inf/Sup) axes of the accelerometers and gyroscopes (not shown in this plot).

B. *Experiment Design*

Based on the advice of fall-analysis expert group [1] a list of ADLs of older adults residing in long-term care (LTC) facilities, was formed. All activities were divided into three categories: (i) walking, (ii) transferring, and (iii) sedentary activities (Fig. 1). In walking trials, three variations were included, which were: (i) walking normally, (ii) walking without arms swinging, and (iii) walking with a mobility aid (a walker). Participants were asked to walk 10 m in each of the three trials, and each trial was repeated three times. Transferring trials involved trunk movements, often without taking multiple steps, to accomplish six selected tasks, which included: (i-ii) rising from sitting with and without using the chair armrests, (iii) descending from standing to sitting, (iv) from sitting to lying, (v) from lying to sitting, and (vi) picking an object from the ground. Each of the six activities was carried out three times by all subjects. In the sedentary category, seven tasks were included, which were: (i) sitting quietly in a chair, (ii-iii) sitting and moving hands – eating meal and reaching, (iv) standing quietly, (v) standing with hands on mobility aid – a walker, (vi) standing and moving hands – washing hands, and (vii) lying/ sleeping. Once again, subjects performed each of the seven sedentary trials three times.

C. *Data Acquisition*

Six inertial measurement units, Opal sensors (APDM Inc. Portland, OR, USA) were used to record body kinematics of each subject, using tri-axial accelerometer and gyroscopes (ranges ±6 g and ±2000 deg/s respectively). The sensors were worn bilaterally on the lateral malleoli, dorsal surface of the wrists, and at posterior aspect of the waist and anterior aspect of the sternum. Data from all sensors were synchronized, sampled at 128 Hz and streamed directly to a computer for storage and subsequent analysis.

D. *Feature Extraction and Feature Selection*

Two seconds time windows were used to calculate eight features from the accelerometers and gyroscope data of each axis (Fig. 2). The features were: (i) mean, (ii) variance, (iii) mean standard deviation, (iv) inter quartile range, (v) correlation between axes, (vi) kurtosis, (vii) number of zero crossings, and (viii) fast Fourier transform energy. The features were selected because they capture the central tendencies and dispersions of sensors signals, and also due to their previous usage in activity classification studies [5]. Furthermore, in order to eliminate the redundant features, which could negatively affect the accuracy of activity classification algorithm, a correlation based feature selection

TABLE I.
SENSITIVITY, SPECIFICITY, PRECISION AND FSCORE FOR CLASSIFYING WALKING, TRANSFERRING AND SEDENTARY TRIALS USING SENSORS AT DIFFERENT BODY LOCATIONS.

	NO. features (n)	Walking (n=180)				Transferring (n=105)				Sedentary (n=90)			
		Sens (%)	Spec (%)	Prec (%)	Fscore (%)	Sens (%)	Spec (%)	Prec (%)	Fscore (%)	Sens (%)	Spec (%)	Prec (%)	Fscore (%)
Individual sensors													
Sternum	48	96	99	99	98	99	97	94	96	100	100	100	100
	21	94	99	99	97	99	96	91	95	100	100	100	100
Waist	48	89	97	96	92	95	100	99	97	93	92	78	85
	25	84	97	97	90	96	99	97	97	93	89	74	82
Left wrist	48	76	98	97	85	100	82	69	81	78	96	85	81
	18	77	95	93	84	100	76	62	76	58	98	91	71
Right wrist	48	80	99	99	88	92	81	65	76	80	97	90	85
	18	79	98	97	87	86	81	63	73	80	95	84	82
Combinations of one upper-extremity sensor with both ankle sensors													
Sternum+Ankles	144	100	100	100	100	100	100	100	100	100	100	100	100
	42	100	100	100	100	100	100	100	100	100	100	100	100
Waist+Ankles	144	99	100	100	100	99	99	97	98	97	99	98	97
	46	96	98	98	97	100	99	98	99	94	97	91	93
Left wrist+Ankles	144	99	100	100	99	98	94	86	92	83	99	97	90
	39	88	100	100	93	98	87	74	84	80	98	92	86
Right wrist+Ankles	144	99	100	100	99	98	92	83	90	79	99	97	87
	39	98	100	100	99	95	93	85	90	84	98	94	89

NOTES: The unshaded rows of the table represent the classification results obtained using complete set of features, whereas the shaded rows show the results from subset of features.

Sens = sensitivity; Spec = specificity; Prec = precision.

(CFS) approach was utilized [6]**.** CFS operates under the assumption that features should be strongly correlated with given class but uncorrelated with each other.

The classification results were calculated with the complete set of features, as well as subset of features from each individual sensor and in combination with ankle sensors.

E. Classification Algorithm

Support Vector Machine implementation in LIBSVM [7] with radial basis function kernel was used. One-versus-all approach was used for classifying ADLs into one of the three categories. The feature vector calculated from the accelerometers and gyroscopes was split into training and testing sets of two equal sizes by randomly selecting five subjects for training and remaining five for testing. The two kernel parameters were optimized through a grid search with exponential growing sequences. Each combination of parameter was tested with 10-fold cross validation, and the parameter combination with the best accuracy was picked. The final model, which was used for classifying test data, was then trained on the entire training set using the selected parameters. The process of training and testing was repeated for each sensor location and the combinations of sensors used in this study. Finally, the classification performance of the algorithm was evaluated by calculating sensitivity, specificity, precision and Fscore. All data analyses were performed in MATLAB (R2015b, The MathWorks Inc.).

III. RESULTS

The performance metrics of the activity classification for each individual sensor location and in combination with ankle sensors are shown in Table 1. With a single sensor, sternum and waist locations were more successful in classifying transfers (with sensitivities of 99% and 95% respectively) and sedentary trials (with sensitivities of 100% and 93% respectively), but were relatively less successful in classifying walking trials (with sensitivities of 96% and 89% respectively). Similarly, sensors at the left wrist and right wrist locations showed relatively high success rate in identifying transfers (with sensitivities of 100% and 93% respectively) but poor in distinguishing walking (with sensitivities of 76% and 80% respectively) and sedentary trials (with sensitivities of 78% and 80% respectively).

With the addition of ankle sensors, a three-sensor combination of sternum and both ankles provided the best classification accuracy of 100% sensitivity across all three categories of walking, transferring and sedentary trials. Waist plus both ankle sensors showed 99% sensitivity for walking and transferring trials, and 97% sensitivity for sedentary trails. Left wrist with ankle sensors and right wrist with ankle sensors, both combinations showed improvement in classifying walking and transferring trials with sensitivities of 99% and 98% respectively, but remained relatively poor with sensitivities of 83% and 79% respectively in identifying sedentary trials.

Finally, the correlation based feature selection technique reduced 48% to 68% of the original number of features from individual sensors, and 68% to 73% from three-sensor combinations, without compromising classification accuracy; except for the left wrist sensor location, where the sensitivity decreased from 78% to 58% in distinguishing sedentary trials.

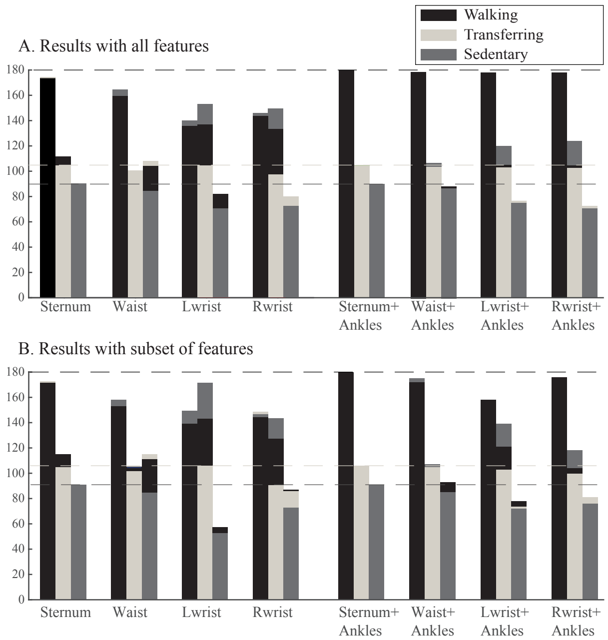

Figure 3. A comparison of accuracy and misclassification of various sensor locations in distinguishing walking, transferring and sedentary trils. The horizontal dotted lines show the actual number of trials, and the height of each bar shows the number of predicted trials.

IV. DISCUSSION

In this study we evaluated the classification accuracy of sternum, waist and wrist sensors, alone, and in combination with ankle sensors, to distinguish walking, transferring and sedentary activities using a machine learning algorithm – support vector machines.

Based on the analysis of the data collected in laboratory experiment with young adults, we found that a three-sensor combination of sternum plus both ankle sensors provided the best performance (100%) in identifying walking, transferring and sedentary trials. For single sensor, not surprisingly, sternum location provided relatively better classification accuracy than the waist. This was perhaps due to the exaggerated and distinct movements that sternum experiences, as opposed to the waist, during certain daily activities, and particularly those that involve transfers such as, sit-to-stand, bending down and reaching. This argument was also supported by the low precision value (78%) observed for waist sensor while distinguishing sedentary trials. This low precision for sedentary trials using waist sensor suggested that the walking and/ or transferring trials were often misclassified as sedentary, as shown in Fig. 3.

Wrists are arguably the most technically challenging body locations for sensors for human activity classification. In this study, we found little differences in accuracies between left and right wrist sensors. This was consistent with the findings by Zhang et al. [8]. Furthermore, we found that with wrist sensors, walking and sedentary trials were often misclassified as transferring activities. This was understandable, as wrists' kinematics are probably a relatively smaller fraction of total body movements during walking (particularly when walking with limited arm swing), and a relatively larger one during some of the sedentary activities such as, sitting and moving hands. Hence, a wrist based activity monitor can potentially over estimate low intensity activities, and at the same time, can under estimate high intensity activities.

There are several limitations of our study. First, all trials were performed by young subjects under controlled laboratory settings. While there are important differences between ADL patterns from laboratory studies of young subjects compared to real-life activities among older adults, we attempted to minimize these differences by including variations in different ADLs conducted in our laboratory. For example, in addition to walking normally, subjects were asked to walk without swinging arms and also by holding a walker. Similarly, sit-to-stand transfers were carried out with and without using the armrests. Another limitation was that our analysis did not attempt to analyze sensor signals by sliding a sampling window along the data stream, as would be necessary in implementation on continuous sensor signal for activity classification. However, our study design allowed for a controlled method of training and testing of our activity classification model.

In summary, our results show that a three-sensor combination of sternum plus both ankles is ideal for classifying walking, transferring and sedentary trials. These results are promising, but how they will generalize to free-living people particularly to the older adults who are the main target for this technology, requires further investigation. Nevertheless, this study represents an important step towards automatically segmenting and classifying sensor data into the above three categories, which could be used with further qualitative and/ or qualitative analysis for differentiating fallers from non-fallers.

ACKNOWLEDGMENT

This work was supported by MITACS and BigMotion Technologies Inc.

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