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3D accelerometer features' differences between young and older people, and between lower back and neck band sensor placements

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Abstract—**In the earlier studies we have developed activity recognition algorithms which are based on features calculated from data of 3D accelerometer sensor placed on the hip, close to the centre of mass. In the development subjects have been young adults. Now we study if the input features of the algorithm are generalized for different set-ups; for older adults and when the sensor is worn as a necklace. From the 3D accelerometer resultant magnitude the following features were calculated for each second: spectral entropy, peak frequency, power and range. The frequency domain features behaved in a relatively stable manner in the set-ups but the time domain features differed significantly from statistical and algorithm perspective between the set-ups. By developing time domain features to be more inter-individual independent would be beneficial for activity recognition algorithms.**

I. Introduction

PREVIOUSLY we have developed algorithms for activity recognition using different sensor setups during daily life. In the current study older people are using activity monitor as part of the service we are testing. In one earlier study we found that most of the interviewed older adults reported to prefer wearing the activity monitoring device as a necklace in the long term use [1]; wrist placement was not an option now since we then wanted to study gait parameters in real world set-up and the parameters are not well presented in the wrist worn accelerometer data. This finding differed from the interviewed young adults who mostly preferred a trouser pocket for the sensor placement.

In [2] we selected some features calculated from a hip-worn accelerometer for an activity recognition algorithm development as they appeared to work well in practice. The algorithm was developed via 3D accelerometer sensor data collected with young subjects who wore the sensor on their hip [2]. However, accelerometer output tends to differ according to age and sensor placement which should be considered when utilizing these algorithms with another user group than they were originally developed with [1].

The first objective of this paper is to study how selected features differ between young adults and older people during the various short activity tasks. The second objective is to study if there are significant differences between the accelerometer signals measured at two different sensor placements: the lower back (we considered this similar to hip placement) and the chest (sensor worn as a necklace). We also discuss the possibilities to use the developed algorithms with the older people who are using the sensor as a necklace.

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II. Methods

A. Subjects and material

The detailed description of the data collection setup can be found in [1]. Fifteen patients (average age 55.2, range [40-68]), 20 older people (76.8, [67-87]), and 19 young adults (27.5, [36-21]) participated in the study. During the study protocol we collected kinetic data with two 3D accelerometers (8 bit, 75Hz, Alive Heart Monitor, Alive Technologies, Queensland, Australia); one attached to the person's lower back (lumbar spine) with an elastic band as in [3] and the other placed on the location which the person him/herself preferred. The protocol included Berg Balance Scale (BSS) test [4] and a short corridor walking test (about ten meters there and back).

The BBS test includes 14 small tasks. During the study, a researcher marked each task's starting and ending moments with computer software [5]. These entries (timestamps) were checked afterwards visually from the raw signal to assure their correctness. The time of the entry was corrected if problems were discovered. In addition to the corridor walking test, some of the BBS tasks are selected to represent physical activity in this paper's study. These tasks were Sitting to standing, Standing to sitting, Transfers, Retrieving object from floor, Placing alternate foot on stool, and Turning 360 degrees. Only young and older people's data are now used in the analysis.

B. Data analysis

Second to second features (no overlapping) were calculated from the recorded 3D acceleration signal's resultant magnitude similar to selected in [2]. The features are:

1) Frequency of the highest peak in power spectral density
2) Spectral entropy

TABLE I

3D ACCELEROMETER RESULTANT MAGNITUDE BASED FEATURE DIFFERENCES BETWEEN YOUNG AND OLDER PEOPLE IN THREE DIFFERENT QUARTILES (25%, 50% AND 75%): GROUP AVERAGE +/- STANDARD DEVIATION

	25%		50%		75%	
Feature	**Old**	**Young**	**Old**	**Young**	**Old**	**Young**
Spectral entropy	0.63 +/- 0.05**	0.55 +/- 0.04	0.70 +/- 0.03	0.67 +/- 0.05	0.74 +/- 0.02	0.74 +/- 0.03
Peak frequency	2.09 +/- 0.68	2.36 +/- 1.12	3.52 +/- 1.74	3.48 +/- 1.90	5.68 +/- 1.39	6.49 +/- 1.00
Power	0.0043 +/- 0.0028*	0.010 +/- 0.012	0.018 +/- 0.015**	0.055 +/- 0.052	0.053 +/- 0.064**	0.12 +/- 0.08
Range	0.48 +/- 0.20**	0.78 +/- 0.41	0.88 +/- 0.38*	1.29 +/- 0.57	1.17 +/- 0.51**	1.61 +/-0.49'

**P<0.01, *P<0.05, According t-test

3) Power i.e. integral of zero mean resultant
4) Range i.e. max – min

Spectral entropy is mainly used to distinct cyclic activities (e.g. walking, running and cycling). Significance of the entropy for activity recognition is explained in more detail in [6].

We calculated quartiles (25%, 50% and 75%) for each feature, for each subject during all the selected physical activities (BBS tasks and walking). This dataset were compared between young (N=18) and older people groups (N=15, some cases were excluded due to bad data quality). Matlab's two sample t-test is now used. All feature quartile were normally distributed according to Kolmogorov-Smirnov test.

The comparison of different locations (the lower back and from the necklace placement) were calculated only fork older people data (N=9, only one young adult used the sensor on the neck). Features were divided into three datasets for the analysis according to lower back sensor data distribution; all samples, samples above median and samples below median. For these three datasets linear regression (without bias term) were calculated to discover relation between the lower back and necklace sensor data.

III. RESULTS

Table 1 presents the differences between young and older adults' data in the three feature quartiles. No statistically significant correlation between the feature quartiles and the BBS score were observed among older adults.

In Table 2 are the results of linear regression analysis for the features. Now in the equation $y = bx$, x represent data measured from the necklace and y the reference i.e. lower back placement.

TABLE II

LINEAR REGRESSION COEFFICIENT BETWEEN LOW BACK AND NECKLACE SENSOR LOCATION FOR OLDER ADULTS (AVERAGE +/- STANDARD DEVIATION); $Y = BX$, X FROM NECKLACE AND Y FROM LOWER BACK PLACEMENT

Feature	All data points	Data under median	Data over median	Data during walking
Spectral entropy	0.94+/- 0.02	0.96+/- 0.03	1.04+/- 0.04	0.89+/- 0.07
Peak frequency	0.91+/- 0.17	0.57+/- 0.15	1.01+/- 0.26	0.95+/- 0.21
Power	0.67+/- 0.40	0.072+/- 0.06	0.17+/- 0.14	1.00+/- 0.57
Range	0.62+/- 0.15	0.25+/- 0.10	0.45+/- 0.12	0.78+/- 0.26

Spearman correlation coefficients during the activity data for spectral entropy is 0.66+/-0.20 (mean +/- standard deviation), for power is 0.78+/-0.15, for peak frequency is 0.18 +/-0.16, and for range is 0.77 +/-0.15.

IV. DISCUSSION

Our objectives were to study how accelerometer features used in the activity recognition algorithm differ between young and older people, and how these features differ whether the accelerometer sensor is worn close to the centre of mass (in this case on the lower back) or on the neck/chest as a necklace. 3D resultant magnitude was used in the feature calculation instead of separate components as developed algorithms are targeted to various sensor placements close to the center of mass. In these set-ups single component based activity recognition algorithms might phase some problems.

The features differed mainly between older and young people for the time domain features as seen in Table 1. The older subjects tended to produce 'smoother' movements i.e. smaller acceleration values. Absolute differences were bigger closer to upper quartile of the distribution; however, the variation is high between the subjects for the time domain features.

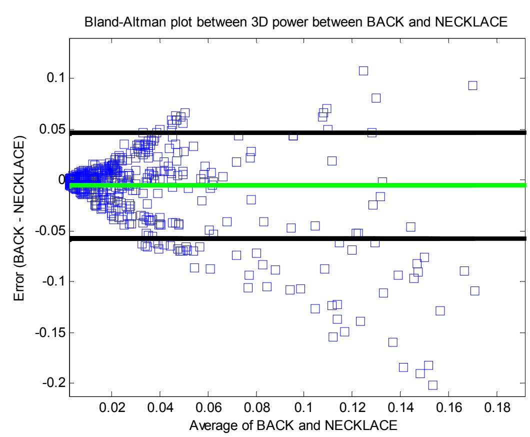

Fig. 2. Blant-Altman plot of lower back (BACK) and necklace (NECKLACE) sensor placements for power feature

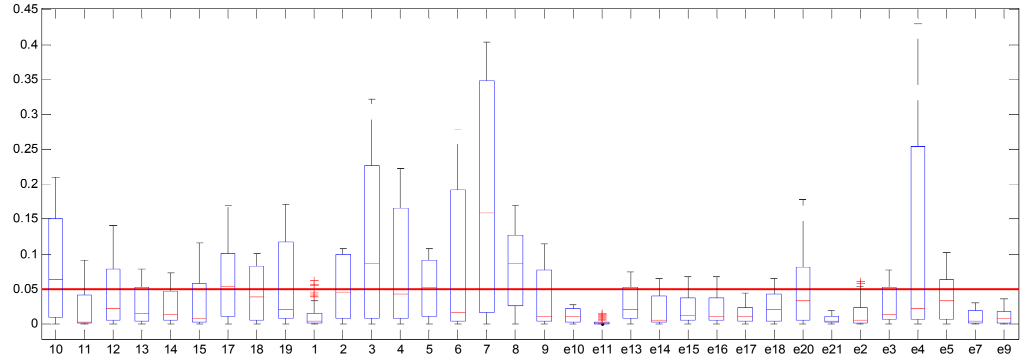

Fig. 1. Boxplot of power feature for young (number) and for older adults (with 'e' identifier) during different physical activities.

The activity recognition algorithm we have developed is based on threshold values for the certain features. Adjusting these thresholds especially for time domain features seems to be relevant for older people population. However, as seen in Fig. 1, the adjustment of the thresholds is not straight forward between these two groups. For example, we are using 0.5 as a threshold for the power feature for a certain classification criterion and as Fig. 1 shows, most of the young people' feature samples are above this value and most of the older people' feature samples are below this value. This causes false classifications. Some discrepancies with time domain features were observed when comparing data collected from the lower back and necklace sensors. Very high linear relations were observed on the individual level in the time domain features. However, as seen in Fig. 2, the group wise transformation between these two placements is not solved with linear equation well.

Results with the frequency domain features were very encouraging between the two age groups and the two sensor placements. Especially spectral entropy seems to be very stable in both set-ups as seen in Fig. 3. Now the necklace sensor placement seems to overestimate slightly the entropy with smaller values and other way around with the bigger. For peak frequency feature we though observed rather low correlations which lower the reliability for using the algorithm for different sensor placements.

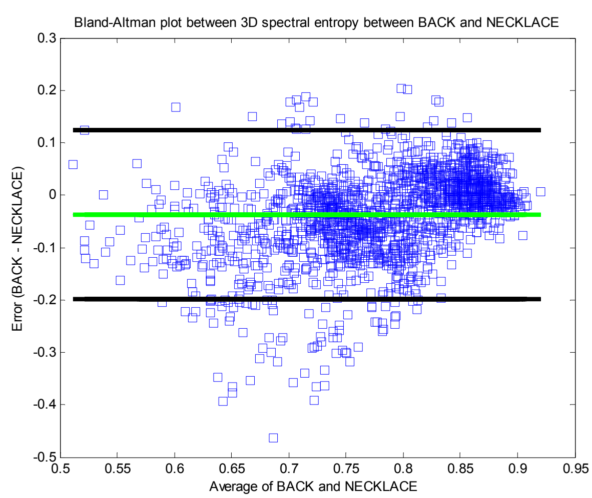

Fig. 3. Blant-Altman plot of lower back (BACK) and necklace (NECKLACE) sensor placements for spectral entropy feature

V. CONCLUSIONS

The features we utilized had a tendency to differ between the studied set-ups, especially the time domain features. Therefore, we see that it is important in further research to look for and study more individual-independent features for time domain or methods to compensate individual differences for example by adjusting the algorithms adaptively.

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