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Human Balance Estimation using a Wireless 3D Acceleration Sensor Network

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Abstract—**Balance and gait are a consequence of complex coordination between muscles, nerves, and central nervous system structures. The impairment of these functions can pose serious threats to independent living, especially in the elderly. This study was carried out to evaluate the performance of a wireless acceleration sensor network and its capability in balance estimation. The test has been carried out in eight patients and seven healthy controls. The Patients group had larger values in lateral amplitudes of the sensor displacement and smaller values in vertical displacement amplitudes of the sensor. The step time variations for the Patients were larger than those for the Controls. A fuzzy logic and clustering classifiers were implemented, which gave promising results suggesting that a person with balance deficits can be recognized with this system. We conclude that a wireless system is easier to use than a wired one and more unobtrusive to the user.**

I. Introduction

MAINTAINING balance while walking and performing other everyday activities has a great impact on quality of life. Disorders of balance and gait have serious consequences, since falling can cause serious injuries or even death. In Finland, falling has been estimated to cause the death of more than one thousand persons annually among people over 50 years old [1]. Preventive measures could reduce the risk of falling by 20 – 40 % [1].

Nowadays, balance and gait evaluations usually depend on visual objective estimation or on expensive laboratory equipment, such as a force platform or video camera system. A wireless acceleration sensor network provides for a reasonably priced ambulatory measurement system that is unobtrusive to the user.

II. Methods

A. Wireless Sensor Network

A fundamental part of this measurement system is a SoapBox (Sensing, Operating and Activating Peripheral Box). Five SoapBoxes are used to implement an acceleration sensing wireless body area network (WBAN) (see Fig. 1). A SoapBox is a flexible and reusable platform for several applications in ubiquitous computing. The matchbox-sized SoapBox module has a processor, five sensors and wireless and wired communication capabilities. Although the SoapBox includes several types of sensors, only the 3D acceleration sensor is used in this application. The acceleration sensor is constructed of two +/-2g Analog Devices (ADXL202JE) [2], [3].

The WBAN arrangement in this research consists of one central SoapBox and four remote SoapBoxes. The remote SoapBoxes measure 3D acceleration at a 41.25 Hz sampling rate and the central SoapBox has a sampling rate of 33 Hz. The central node receives the data from the remote nodes wirelessly using a 1 mW licence free 868.35 MHz radio (RF Monolithics TR1001). A time division multiple access (TDMA) based medium access control (MAC) protocol is used for data transfer. The central node forwards both its own and the received data to a Nokia Series 60 mobile phone. This time a Bluetooth connection (F2M01 serial-to-Bluetooth adapter) is used for data transfer [2], [3].

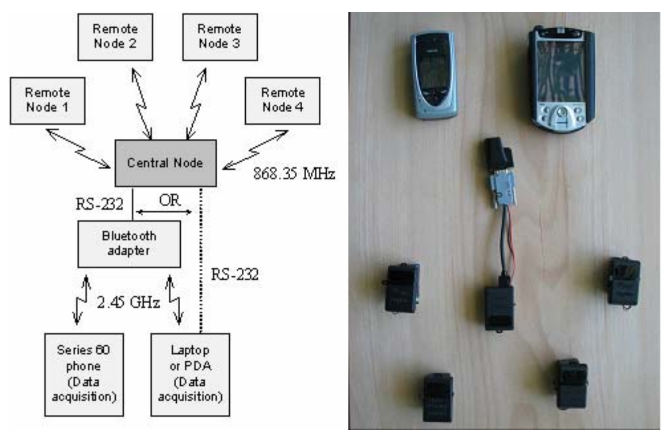

Fig. 1. The overall network topology and device setup.

A MotionLogger (Series 60 Symbian [4] application) is created on the mobile phone for storing the WBAN data. An annotation feature is added to help distinguish between different events in the data at the data processing phase. The user adds an annotation label to the data, which stands as a mark for the starting point or ending point of a certain event. The measured data is transferred to a PC via a Bluetooth connection.

B. Measurements

The system was tested by executing balance and mobility

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tests at the Rokua and Kajaani Rehabilitation Centres under the supervision of a trained physical therapist. The test subjects performed several tasks, for example, walking 10m as fast as possible, standing up from a chair, Berg's balance test etc. wearing the wireless sensor network. The SoapBox sensors are attached with five specially made rubber bands, where a pocket for the SoapBox and its battery is sewed to each band. The rubber bands are fastened into place with a two-sided adhesive sticker, which is sewed to the rubber band so that it doesn't lose its elasticity. One sensor is placed on the lower back at approximately the height of the centre of mass. Two of the sensors are attached to the outsides of the knees and two to the outsides of the ankles. The purpose is to align the sensor axes so that when a person is standing in an upright position, one axis is pointing to the side, one axis backward or forward and one axis up or down.

We have included eight patients and seven healthy controls in this study (Table I). The study was carried out in all subjects after informed consent and in agreement with the Helsinki declaration. The subject qualifies as a patient if he/she has an illness that may affect his/her balance. The results of the 10-meter walk task are presented.

TABLE I
BACKGROUND INFORMATION OF THE TEST SUBJECTS

Subject Patient (P)/ Control (C)	Male (M)/ Female (F)	Age (years)	Diagnosis
P1	M	51	MS, spastic, ataxia
P2	M	55	Dystonia, backwards falling attacks
P3	F	77	Left falling attacks occasionally, left hearing deficiency
P4	F	49	Rheumatism, shortening of right leg (3cm), stiff right ankle, artificial joint in both hips and left knee
P5	F	55	Rheumatism, shortening of right leg (3cm), knee valgus, stiff ankle, left knee instability, artificial joint in both hips and left knee
P6	F	54	Left hemiplegia
P7	M	61	Mild left leg paralysis
P8	M	64	Right hemiplegia, ankle support, stick
C1	M	81	-
C2	M	80	-
C3	F	79	-
C4	F	67	-
C5	F	20	-
C6	M	56	-
C7	M	49	-

C. Tilt Normalization

Tilt normalization is performed for the hip sensor. The sensor axes are rotated so that the up – down axis is in the same direction as the gravitational force. This algorithm, adopted from [5], only corrects the average tilt due to inaccurate attachment of the sensor or different body shapes, not the dynamic tilt caused by human movements. The same tilt normalization method was found useful in user-independent gesture recognition in [5].

D. Parameters

As stated in [6] and [7], a person can be identified from the gait data measured using accelerometers. Thus, it is reasonable to believe that disorders affecting balance of gait are also noticeable from the acceleration data measured while walking. The human gait has been studied several times before in the context of balance estimation using different types of measurement systems. One example is Hausdorff *et al* [8], who investigated gait variability and its relationship to fall risk among older adults using force-sensitive insoles. This approach is now applied to the accelerometer-based system. A hip sensor placed on the lower back is most suitable for detecting time variables of gait, since it contains information from both legs (right and left leg). Heel strikes cause peaks in the vertical acceleration signal measured from the hip. The maximum peaks are detected from the data, and the step times are calculated using the time span between the peaks. A standard deviation of the step times within a data clip is calculated.

The amplitude values of the position trajectories of the sensor are also interesting. As Dodd *et al* [9] investigated lateral pelvic displacement (LPD) in stroke patients, this research also studies the same feature and its relationship to the balance and stability of walking. Position trajectory of the sensor is calculated for the walking data by double-integrating the acceleration signal. An offset fluctuation is diminished by calculating a correction curve, which is then subtracted from the integral. The correction curve is obtained by calculating an offset value for every point, which is an average of two consecutive steps that is, one step before and one step after the point in question. The underlying assumption when calculating the position trajectory of the sensor during gait is that, on a level surface, the accelerations in lateral and vertical directions should have a zero mean value. The correction curve may somewhat attenuate real transitory peaks in position trajectory. Similarly, the swinging and slight deflection of the sensor during walking makes the absolute values of the position partly indicative, but differences between position trajectories of different persons can still be distinguished. Maximum and minimum amplitudes in the lateral position trajectory represent displacements to the right and left. The total amplitude value is a sum of average right and average left amplitudes, that is, an average of total lateral amplitude of the sensor. The total vertical displacement amplitudes are also investigated where the averages of up and down amplitudes are combined.

E. Subject Classification

The subject classification utilizes the self-organizing map (SOM) clustering [10] and fuzzy logic methods. The clustering is carried out with algorithms implemented in the

SOM toolbox from [11]. Prior to clustering, the variables are normalized using the toolbox's functions so that their variance is set to unity and their mean to zero. This ensures equal emphasis on every variable regardless of their numerical range. In the fuzzy logic analysis, the leave-one-out method is used to obtain membership functions for the two groups Patients and Controls. For the subject left out, the degrees of membership are determined from the functions obtained with the other subject's parameters. The four nearest to the median values of the Patients are used to define the membership function for that group. The average value of them is set to 1 and the minimum and maximum values to 0, which results in a membership function shaped like a triangle. The membership function for the Controls is evaluated similarly. The degree of membership of the subject in both groups is determined with the membership functions for every three variables separately. The total degree of membership is obtained by adding all three degrees of membership values in the Patients group and all three degrees of membership values in the Controls group. Thus, the maximum total degree of membership in a group can be three. The subject is classified as belonging to the group in which it has the larger degree of membership.

III. RESULTS

Vertical acceleration of the hip sensor during walking is used in the evaluation of time values. Fig. 2 presents standard deviations of the step times for both Patients and Controls.

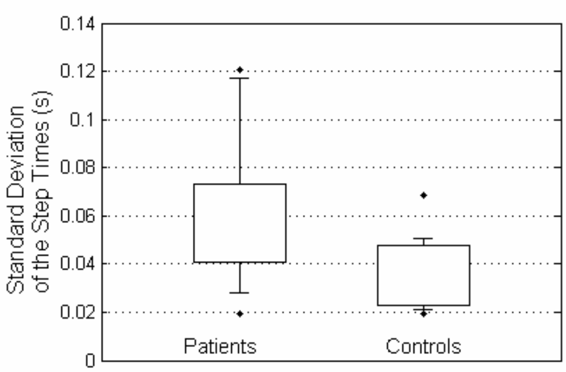


Fig. 2. Standard deviations of the step times evaluated from the acceleration measured from the hip during walking. The white boxes contain the four nearest to the median values of the Patients (n=8) and the three nearest to the median values of the Controls (n=7). Line markers represent the next values under and above the box. The dots represent the smallest and largest values in both groups.

Fig. 3. presents lateral and vertical displacement amplitudes of the hip sensor during walking in both subject groups. The lateral amplitude value used is a sum of average right and average left amplitudes. On the other hand, the averages of up and down amplitudes for the vertical displacement are combined.

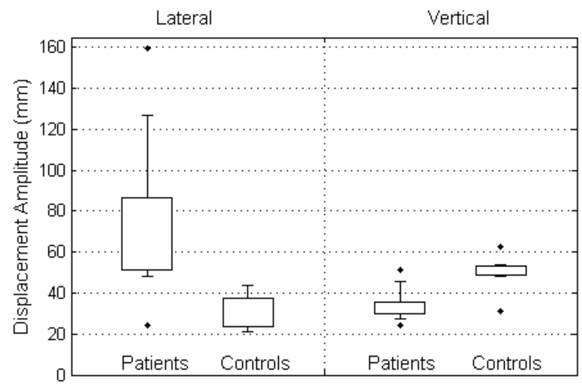
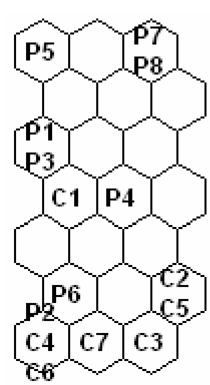


Fig. 3. Lateral and vertical displacement amplitudes of the hip sensor measured during walking. The white boxes contain the four nearest to the median values of the Patients (n=8) and Controls (n=6) in lateral direction, and the four nearest to the median values of the Patients (n=8) and the three nearest to the median values of the Controls (n=7) in vertical direction. The line markers represent the next amplitude values under and above the box. The dots represent the smallest and largest values in the group. (Control subject C6's walking sample was too small for lateral position assessment, thus it was left undefined.)

The parameters "standard deviation of the step times", "total amplitude of the lateral position of the hip sensor" and "total amplitude of the vertical position of the hip sensor" are taken into subject classification analysis. The clustering is carried out for subjects P1 – P8 and C1 – C7. The plot in Fig. 4a) illustrates how the subjects are distributed on the map. The fuzzy logic analysis is carried out for subjects P1 – P8 and C1 – C7, excluding subject C6, since it does not have values for all three parameters. The results for the fuzzy classification are found in Fig. 4b).



Subject	Result (P → Patient, C → Control)
P1	P
P2	C
P3	P
P4	P
P5	P
P6	C
P7	P
P8	P
C1	P
C2	C
C3	C
C4	No result
C5	C
C7	C

a) b)

Fig. 4. a) The subject distribution on the clustering map. b) The fuzzy classification of the subjects into two groups Patients (P) and Controls (C).

IV. DISCUSSION

Standard deviations calculated from the step times show a difference between Patients and Controls. The larger standard deviation in this context means a more irregular gait. The results are consistent with those previously reported [8], even though the distance walked was shorter in this testing arrangement. Lateral displacement amplitudes of the Patients are also greater than those of the Controls, which is concordant with the data recently reported [9]. A difference between the two groups can also be found in vertical displacement amplitudes.

The clustering and fuzzy logic methods provide similar results. Subject C1 is closer to the Patients cluster and it was also declared a Patient in the fuzzy logic analysis. The age of subject C1 might have had some effect on his gait, thus bringing him closer to the Patients group, as the incidence of falls increases markedly with age. In addition, subjects P2 and P6 are more in the Controls cluster than in the Patients one, and they were declared Controls with the fuzzy logic classifier as well. Patient P6 has left hemiplegia, which is mostly emphasized in the left arm. This explains why the illness does not affect the patient's gait very much. Patient P2 has an illness, which causes backwards falling attacks. According to a medical assessment, the person walks with his slightly spastic legs straight forward without any abnormal sway between the falling attacks. Two clusters can still be separated, one with more Patients in it and the other with more Controls in it, and the results are comparable with the ones obtained using the fuzzy logic method.

To improve the testing arrangement, the walking distance could be longer than 10 metres e.g. 50 metres depending on the condition of the subjects. More subjects could also be used in the study. It could also be useful to divide the subjects into more specific groups, such as subjects with a high fall risk, subjects with a moderate fall risk, and subjects with no fall risk. This kind of five-sensor system provides a large amount of data. Including the sensor data obtained from the knee and ankle sensors to the data analysis would provide more accurate results. For example, different phases of the gait cycle can be studied further to obtain information about the rhythmics of the gait. The dynamical tilt of a sensor can be reached with additional sensors, e.g. gyroscopes, making it possible to calculate the temporary 3D position of the acceleration sensor. This in turn enables definition of the continuously changing offset values of the acceleration signals caused by the gravity, and thus substantially improves the estimation of the position trajectory during the gait.

All in all, the parameters calculated from the walking data appeared to have dependence to balance even with quite a small test subject group. A reliable classifier was also introduced for identifying subjects with balance deficits. This provides a method for creating a new ambulatory on-line balance analyzer tool for doctors and physical therapists. The balance analyzer could be used in addition to a physical examination or home health care as a means of detecting balance deficits at an early stage and identifying the need for fall-preventive measures.

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