A smartphone-centered wearable sensor network for fall risk assessment in the elderly

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ABSTRACT

Fall prevention is an important aspect to keep high the quality of life in aging. In this work, a wearable sensor network to automatically assess movement and its indicator for fall risk is proposed. The method is based on a smartphone linked to wearable devices. The proposed approach starts estimating the physical activity level using activity recognition algorithms running on the phone. Such estimation can be conducted by simply using the smartphone on its own. Activity recognition can also identify walking bouts to drive gait assessment tools using different sensing sources. In this regard a strategy to estimate stride-based gait stability indexes during ambulation was implemented. Waist and shank sensing nodes were involved in the computation of stride time, stride time variability, vertical acceleration variability and harmonic ratios. The proposed method can correctly recognize activity with a 95% accuracy within four classes. Ambulation in particular is recognized correctly in 97.2% of cases and gait stability indexes are then estimated capturing differences between controls and patients at high risk of falling.

Categories and Subject Descriptors

I.5.4 Computing methodologies: pattern recognition: applications
J.3 Computer applications: life and medical science: health
K.5.4 Computers and society: social issues: assistive technologies for persons with disabilities

General Terms

Algorithms, Measurement, Experimentation.

Keywords

Wearable sensor networks, fall risk assessment, gait stability, activity recognition.

1. INTRODUCTION

Falls are a major cause of death and injuries that can seriously limit independent living in the elderly. More than one-third of home-dwelling people aged over 65 years and two-thirds of those living in residential care fall each year at least once [1]; the trend for a person experiencing a fall is to fall again [2], which often leads to fear of falling, decreased mobility and independence [3].

Technologies to monitor body kinematics, ground reaction forces and electromyographic signals provide objective quantitative measures for fall risk assessment, but the associated equipment requires dedicated facilities, time consuming setups and its deployment in clinical practice is difficult [4]. Analyzing movement by means of wearable sensors is a widely developing research stream to improve effective usability of quantitative methods of fall risk assessment [4]. There is not yet a wide consensus on these methods, given that wearable sensor systems have not been validated thoroughly, using large datasets [5]. However, many studies are now pursuing this approach, involving typically inertial sensors (accelerometers and gyroscopes), the assumption is made that a wearable sensor system can efficiently capture and analyze quantitative mobility data that could help improve fall risk assessment, [4]. Postural sway, gait variability, gait stability, movement smoothness, walking speed and duration of a sit-to-stand transition are commonly considered quantities for fall risk assessment using wearable sensors [4]. In this regard, many works focus on the instrumented version of the timed-up-and-go (TUG) test [6], quantifying the various components of the test (sit-to-stand transitions, walk, turn, stand-to-sit transitions) [5, 7-9]. Most of studies based on wearable motion sensors focused on gait, given that most of falls occurs while walking and that, as said before, gait function is often compromised in individuals at high risk of falling [7, 10, 11].

In our opinion, fall risk has to be estimated with a multi-factorial approach to the analysis of movement data. The main solutions proposed in the literature tend, often, to propose standalone setups that address specific problems in isolation, such as estimation of physical activity level and gait assessment. The approach we intend to pursue here consists of casting these two aspects in a single, admittedly more complex problem. Accordingly, we attempt to move the first step in this direction by designing a wearable sensor network, which aims at jointly estimate several quantities potentially useful for fall risk estimation. As it is usual, different sensor placement sites can be helpful to address specific aspect of our overall problem: for instance, the shank is a good site for measuring temporal parameters of normal or pathologic gait, however, it cannot be chosen if the interest is for extracting useful indicators of walking stability (e.g., harmonic ratios); at the same time, the waist is widely considered to analyze the gait stability, but its usefulness to estimate reliably temporal parameters of gait is generally limited to normal gait. Of course, the availability of a body area network (BAN) may allow the different nodes to talk each other,

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each of them being specialized in fulfilling specific computational tasks. The idea is that the information shared by the different BAN nodes could promote a better global knowledge about the human being that produces the observed movement data. Previous examples of BAN frameworks for human movement evaluation are in [12, 13]. In this work, two main problems related to fall risk assessment are discussed as an application niche for the proposed wearable sensor network: gait assessment and estimation of physical activity level through activity recognition. Activity recognition was performed directly on the smartphone that was used as the central node of the network. Activity information was also used for enabling gait stability assessment during walking bouts. A shank sensor was used for obtaining an accurate gait segmentation that drove stride-based gait stability indexes estimation using waist sensor data.

2. PROBLEM BACKGROUND

2.1 Activity recognition for fall risk estimation

The knowledge about the activity being performed throughout the day gives the clinicians an important tool for assessing the physical activity level and the mobility of patients. A lack of physical activity in elderly is known to be correlated with enhanced risk of fractures [14], cardio-vascular mortality [15], un-healthy body fat distribution [16]. There is not an unanimous consensus about the effects of physical activity in the elderly in relation to fall risk [17]. Intuitively, the positive relation between a physically active lifestyle and fall risk cannot be extended monotonically to all physical conditions in the elderly: a strong limitation of mobility would reduce the fall risk, despite the lack of physical activity. Moreover, exercising cannot reduce many fall risk factors such as those related to impaired vision or extrinsic risk factors (e.g., walking on slippery surfaces, improper footwear). However, the positive effect of improving physical activity on gait, strength and balance are known [17-20]. Several epidemiological studies evaluated the relationship between fall risk and inactive lifestyle in the elderly. In [19], 439 people aged 69-92 years were studied; a significant increase of fall risk was observed for those who did less than 75 minutes of activity per day, including walking, cycling, gardening, household activities and sports. Such basic activities nicely pair with those that are usually considered in automatic activity recognition methods, based on wearable sensors.

Automatically recognize the activity of a person using light-weight wearable sensors, allows estimation of his/her physical activity level, and to monitor its time evolution. Wearable inertial sensors are becoming very common to solve this particular problem, and commercial devices to this purpose start becoming available. Accelerometer-based activity monitors are capable of quantifying human motion, covering the range of acceleration amplitudes and frequencies required to measure human movement [21]. Moreover, their low power consumption, small dimensions, and light weight contribute to wearability and make long term activity monitoring practical. Although complex multi-sensor systems for a detailed activity recognition are becoming more practical [22], single-sensor systems may improve acceptability for long term studies, simplify study administration and lower cost and are therefore current practice in larger studies [23, 24]. Recently, single sensor solutions for activity classification are being implemented using sensors embedded in smartphones and smartwatches. First mobile health studies involving physical activity evaluation date back to early 2000s when mobile phone-based frameworks for vital signs and activity monitoring were proposed. The solution in [25] included a wearable accelerometer connected to the phone via Bluetooth to evaluate the posture and detect walking episodes. The phone was used to extend the communication between the user and a server where all the processing was done. In 2008, Hong et al suggested the possibility of using emerging devices, the smartphones, with embedded accelerometers as the platform for activity recognition research in the future developments of their method, [26]. In the same period, first implementation of activity classification in smartphones were presented: data were collected from body-worn sensors and classified using a smartphone [27, 28]. The high computational capabilities of current smartphones allow the implementation of online methods for recognizing daily activities. Some examples of this are the work by Del Rosario et al. [29], where a validation over both young and elderly users was done, the work by Antos et al, involving both activity recognition and smartphone localization [30], and the study by He and Li, where fall detection capabilities were also included [31]. Other smartphone based solutions for activity recognition are in [32, 33]. Many commercially available solutions and apps including simple activity recognition tasks are now being offered in application stores. Commercially available apps are based on inertial sensors or may rely on different sources such as network localization information from which the ambulation tasks are inferred. However, the vocabulary of recognized activities is limited and their level of accuracy is still perceived as approximate from final users.

2.2 Gait stability assessment for fall risk estimation

Gait is the most important human activity, and its assessment is often oriented to the evaluation of gait stability. This particular aspect is strongly related to fall risk assessment. Gait stability is a precondition for walking without falling: a decrease in the value of a gait stability index is generally associated to an increased risk of fall. Gait stability can be estimated using stability measures (direct methods) or studying foot kinematic trajectories (indirect methods). [10]. Some direct methods are based on the evaluation of Floquet multipliers [34, 35], Lyapunov exponents [36, 37] or Poincaré plot indexes [38, 39]. Gait variability is the most widely used feature in indirect methods proposed for gait stability estimation: variability is related to fall risk given that an increased variability may bring the dynamic state of a person closer to his/her limit of stability [10]. Other kinematic quantities that have been associated to gait stability are the foot clearance [37, 40], the step width [41, 42] and the double support time [43]. Several models to estimate fall risk indexes or to recognize faller from non-fallers using wearable sensors measurements has been proposed in literature, as reviewed in [4]. Of great interest are also the so-called harmonic ratios (HRs), for which a quite extensive literature exists to show their applicability in the analysis of abnormal gait [44, 45].

3. MATERIALS AND METHODS.

3.1 Wearable sensor network

The experiments of this paper were performed with three battery-powered barometric-inertial-magnetic measurement units we developed and named WIMU (wearable IMU, figure 1). Each

WIMU is endowed with a 32-bit ARM Cortex processor (NXP Semiconductors LPC1768) and a Bluetooth (BT) transceiver and is currently implemented in a version for data communication with an Android smartphone. The WIMU sensors are a digital tri-axial gyro (InvenSense ITG-3200, with range ± 2000 °/s), a digital tri-axial accelerometer (Bosch BMA180, with range ± 4g, where g = 9.81 m/s2 is the gravity acceleration), a digital tri-axial magnetic sensor (Honeywell HMC5843) and a digital barometric altimeter (Bosch BMP085, with resolution 1 Pa). Inertial sensor data were sampled at 50 Hz and on-board digitally filtered using a Butterworth second-order low-pass filter (cut-off frequency: 10 Hz); air pressure sensor data were sampled at 50 Hz in the ultra-low power mode (oversampling was not performed internally to the sensor) [27]. The sensor data, logged into the ARM memory, were transmitted to the smartphone via BT.

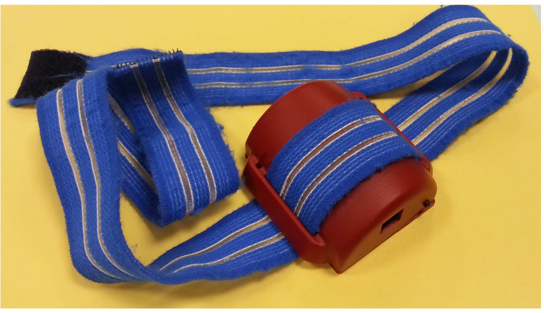

Figure 1. The WIMU sensing node.

We focused on a smartphone as the center of the wearable sensor network (figure 2). Smartphones are becoming pervasive devices, and their computational capabilities allow online processing to deal with many of the cited problems. In particular, our solution was tested on a Samsung Galaxy S3 (GT-I9300) device equipped with Android 4.3 operative system. We choose the smartphone Bluetooth connection capability to link the three WIMUs. The selected placement sites were shank, wrist and waist. WIMUs were fixed with elastic Velcro bands: the shank sensor was placed above the lateral malleolus, the waist sensor was placed in correspondence of the L3 vertebra and the wrist sensor was placed as it would be done for a wrist-watch. Actually, we did not use the wrist sensing source for this work. However, we included this site in the network to stimulate future developments involving a smartwatch. Accelerometers and many other sensing sources are embedded in smartphones and can then be processed for several fall risk assessment applications, giving the fourth placement site, (trousers pocket).

3.2 Activity recognition for fall risk estimation

In this work we adopted a previously validated offline method for activity recognition [46]. First, the automatic classification methodology was applied to an existing dataset for offline training and validation purposes, using a PC running Matlab (The Mathworks, Natick MA). Second, the testing phase of the algorithm was implemented on the smartphone. Even if there was not any reason preventing us from doing activity recognition using data from the shank or waist sensors, as we previously did in [46], we preferred here to implement a solution capable of running on the smartphone. In particular, the previously validated methodology was applied to data from the accelerometer embedded in the smartphone assuming that during its use the smartphone is stored in the user's trousers pocket.

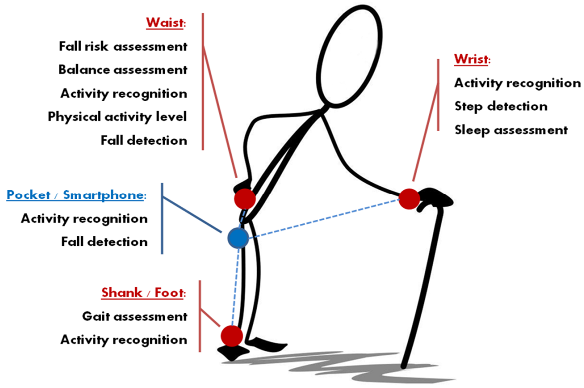

Figure 2. Sensor network placement sites and possible outcomes of sensor data processing.

The offline validation tests of the method were done using a previously available datasets [47]. In particular, data acquired using thigh-fixed sensors were considered from that dataset. This placement site slightly differs from the trousers front-pocket. However, previous literature confirms that features in time and frequency domain extracted from accelerometer magnitude data do not vary significantly when the sensor is moved within the same body region, including thigh [48]. During preliminary tests we observed that actually this was the case using the smartphone in the pocket. The only limitation to this was observed when the user wore very large trousers, which caused the smartphone to move unpredictably within the pocket. The dataset included data from 33 participants while doing a large set of activities grouped in four main classes: ambulation (including level, uphill, downhill on both treadmill and ground), cycling, sedentary activities (such as working at a desk) and a class named "others", which includes non-locomotion activities done in an upright position (such as sweeping and painting) [46, 47]. Time and frequency domain features were extracted by windowing the norm of the accelerometer data channels. Signals were windowed using 512-samples non-overlapping windows. The classifier chosen was a Support Vector Machine (SVM) with a radial basis function kernel [46]. The validation was conducted following a leave-one-subject-out strategy [46, 47].

After running offline validation tests, all the available data were used to train a general classifier, which was implemented in the smartphone. In the online testing phase, implemented using an *ad hoc* android application, 512-samples 90%-overlapping sliding windows were segmented and features were calculated from them. A soft-assignment classification strategy was then considered. A soft-assignment approach was preferred in the online test to allow discarding outputs from the classifier when the classification confidence was not acceptable. The soft-assignment was obtained by cascading a logistic regressor to the SVM classifier output.

3.3 Gait stability assessment for fall risk estimation

Data from 11 control subjects C (55±6.3 years old) and one 68 years old person (P) at high risk of fall were processed. Data were part of the preliminary studies we conducted for the IDONTFALL research project [49]. The tests consisted of instrumenting 30 meters walking bouts by using the described wearable sensor network. In particular, the shank and the waist sensor were considered in this part of the study. The test consisted of asking the person to walk along a 30-m long corridor: during tests data from the shank sensor were used for gait segmentation purposes, and segmented data from the waist sensor were processed to estimate parameters potentially useful for fall risk assessment. Gait segmentation was obtained by using the hidden Markov models (HMM) based strategy we previously validated and tested online in [50, 51]. HMM-based methods found application in this field because they improve results reliability, in the face of high inter-subject variability. The online version of our HMM-based gait segmentation algorithm was implemented in the shank sensing node to provide gait events time labels that drove the procedure for estimating stride-based HRs [51]. Segmentation information (toe-off and foot-strike events) from the shank, jointly with inertial sensor recordings from the waist were sent to the smartphone via BT. The set of parameters considered to describe gait stability were: stride time, stride time variability, expressed as coefficient of variation in %, root mean square (RMS) value of the component of vertical acceleration (gravity removed) and HRs of the three component of acceleration (medio-lateral, antero-posterior and vertical). Stride time information was derived from HMM based gait segmentation at the shank, by evaluating the time between consecutive foot-strike events. The vertical acceleration RMS was estimated using the complete acceleration trace acquired during the walking bouts. HRs were computed by submitting stride acceleration data to Fourier harmonic analysis, as described, e.g., in [44].

4. RESULTS AND DISCUSSION

4.1 Activity recognition

Some results for the leave-one-subject-out cross validation study are reported as a confusion matrix in Table 1. The algorithm confirmed to be effective in automatically recognizing activities using sensor information from a single placement site [46]. The overall recognition accuracy was 95%: the worst result was achieved for the “other activity” class (80.1%), where the amount of training data was smaller. Walking bouts were automatically recognized with 97.2% accuracy. This high accuracy justifies our initial intention to drive gait parameters estimation using activity recognition outputs.

Two screenshots of the online implementation are shown in figure 3. Classification results and *a posteriori* classification probabilities were reported online to the user. Notifications can be raised if the detected sedentary behavior lasts for more than a predefined time, which can be set by, e.g., the user or a therapist. A diary tool was also included to give the user an activity summary of the previous outputs from the classifier. Even though a quantitative test of outputs was not performed online yet, qualitatively the app showed correct classification for most of the tested windows. The availability of the *a-posteriori* classification probabilities, which were obtained as the result of the logistic regression, allowed us to add an additional “uncertain” class for those output showing uncertain classification output.

The battery consumption of the app was not negligible, given the high rate of accelerometer sampling (~100 Hz), however, the batteries of the tested phone (Samsung Galaxy S3, I-9300) using the app lasted for 12 hours. It is our plan to reduce the sampling rate to 40 Hz in future tests, given that offline tests indicated that this reduced sampling rate does not affect classification accuracy.

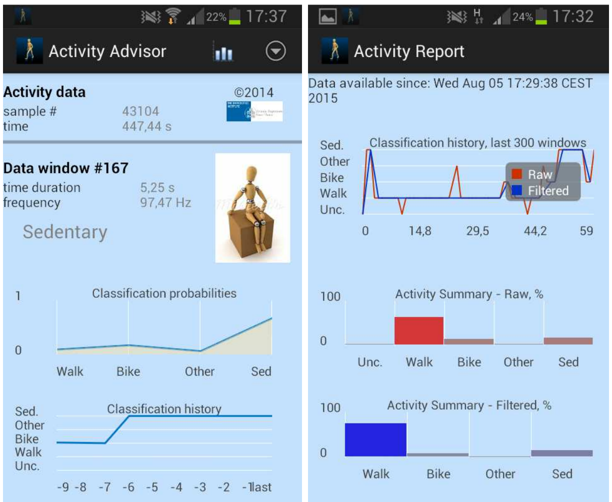

Figure 3. The Activity Advisor app for activity recognition using a smartphone.

Table 1. Confusion matrix for activity recognition

		Classified as			
		Ambulation (A)	**Cycling (C)**	**Other (O)**	**Sedentary (S)**
Actual label	**A**	**6615** (97.2%)	62 (0.9%)	51 (0.7%)	76 (1.1%)
	C	33 (1%)	**3167** (95.9%)	53 (1.6%)	48 (1.5%)
	O	24 (1%)	36 (1.4%)	**2002** (80.1%)	438 (17.5%)
	S	5 (0.1%)	41 (0.5%)	230 (3%)	**7506** (96.5%)

Table 2. Gait stability indexes

	ID	**Stride time**	**Stride time variab.**	**Vertical acc., RMS**	**HR ML**	**HR VT**	**HR AP**
C	1	1.05	1.04	2.77	1.84	2.38	2.95
	2	1.07	0.92	3.41	1.80	2.02	2.10
	3	1.22	2.13	1.58	2.01	2.29	2.26
	4	1.15	0.97	1.59	2.18	1.85	2.83
	5	1.11	2.52	2.10	1.72	2.89	3.35
	6	0.95	1.70	2.99	3.31	3.20	3.21
	7	1.08	0.82	2.51	1.69	1.95	1.48
	8	1.03	1.47	2.00	1.30	2.10	1.94
	9	0.93	1.91	3.07	3.03	3.54	2.71
	10	1.08	1.58	1.64	1.94	2.08	2.57
	11	0.96	2.58	2.14	1.63	3.08	3.32
	avg	**1.06**	**1.60**	**2.35**	**2.04**	**2.49**	**2.61**
P	*12*	*1.02*	*7.37*	*2.34*	*1.69*	*1.69*	*1.91*

4.2 Gait stability indexes

Results for gait assessment using shank and waist-mounted sensors are summarized in Table 2. It is worth noting that the values reported for the controls match closely normative values reported in the literature. It does not come as a surprise that the person known to be at risk of fall according to clinical screening (Tinetti scale score: 20 out of a maximum 28) exhibits a higher stride time variability and lower values of HR, which reflects a less regular and stable gait, according to the interpretation given to these parameters in the literature [43].

5. CONCLUSIONS

A body sensor network including a smartphone and three wireless sensing nodes has been proposed for the estimation of fall risk in the elderly with a multi-factorial approach. The proposed strategy involves the physical activity level estimation through activity recognition and gait stability assessment through gait spatio-temporal parameters estimation and signal harmonic ratios evaluation.

Concerning the activity recognition problem, we obtained a high accuracy online activity recognizer using a smartphone. This allowed raising a warning to the user if her/his activity does not fit the expected behavior during its use. The activity recognition output can be used in isolation from the rest of the processing or eventually, activity recognition output can drive other estimation such as the one proposed about gait stability assessment.

Concerning the fall risk assessment using measures of gait variability and symmetry, we are in the position to combine robust estimation of gait temporal parameters (even in conditions of pathologic gait), with a stride-based computational scheme that lead to estimate HRs with good precision.

In this work only few of the possible application of the proposed sensing network were reported. Many other applications such as gait spatial parameters analysis, pedestrian navigation, sleep monitoring, fall detection and so forth can be included, but their description is out of the scope of this paper.

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