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Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes

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Abstract

A clinical tool and an associated test that can assess fall-risk in elderly patients have been designed. The clinical tool was based on a wearable device with accelerometers and rate gyroscopes to identify trunk kinematic parameters. The test was based on a posturography protocol with different constraints and statistical analysis of the kinematic parameters. Statistical clustering based on the Mahalanobis distance was carried out using three groups of 30 subjects (1, age <65 years; 2, age \geq 65 years and 3, age \geq 65 years and a fall history). The method was statistically validated using three groups of 100 subjects. The test allowed discrimination of elderly subjects with a high fall-risk with high specificity \geq 0.930 and sensitivity \geq 0.939.

Keywords: patient-monitoring, accelerometer, gyroscopes, simulation, 3D rigid body position and orientation, human movement analysis, accuracy, fall-risk, fall prevention

1. Introduction

Postural stability is affected by complex internal neural and muscular models (Massion 1994, Morasso *et al* 1999). Temporary disabilities, such as particular bone fractures, or permanent disabilities, such as Parkinson's disease and Alzheimer's disease, and damage to the vestibular system seriously affect the control of these internal neural and muscular models, and thus the postural stability, increasing fall risk (FR), which is a major cause of morbidity. Current FR research is focused on both preventional aspects and analysis of the fall event itself. In both cases the core problem is the definition of suitable parameters for investigating postural stability. The literature reports that kinematic sensors (KSs) such as accelerometers (ACCs) used singly (Mathie *et al* 2003) or arranged in assemblies (Morris 1973, Padgaonkar and King 1975) are useful for analysis of human motion. In particular, Moe-Nilssen showed that

under various task and environmental constraints, ACCs could furnish important parameters correlated to posture stability, free of drift and with absolute test and retest reliability (Moe-Nilssen 1999). Mathie *et al* showed that the oscillation frequency and amplitude of ACCs signals were correlated to postural imbalance (Mathie *et al* 2004). ACCs are also currently used, arranged on the trunk and upper-leg level, for a wide range of investigations (gait, sitting, standing, falling) involving long-term patient monitoring during daily activity, as reported by Lyons *et al* (2005), Veltink *et al* (1993) and Veltink and Bussmann (1996). Other kinematic sensors such as rate gyroscopes (R-GYs) can also be useful. These need a careful design consideration for drift compensation, but are insensitive to gravity error and are currently successfully used in integrated KS assemblies (Giansanti *et al* 2003, 2005, Giansanti and Maccioni 2005).

1.1. Problem definition

Mathie *et al* (2004) showed that very few authors have used ACCs to specifically investigate falls, in particular for fall detection and analysis. The basic investigative approach was defined by Williams *et al* (1998) and Doughty *et al* (2000), who classified the sequence of states of the kinematic variables indicating a fall event. Successive studies have focused on algorithm improvement for fall detection using ACCs (Salleh *et al* 2000, Mathie *et al* 2001) or, more recently, R-GYs, as by Nyan *et al* (2006).

1.2. Aim of the paper

The goal of this paper was first to focus on fall prevention using KSs, which has not been investigated to any great degree, and second to design a clinical tool (based on a simple wearable device (WD) for furnishing trunk kinematic parameters (Giansanti *et al* 2005, Chiari *et al* 2005)) with an associated test (based on a posturography protocol with different constraints and statistical analysis) that can assess FR in the elderly.

2. Materials and methods

The methodology was based on a WD for the assessment of kinematic variables related to the biomechanical energy using a posturography protocol with different constraints performed on different subjects and statistical analysis to identify the test power.

2.1. Instrumentation

A full description of the simulation of the WD can be found in Giansanti and Maccioni (2005). A full description of the design and construction, used algorithms and validation of this device can be found in Giansanti *et al* (2005), Giansanti and Maccioni (2006). For the sake of clarity, we report in the following a brief description of the main characteristics of the WD.

2.1.1. The wearable device: sensor assembly. The WD features three mono-axial ACCs (3031-Euro Sensors, US) and three R-GYs (Gyrostar ENC-03J-Murata, Japan) assembled together and oriented according to an orthogonal reference system. To achieve this, each of the three sensor types is first orthogonally arranged and split on two separate boards. The two boards are housed in a case for complete 3D assembly. A precise Mantis Visor (Vision Engineering, USA) was used for the montage. All the used components were based on the surface montage technology (SMT) to minimize the area occupancy. Figure 1(A) shows the



Figure 1. (A) The positioning of the sensors: accelerometers (ACCs) and rate-gyroscopes (R-GYs) are positioned in two different boards. (B) The signal processing: accelerometers (ACCs) and rate-gyroscopes (R-GYs) are low-pass filtered, amplified and calibrated. C_a and C_{ω} are the calibration matrices.

(This figure is in colour only in the electronic version)

two boards with the sensors before the affixation of the SMT components and before closing the case.

2.1.2. The wearable device: signal conditioning and calibration. Sensors furnish acceleration and angular velocity signals, which are low-pass-filtered (smoothed) by means of six Sallen and Key cells, then amplified and calibrated. Signal processing and calibration parameters have been optimized for posturography using the simulation environment described in Giansanti and Maccioni (2005) and the optoelectronic acquisitions described in the following as inputs. The first two optimized parameters were the cut-off frequency of the filters which was set to 11.5 Hz and the amplification gain set to G = 10. The second optimized parameters were the range and the step of increment of the angular velocities imposed for calibrating the R-GYs by means of a step-wise equipment based on the Galil motor (Galil, USA) (Giansanti *et al* 2005); the angular velocity rotation ranged from $\omega_m = 0.1^\circ \text{ s}^{-1}$ to $\omega_M = 5^\circ \text{ s}^{-1}$ incremented in steps of $\Delta \omega = 0.1^\circ \text{ s}^{-1}$. The ACCs were calibrated using static procedures as in the previously cited papers. Figure 1(B) shows the final signal processing, C_a and C_{ω} are the calibration matrices.

2.1.3. The wearable device: data recording. The sample rate was fixed to 1000 samples s^{-1} . An 8 bit differential quantization of each sample was performed. Data were stored in a dedicated recording-unit to a 4 GB compact flash type II memory card (Itachy, Japan) after an electric trigger generated by the physician (Giansanti and Maccioni 2006) during the clinical application. The recording unit, which weights 150 g, may be held by the physician, who triggers the data acquisition. 2.1.4. The wearable device: fixation on the subjects. The WD (case included) is very small $(4 \times 5 \times 2 \text{ cm}^3)$ and weighs 100 g, light enough for clinical posturography applications. The WD was designed to be placed inside a rigid pocket and firmly affixed by means of a belt on the subject's back at level L5, taking the subject's navel as a reference. L5 was chosen because this position is very close to the centre of mass. We have already used this set-up successfully for a wide range of locomotory tasks (Giansanti *et al* 2005, Giansanti and Maccioni 2005), for the sit-to-stand monitoring (Giansanti and Maccioni 2006) and during a very complex biofeedback application that required high precision and accuracy in posturography (Chiari *et al* 2005).

2.1.5. The wearable device: reference systems. We used a representation based on nautical angles (pitch, roll, yaw) for the mobile reference system centred on the WD. This representation is useful for the objective of the paper. For the principal reference, y is aligned like the antero-posterior (AP) direction, considering positive the forward inclination, z is aligned like the opposite direction of the **g** vector, x is aligned like the medio lateral (ML) direction, considering positive the right lateral oscillation. The origins of the two references are, before the motion, centred on the WD. With this alignment, y-z is the sagittal plane, θ is the pith inclination in the sagittal plane with the x-axis. The roll ϕ is the angular rotation with the y-axis.

2.1.6. The wearable device: parameters furnished for the clinical analysis. The WD has the potentiality to furnish in real time the components of the acceleration and angular velocity (see again figure 1(B)). Equation (1) (Giansanti *et al* 2005) also permits in real time the determination of the components of nautical angles (pitch, roll, yaw), starting from the angular velocity components. These are the variables useful in posturography; however the WD, by means of dedicated post-processing procedures could also furnish a full 3D reconstruction of the trajectories (Giansanti *et al* 2005). For this specific application the ACCs were used in real time as an inclinometer to vertically fix the initial orientation of the subjects involved in the clinical application; and the components of the angular velocity from the R-Gys were used to obtain parameters related to the kinematic rotational energy to investigate the energetic biomechanical modifications of the subjects by changing posturography tasks.

$$\frac{\mathrm{d}\mathbf{R}}{\mathrm{d}t} = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix} \cdot \mathbf{R} \quad \text{(pitch, roll, yaw)}. \tag{1}$$

2.2. Test: protocol, energetic analysis and statistics

2.2.1. Protocol. The standing sway of subjects was recorded during 60 s trials under three different conditions: eyes open on a solid surface (EO); eyes open on a foam cushion surface (EOF); and eyes closed on a foam cushion surface (ECF), with ten trials performed for each condition. The foam had the following characteristics: indentation force deflection at 25%: 114 N, tensile strength: 124 kN m^{-2} , elongation: 108%, when temperature is 72 F and relative humidity is 50%, thickness 9.5 cm. These tasks have a large use in posturography and are investigated according to the one-segment inverse pendulum model (Chiari *et al* 2005). The order of the trials was randomized. The WD was designed to be placed on each volunteer's back at position L5. This protocol was performed for two configurations.

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Table 1. Subject inclusion in the statistic clustered space training and testing (validation).				
	Training configuration		Testing configuration	
Group	Age (years)	Height (cm)	Age (years)	Height (cm)
G1 (age <65)	23-64	151–187	23-63	151-185
Tinetti level 1	Mean 43	Mean 168	Mean 45	Mean 169
G2 (age ≥65)	65-84	150-185	65-83	152-183
Tinetti level 1	Mean 72	Mean 166	Mean 75	Mean 167
G3 (age ≥65, falls)	65-81	153-184	65-82	151-183
Tinetti level 3	Mean 73	Mean 168	Mean 73	Mean 169

Table 1. Subject inclusion in the statistic clustered space training and testing (validation).

The first configuration (training configuration) permitted the design and construction of a statistical cluster space, while the second was used to validate (validation configuration) the statistical cluster space and then assess the test power.

2.2.2. Training configuration. Three groups of subjects were recruited (50% males and 50% females): (1) 30 healthy subjects at level 1 of the Tinetti balance assessment test (Kandel *et al* 2000) and age ≤ 65 years; (2) 30 subjects at the same level of the Tinetti test, but age ≥ 65 years; and (3) 30 subjects with pronounced imbalance problems, at level 3 of the Tinetti test, but who could rise from a chair without using their arms and age ≥ 65 (table 1).

2.2.3. Validation configuration. For validation, 100 subjects were recruited for each of three groups chosen using the criteria shown in table 1.

2.2.4. Energetic analysis. We are interested in investigating the energetic biomechanical changes in trunk posture by varying the task (EO, EOF, ECF). The three R-GYs signal ones properly conditioned and calibrated allow the estimation of the squared angular velocity module, $|\omega|^2 = \omega_x^2 + \omega_y^2 + \omega_z^2$. The rotational kinematic energy (RKE) of the trunk is proportional to $|\omega|^2$, RKE = $1/2I|\omega|^2$, where *I* is the inertia momentum.

The mean value of the squared modulus of the angular velocity was assessed over the full time interval according to equation (2) under the three different tasks:

$$\left|\overline{\omega_{\text{task}}}\right|^2 = \text{mean}\left|\omega_{\text{task}}(t)^2\right|_T \tag{2}$$

where T = 60 s and task = EO, EOF, ECF.

The values were used to determine the following two parameters (see figure 2):

$$R_{\rm (EOF/EO)} = |\overline{\omega_{\rm EOF}}|^2 / |\overline{\omega_{\rm EO}}|^2 \tag{3}$$

$$R_{\rm (ECF/EO)} = |\overline{\omega_{\rm ECF}}|^2 / |\overline{\omega_{\rm EO}}|^2. \tag{4}$$

Equation (2) is related to the ratio between RKE assessed during the EOF and EO tasks; this value measures the increment of the RKE between the EOF condition and the EO condition. Equation (3) is related to the ratio between kinematic energy as assessed during the ECF and EO tasks; this value measures the increment of the RKE between the ECF condition and the EO condition. Both the two parameters are independent of the inertia momentum which is eliminated by means of the ratio operator.

2.2.5. *Statistics*. The sample number of 30 subjects assured a normal distribution for these above-listed parameters as tested by means of the Smirnow and Kolmogorov method. The



Figure 2. Post-processing of the angular velocity values: the mean value of the squared modulus of the angular velocity was assessed over the full time interval of 60 s under three different tasks, eyes open (EO), eyes open on foam (EOF) and eyes closed on foam (ECF). The ratio between the EOF and EO tasks and the ratio between the ECF and EO tasks are finally furnished. These parameters are used for the energetic investigation.

standard ANOVA-repeated measures method was also used to assess the confidence. We fixed the sample number of subjects to N = 30. The statistical significance with N = 30 was equal to 0.1%; the addition of a subject to the sample did not increase the significance.

2.3. Statistical clustering

We used data from the training configuration to design a statistical clustered space. On the basis of minimum-distance discrimination analysis, we generated an algorithm that classified each data pattern into three classes corresponding to each group (G1, G2, G3) in a multidimensional space defined by the two proposed parameters. Within this space, each class is represented by a point (centroid), the coordinates of which are the means of the parameters for the training data set. The Mahalonobis distance was used to account for the correlation among the parameters and the variance within each class (Cohen 1986). In this metric the distance is weighted by the parameter covariance matrix. The Mahalonobis distance d(i, j) is defined as:

$$d(i, j) = (1/H) \times (\mathbf{X}_i - X_j)^T \times \mathbf{W}_j^{-1} \times (\mathbf{X}_i - X_j)$$
⁽⁵⁾

where *H* is the number of parameters; the *H*-dimensional column vector \mathbf{X}_i represents the feature vector of the pattern to be classified; X_j is the centroid of class *j* and \mathbf{W}_1^{-1} is the inverse of the covariance matrix of the parameters for class *j*.

3. Validation

3.1. Instrumentation validation

3.1.1. WD bench test validation. The wearable device was bench tested statically for the ACC channels and dynamically for the R-GY channels using a Galil step-wise motor (Giansanti

Table 2. Difference in percentage error between the parameters assessed by the two methods.

Item	Parameter	Mean value (%)	Maximal value (%)	Standard deviation (%)
1	$R_{(\rm EOF/EO)}$	0.35	0.43	0.03
2	$R_{(\rm ECF/EO)}$	0.43	0.49	0.04

Table 3. Mean and maximum values and standard deviation for the parameters $R_{(EOF/EO)}$ and $R_{(ECF/EO)}$ as assessed for elderly subjects (G3) and the two control groups (G1, G2).

Item	Group	Parameter	Mean value ratio	Maximal value ratio	Standard deviation
1	G1	$R_{(\rm EOF/EO)}$	1.08	1.16	0.05
2	G2	$R_{(\rm EOF/EO)}$	1.13	1.25	0.06
3	G3	$R_{(\rm EOF/EO)}$	1.19	1.34	0.12
4	G1	$R_{(\rm ECF/EO)}$	1.17	1.28	0.07
5	G2	$R_{(\rm ECF/EO)}$	1.22	1.34	0.08
6	G3	$R_{(\rm ECF/EO)}$	1.29	1.49	0.14

et al 2005) by imposing 60 s sinusoidal angular functions at a maximum frequency $F_{\text{max}} = 5$ Hz and at maximum angular amplitude equal to $|\theta_{\text{max}}| = 5^{\circ}$ (much higher than preliminary values obtained using optoelectronic Vicon acquisition (Giansanti *et al* 2005)).

The maximum angular velocity error was less than $0.01^\circ~s^{-1}$ and the maximal angular error was less than $0.15^\circ.$

3.1.2. Optoelectronic validation. For comparison we used a Vicon system (www.vicon.com) with a field of view of and a sampling rate of 1000 Hz. Three markers were fixed on the WD at three non-collinear points to allow for reconstruction of its positioning and orientation (P&O) (Cappozzo *et al* 1997).

3.1.3. Vicon precision. The precision of the Vicon equipment was previously tested for movement in the posturography range (Moe-Nilssen 1999, Moe-Nilssen 1998); the WD with markers was fixed on the extreme point of a pole (length 1 m), which was attached to the rotative joint of a Galil stepwise motor (Giansanti *et al* 2005). The pole was rotated 5° at 1 Hz; the error of the Vicon system after 60 s was negligible ($<4 \times 10^{-4}$ m and $<9 \times 10^{-3}$ °).

3.1.4. Outcome. We compared the parameters $R_{(EOF/EO)}$ and $R_{(ECF/EO)}$ obtained using the two different systems during the clinical tests. We found it useful to express the difference as a percentage error. Table 2 shows the comparison results presented as percentage errors. In particular, the difference in maximum error for these parameters was never higher than 0.5%. This error tolerance did not affect the statistical analysis.

3.2. Clinical validation

3.2.1. Training configuration. Table 3 shows the outcome represented by numerical ratios. For each of the three groups the parameter $R_{(ECF/EO)}$ was higher than $R_{(EOF/EO)}$. The parameters showed the best value (ratio close to 1) for younger subjects (control group G1) and the worst value for elderly subjects with a fall history (group G3).

 Table 4. Performance of the classification algorithm in discriminating subjects with fall-risk from subjects with the two different control groups.

Discrimination	Specificity range (01)	Sensitivity range (01)	TCCR range $(0 \dots 1)$
G3 and G1	0.940	0.949	0.945
G3 and G2	0.930	0.939	0.935

3.2.2. Validation configuration. For classification of each data pattern, Mahalanobis distances from the three centroids were calculated. The pattern was then classified into the closest class, that is, corresponding to the smallest Mahalanobis distance. Table 4 shows the outcome of the classification algorithm. We considered the event 'subject with FR' as the positive objective of the classification. We considered each control group (G1 and G2) separately in comparison with G3 to obtain information about the test power and to pose the unresolved question as to whether the propensity for falling is a function of age. The procedure investigated the sensitivity (ratio between true positives and positives), the specificity (ratio between true negatives and negatives) and the TCCR (ratio between the patterns correctly classified and the total patterns) (see table 4). Each one of the quantities can variate in a pure numerical range between $(0 \dots 1)$; the more these quantities are near to 1 the more the goodness of the test is high. In the two cases, the procedure showed high sensitivity, high specificity and a high TCCR. Moreover, the test power did not show a significant difference when using the two different control groups with subjects of different ages.

4. Discussion and conclusions

In this paper we presented a novel methodology for FR prevention based on a clinical tool with an associated test. The clinical tool was based on a WD with ACCs and R-GYs suitably conditioned and calibrated for the application. The test was based on a posturography protocol designed with different constraints (EO, EOF, ECF), two specific parameters ($R_{(EOF/EO)}$) and $R_{(ECF/EO)}$) related to the kinematic rotational energy (Giansanti *et al* 2006) and a statistical environment. Two control groups of 30 subjects different in age (G1 age <65; G2 age ≥ 65 years) and a group of 30 elderly subjects (age ≥ 65 years) with a fall history were used to construct a statistical clustered environment based on the Mahalanobis distance. This clustered space was also validated with three different groups of 100 subjects chosen using the same criteria as for the test groups. The test showed high sensitivity (percentage ratio between true positives and positives), high specificity (percentage ratio between true negatives and negatives) and high TCCR (total number of patterns correctly classified as a percentage of the total patterns presented). Furthermore, validation did not show a sensible decrease in test performance in discriminating healthy from pathologic subjects aged ≥ 65 years.

4.1. Perspectives of the clinical tool

We have planned a full medical investigation focusing on different subject categories presenting FR, such as with Parkinson's or Alzheimer's disease or with an injury. We will use also artificial intelligence such as neural networks, to furnish medical knowledge of these pathologies using the parameters defined in this study. The WD also shows the potentiality to be used in real time for closed loop applications, such as the biofeedback applications in posturography (Chiari *et al* 2005). In fact, all the variables furnished in real time, such as the nautical angles, the acceleration and angular velocity can be processed by means of a sound based

or vibrotactile based coding and given back to subjects with unbalance problems (caused by the vestibolar loss or by the ageing) to improve the stability (Chiari *et al* 2005, Dozza *et al* 2005, Speers *et al* 2002). The optimal choice of such parameters and restitution methodology is today one of the core problems in prosturography. The WD could be then an useful tool for the biofeedback real-time applications; furthermore, the energetic analysis by means of equations (2), (3) could be useful for investigating the improvement of the posture stability by changing the biofeedback methodology (Giansanti *et al* 2006).

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