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Dimensionality Reduction for the Quantitative Evaluation of a Smartphone-based Timed Up and Go Test

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Abstract—**The Timed Up and Go is a clinical test to assess mobility in the elderly and in Parkinson's disease. Lately instrumented versions of the test are being considered, where inertial sensors assess motion. To improve the pervasiveness, ease of use, and cost, we consider a smartphone's accelerometer as the measurement system. Several parameters (usually highly correlated) can be computed from the signals recorded during the test. To avoid redundancy and obtain the features that are most sensitive to the locomotor performance, a dimensionality reduction was performed through principal component analysis (PCA). Forty-nine healthy subjects of different ages were tested. PCA was performed to extract new features (principal components) which are not redundant combinations of the original parameters and account for most of the data variability. They can be useful for exploratory analysis and outlier detection. Then, a reduced set of the original parameters was selected through correlation analysis with the principal components. This set could be recommended for studies based on healthy adults. The proposed procedure could be used as a first-level feature selection in classification studies (i.e. healthy-Parkinson's disease, fallers-non fallers) and could allow, in the future, a complete system for movement analysis to be incorporated in a smartphone.**

I. Introduction

THE Timed Up and Go (TUG) is one of the most used clinical tests to assess balance, mobility, and fall risk in the elderly [1] and in pathologies such as Parkinson's disease [2], [3]. In this test the subject is asked to stand up from a chair, walk, turn, walk back, and sit down again. The traditional measured outcome of this test is its duration. Lately instrumented versions of the test are being considered [2], [3] where inertial sensors are used to quantitatively assess the characteristics of motion. Nowadays smartphones embed a large suite of sensors, including accelerometers. For this reason we evaluate the use of a smartphone's accelerometer as the measurement system for an instrumented Timed Up and Go (iTUG). This could favor a better pervasiveness, by keeping competitive the ease of use and the cost of the test. Moreover, as a future development, one could envision that a complete solution for quantitative TUG analysis, together with other instrumented motor tasks, could be incorporated in the smartphone as an app.

A very high number of parameters can be computed from the iTUG signals [2], [3]. Many of these parameters are highly correlated with each other (i.e. they represent similar locomotor aspects) [4]. In redundant datasets, it is desirable to have a reduced set of features which represent only useful information. Reducing the number of features can aid in the interpretation of the results. For classification purposes (e.g. fallers-non fallers; healthy-Parkinson's disease patients) it is also desirable to have a small subset of parameters (feature selection) to avoid the so-called "curse of dimensionality": the difficulty for classifiers to learn effective models when the number of features is high and the number of samples is limited. High dimensionality may lead to the overfitting of the classification algorithm in the considered dataset. The aim of this study is to identify the subset of parameters that are most sensitive to the locomotor performance of healthy adults, avoiding redundancy. The principal component analysis (PCA) [5] is used to extract a reduced set of non-redundant features (principal components, PCs) which are linear combinations of the original parameters. These new features can be useful for the purpose of exploratory analysis and outlier detection (which will be discussed later on). Then, from these PCs, a reduced set of the original parameters is obtained through correlation analysis.

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II. Methods

A. Subjects

In total 49 healthy adult subjects of different ages (range: 28-87; average: 58.9±16.5), were recruited by their general practitioner. All subjects gave written informed consent prior to participation. The tests were done in a clinical setting (the doctor's office) with the supervision of the general practitioner, who excluded subjects with motor impairments from the study. The age distribution of the subjects was: 8 subjects ≤ 40 years; 8 subjects in the range 40-50 years; 11 subjects in the range 50-60 years; 7 subjects in the range 60-70 years; 11 subjects in the range 70-80 years; 4 subjects ≥ 80 years.

B. Test

As seen in Fig. 1, the iTUG test consists of standing up from a chair (Sit-to-Stand section), walking 7m at preferred speed, turning around, walking back to the chair and sitting down again (Stand-to-Sit section). The Gait section starts after the Sit-to-Stand and ends before the Stand-to-Sit. The iTUG is a modified version of the traditional TUG with a longer distance to walk (7m instead of 3m), which was proposed by [2] to provide enough steps for gait analysis.

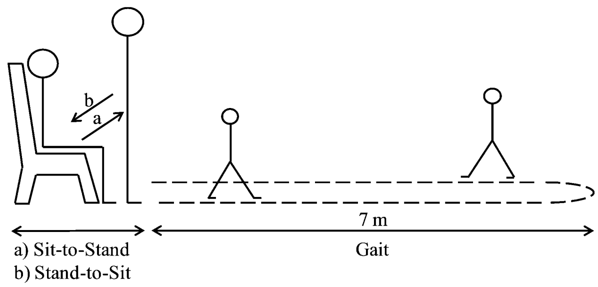

Fig. 1. Schematic representation of the instrumented Timed Up and Go test: the subject stands up from a chair, walks for 7m, turns around, walks back, and sits down again.

C. Measurement System

To instrument the iTUG we used the accelerometer embedded in the HTC Desire smartphone (Operative system: Android 2.1). It is the BMA150 tri-axial accelerometer, which has a range of ± 2*g*, a sample frequency of 50 Hz, and a sensitivity of 4 m*g*. The smartphone was worn by the subjects on the lower back by means of an elastic belt. The position was chosen according to recent studies which found the trunk position to provide reliable accelerometer signals in standing and gait tests [6], [7]. Custom software was developed to manage the sensor inside the smartphone: Android Software Development Kit was used for this purpose.

D. Parameter Computation

The accelerations along the two orthogonal axes of the accelerometer were considered: the first aligned with the direction of gait progression and coincident with the biomechanical antero-posterior (AP) axis of the body; the second coincident with the medio-lateral (ML) axis of the body.

Three different sections of the iTUG (Sit-to-Stand, Gait, Stand-to-Sit) were segmented from the whole recording as in [3]. In Fig. 2 there is a representative example of the raw AP acceleration of a representative subject, with the resulting segmentation. Twenty-eight parameters were computed from the acceleration signals in the different sections of the iTUG (Sit-to-Stand, Gait, Stand-to-Sit).

Three temporal parameters were computed by considering the total duration of the test, the duration of the Sit-to-Stand and of the Gait sections.

In the Sit-to-Stand section the root mean square value (RMS) and Jerk score of the accelerations were computed along AP and ML directions. The preparatory phase of Sit-To-Stand was also considered by computing the RMS and Jerk score values of the AP signals before the start of the standing.

In the Gait section, step duration was computed by identifying heel strikes, as in [8]; step duration was computed for each step but for the following analysis only the mean, the standard deviation (STD) and the coefficient of variation (CV) of the step duration across all the steps were considered. We defined a gait cycle as the time between one heel strike and the consecutive heel strike of the same leg; the interval between the start of a gait cycle and the time when the other leg's heel strike occurs, normalized to the gait cycle duration, is defined as the phase [4]. Six parameters were considered related to the gait phase: mean, STD, CV across steps, absolute phase, STD of the absolute phase and phase coordination index (PCI). All of these are reported in [4]. Among them, PCI measures the gait symmetry. Normalized Jerk score (NJS) was computed as an index of movement smoothness for each step [9], both in the AP, ML and planar direction. Mean, STD, and CV across all the steps were considered for the analysis.

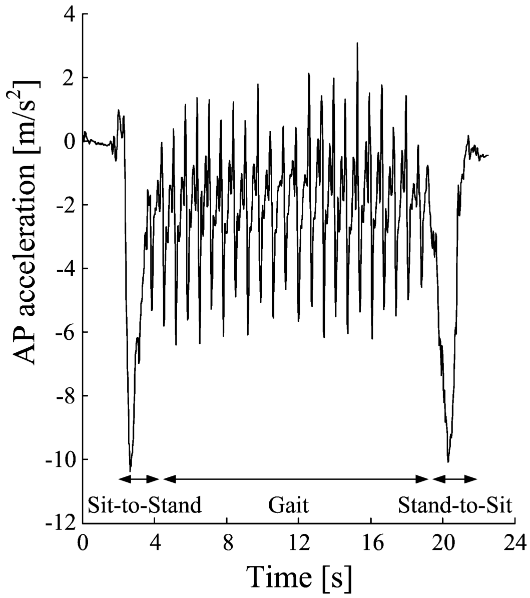

Fig 2. Raw AP acceleration and resulting segmentation of a representative subject of the study, who is 37 years old.

In the Stand-to-Sit section the maximum AP acceleration was considered.

In total 28 parameters were computed from the signals.

E. Principal Component Analysis

The PCA procedure was applied to the computed parameters. The correlation matrix (instead of the covariance matrix) was used to estimate the PCs, because the parameters were very different in scales and variance [5]. To determine the number of PCs that should be kept for further analysis, we chose to retain just enough PCs to account for a determined percentage of the data variation [5]. In the present study, we chose the number of PCs that accounted for at least 90% of the total variance. The number m of PCs considered defines the dimension of the reduced dataset. The first m PCs define a new co-ordinate system, and each subject is identified by new co-ordinates in this m-dimension.

After the PCA was completed, a Pearson's correlation

TABLE I
ORIGINAL PARAMETERS WHICH ARE HIGHLY CORRELATED WITH THE FIRST TEN PRINCIPAL COMPONENTS

Parameter	Section	PCs they correlate with
Duration	Sit-to-Stand	1
RMS AP	Sit-to-Stand	4
Jerk AP	Sit-to-Stand	2
Jerk ML	Sit-to-Stand	2, 4
preparatory RMS AP	Sit-to-Stand	5, 6
mean step duration	Gait	2
STD of step duration	Gait	1
PCI	Gait	1
mean phase	Gait	3
mean NJS AP	Gait	8
CV of NJS ML	Gait	5
Maximum value of acceleration	Stand-to-Sit	7

analysis was performed to identify the original parameters that are most descriptive of each PC. We chose the correlation analysis among several possible criteria, which associates with each of the *m* PCs, the original parameters that correlates most with the PC itself, as in [10]. This procedure aimed at making the *m* PCs more interpretable (by understanding which are the parameters that most determine each PC), and at selecting a reduced set of the original parameters which can describe most of the variability of the motion data with low redundancy.

Matlab R2009b was used for the principal component analysis and for the correlation analysis.

III. RESULTS

Ten PCs are enough to account for more than 90% of the variance of the original data. The first PC (PC1), which accounts for the 33% of the variance, is characterized mostly by the STD of step duration: its correlation with PC1 is very high (R=0.93). Also all the phase-related parameters are highly ($0.4<|R|<0.9$) correlated with PC1 (mean phase, STD and CV of the phase, absolute phase, STD of the absolute phase and PCI). Since these parameters are also highly correlated with each other, we will consider only PCI among them because it is the one which shows the highest correlation (R=0.88) with PC1. This is done to avoid unnecessary redundancy. Duration of the Sit-to-Stand is also highly correlated with PC1 (R=0.58). Therefore PC1 simultaneously represents the variability and symmetry of the steps and the duration of the Sit-to-Stand. Based on the signs of the correlations, subjects with high values of this PC tend to have steps that are different from each other, low gait symmetry, and a long time to perform the Sit-to-Stand.

The second PC (PC2) is characterized by parameters from all the sections: the mean step duration (R=0.75) during Gait; AP and ML Jerk scores (R=-0.59 and R=-0.57, respectively) during Sit-to-Stand; the maximum AP acceleration (R=-0.4) during Stand-to-Sit. PC2 represents global characteristics of motion: subjects with high values of this PC tend to have slow steps, smooth movements (with low variability) during Sit-to-Stand and a slower sitting process. These first two PCs account for almost the 50% of the variance of the original parameters (47.3%).

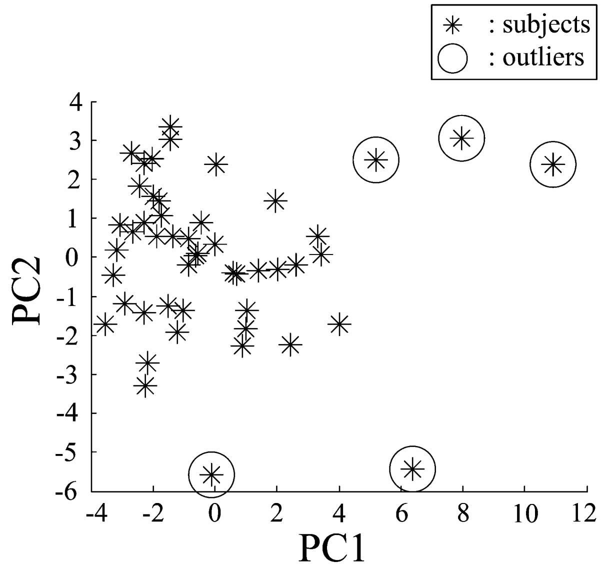

Fig. 3. 2-d Plot of the first two PCs. Each sample is a subject. Outlier subjects are highlighted with a circle.

Repeating this correlation analysis for the remaining eight PCs leads to a reduced set of twelve original parameters which are highly correlated with at least one PC. These parameters are: Duration, RMS AP, Jerk AP, Jerk ML, and preparatory RMS AP for the Sit-to-Stand section; mean and STD of step duration, PCI, mean phase, mean NJS AP and CV of NJS ML for the Gait section; maximum value of AP acceleration for the Stand-to-Sit section. They are reported in Table I.

IV. DISCUSSION

First, a set of ten principal components (linear combinations of the 28 original parameters) were extracted, which can explain most of the variability of the original data. Second, in order to obtain a result appropriate for clinical purposes (i.e. without introducing new and possibly misleading variables), a reduced set of twelve original parameters was selected through correlation analysis with the principal components.

These two results could be useful for two different kinds of applications.

The reduced-dimensional system of the principal components could be used for explorative analysis and outlier detection. In Fig. 3 we plot the subjects' samples along the first two PCs. Since each PC embeds different characteristics (different parameters), we can have a summary view of more than one property in only one dimension. This can be useful for clustering subjects with the same behavior and to detect outlier subjects, which have a locomotor performance very different from the average. A possible application of outlier detection could be fall risk assessment. Just as an example, in Fig. 3 it can be seen that there are 5 subjects that have the typical characteristics of outliers (extreme values, far from average); in a possible fall risk application those subjects would be considered with a motor pattern far from normal and therefore at a higher risk of falling. Obviously, because of the small sample considered, the absence of motor impairments in the considered subjects, and the almost uniform distribution of age in our data set, we cannot conclude that the subjects highlighted in the plot have a motor pattern which is significantly different from the normal one. However, it has to be noted that, even if principal component analysis was not made to discriminate between different ages, these "outliers" all belong to elderly subjects (≥ 65 years old), who are the most probable to show extreme values in motor patterns (because of effects of aging in the motor function).

The second result is a reduced set of original parameters that could be used as a first step for feature selection aimed at the classification between two different populations of subjects (e.g., healthy and Parkinson's disease, fallers and non-fallers). It is worth mentioning that in the case of considering different populations, the same selection procedure based on PCA could result in a different reduced subset. Future work will allow us to define a minimum set of parameters that would be recommended for specific populations.

In a classification perspective, after this PCA-based feature selection, different parameter combinations from the reduced set can be tried and compared based on their classification performance. This can be useful both to speed up the whole classification procedure (exhaustive search of the best combination of parameters can be computationally unfeasible) and to avoid overfitting (a "more variables than samples" situation).

The lack of comparison with a gold standard is a limit of the present study, which can be overcome by future experiments.

V. Conclusion

Nowadays smartphones embed a large set of sensors which enable a wide variety of sensing possibilities. In this study a smartphone was used to instrument a well-known clinical test. Dimensionality reduction was performed to reduce the computational time and resources needed for parameter computation, to simplify exploratory analysis, to have a first-level feature selection that could be used in future classification studies. These results will help in the perspective of incorporating a complete solution for quantitative movement analysis directly in the smartphone.

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