A Statistical Analysis for the Evaluation of the Use of Wearable and Wireless Sensors for Fall Risk Reduction

Giovanna Sannino, Ivanoe De Falco and Giuseppe De Pietro
Institute on High-Performance Computing and Networking (ICAR), National Research Council of Italy (CNR), Naples, Italy

Keywords: Falling Risk, Physical Activity, Body Mass Index, Statistical Analysis, Correlation, Wearable Sensors, Mobile Devices.

Abstract: The aim of this study is to investigate the correlation between, on the one hand, personal and life-style indicators and, on the other hand, the risk of falling. As indicators we consider here for each subject age, body mass index, and information about physical activity habits, while a subject's risk of falling is estimated by the Mini-BES test score. Three different groups of subjects are taken into account, namely healthy, suffering from metabolic diseases and suffering from cardiovascular diseases. Firstly, we aim at finding explicit linear correlations for any pair of parameters. Secondly, we wish to pay attention to whether or not these correlations change as the health state of the subjects does. The final goal is to move the first steps towards the design of a system composed by wearable sensors, a mobile device, and an app that would be able to help people in improving their life-style so as to decrease their falling risk.

1 INTRODUCTION

Falls have been shown to result in increased morbidity and are considered the cause of the yearly loss of more than 17 million years worldwide that are spent in disability (World Health Organization . Ageing and Life Course Unit, 2008). Many studies have been dedicated to fall detection, as e.g. (Sannino et al., 2015). Identifying individuals with a high fall risk is often a significant part of prevention programs. The assessment of the risk of falling is a major and effective prevention tool that allows identifying intrinsic and extrinsic risk factors. These latter help determine the most suitable interventions, thus reducing, or in some cases even eliminating, falls.

The goal of this study is threefold.

Firstly, we aim to carry out a statistical analysis to inquire into the existence of clear correlations between, on the one hand, some of the most widely considered body parameters, as age and Body Mass Index, and physical activity tests, and, on the other hand, the risk of falling, represented through the score of the Mini-Balance Evaluation Systems (Mini-BES) test (Franchignoni et al., 2010).

Secondly, we wish to diversify our statistical analysis, so as investigate whether or not these correlations change when healthy or unhealthy subjects are considered. We wish to take into account here two different wide classes of diseases. The first class contains metabolic problems such as hypo- and hyper-thyroidism, hypo- and hyper-glycemia, and so on. Approximately 34% of the worlds adult population has the cluster of risk factors that is metabolic syndrome (Mozumdar and Liguori, 2011). The second class, instead, makes reference to diabetes, hypo- and hyper-tension, vascular and heart-related problems. Cardiovascular diseases (CVD) are responsible for 30% of all deaths (17.5 million) (World Health Organization and others, 2005).

Thirdly, we wish to move the first steps towards the opening of a path to the use of wearable sensors and mobile devices for the on-line monitoring and the real-time evaluation of a subject's falling risk through the consideration of the above found relationships.

This latter goal would make fall risk assessment much easier, because subjects would not need to undergo the classical Mini-BES test, rather they could estimate it at home in their everyday life by simply using a small set of wearable sensors. Namely, a sensor could estimate the Body Mass Index (BMI), whereas a second could keep track of the subject's physical activity. Based on the measured data, an app on the subject's mobile device could act as a kind of an advisor, by providing them with a view of their general health state, and with useful suggestions as well. Moreover, subjects with a potentially moderate-to-high falling

Sannino G., De Falco I. and De Pietro G.
A Statistical Analysis for the Evaluation of the Use of Wearable and Wireless Sensors for Fall Risk Reduction.
DOI: 10.5220/0006295805080516

risk assessment would be adviced to meet a doctor so as to possibly undergo a real test. This approach could lead to easily performing a kind of a 'mass screening' with reference to the risk of falling. To fulfill the two first above statistical goals, in this paper we will make use of a set of personal and life-style information contained in a real-world database making reference to to the risk of falling. Then, we will describe the body system we propose, based on some wearable senors, a mobile device, and an app.

This paper is organized as follows. Section 2 reports on the related work on finding correlations between personal parameters and falling risk. Information about the database is provided in Section 3. The statistical analysis is shown and discussed in Section 4. In Section 5 some considerations are given on the use of the results of the statistical analysis for the design of a monitoring system based on wearable sensors. Finally, our conclusions and future works follow in Section 6.

2 RELATED WORKS

One of the first papers trying to find correlations between personal parameters and falling risk was (Gardner et al., 2000). In it, the objective was to assess the effectiveness of exercise programs in preventing falls (and/or lowering the risk of falls and fall related injuries) in older people. Their conclusion was that exercise is effective in lowering falls risk in selected groups and should form part of falls prevention programs.

In (Hue et al., 2007) the aim of the study was to determine the contribution of body weight to predict balance stability. Their experiments suggest that body weight may be an important risk factor for falling.

In (Faulkner et al., 2009) the authors examined potential independent effects of lifestyle on fall risk. Not smoking and going outdoors frequently or infrequently were independently associated with more falls, indicating lifestyle-related behavioral and environmental risk factors are important causes of falls in older women.

Although not directly tied to fall risk, the paper (Shekharappa et al., 2011) dealt with similar ideas, in fact the aim was to find a correlation between body mass index and cardiovascular parameters in obese and non-obese in different age groups. The results showed a statistically significant increase in heart rate, systolic blood pressure and diastolic blood pressure in obese subjects when compared to non-obese in all age group. Moreover, there was a positive correlation between body mass index and heart rate, systolic blood pressure, diastolic blood pressure, mean blood pressure and pulse blood pressure.

The relationship between Body Mass Index and stability has been investigated in (Ku et al., 2012). Namely, the aims of that study was to examine the impact of BMI and gender on static postural control. Their conclusion was that BMI do have an impact on postural control during both bipedic stance and unipedic stance.

The effect of the type, level and amount of physical activity in falls and fall-related injuries was examined in (Pereira et al., 2014). Their conclusions were that being active, especially sufficiently active, reduces fall-related injuries by decreasing falls and by safeguarding against severe injuries when falls occur.

A study was conducted in (Shahudin et al., 2016) to investigate the effects of age on physical activity level, strength and balance towards fall risk index (FRI) among women, as well as identifying the main contributing factors towards FRI test performance. That study suggested that women aged 20–73 years were found to associate their FRIs mostly with age, followed by strength, balance, and lastly, physical activity.

3 THE DATABASE

To carry out our investigation, we have taken advantage of the Human Balance Evaluation database, collected at the Biomechanics and Motor Control Laboratory (BMCLab) of the Federal University of ABC, Sao Paulo, Brazil (http://demotu.org/datasets/balance/), and freely available in PhysioNet (Goldberger et al., 2000).

This database was collected while performing stabilography tests over a set of subjects. Each of those subjects had to perform standing tasks under four different conditions: by keeping their eyes opened or closed, and while standing on a rigid surface or on an unstable one. Each condition was tested three times, with the order of the conditions being randomized among subjects. A total of 1930 trials performed by 164 different subjects are given in this database. Each 1 minute recording is sampled at 100Hz and low pass filtered at 10Hz.

Moreover, and most importantly to us, the following qualitative tests were employed on each subject, and the replies/outcomes recorded in the database: Short Falls Efficacy Scale International (FES-I) (Kempen et al., 2008) (seven questions plus the score), the Short version of the International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003) (eight questions plus the score), Trail Making Test (four pieces of information), Mini Balance Evaluation Systems (Mini-BES) Tests (Franchignoni et al., 2010) (fourteen values plus the score). Furthermore, the subjects were also interviewed about some of their socio-cultural, demographic, and health information, including their age, medications, and illnesses.

Consequently, each database item contains 63 attributes. The database, apart from the raw data recordings, also includes a BDSinfo file that contains metadata describing the conditions of the stabilography trials, the information from the anamnesis, and the results of the qualitative evaluations. Because, as stated above, a subject has 12 files for the force platform data, there are 12 rows for each subject in this file. In these 12 rows, the only column that has rows with different values is the column identifying the trial (the file name). The content of all the other columns are simply repeated over the 12 rows. As result, the BDSdata file has the header plus 1930 rows and 64 columns. The complete list of the attributes can be found in (Santos and Duarte, 2016).

Starting from this database, we have conducted an analysis phase by creating a new database composed by 6 items for each of the 164 subjects. The parameters taken into account in our study are:

- x_1: age group
- x_2: Body Mass Index (BMI)
- x_3: IPAQ_1: minutes per week of vigorous physical activity according to the short IPAQ questionnaire
- x_4: IPAQ_2: minutes per week of moderate physical activity according to the short IPAQ questionnaire
- x_5: IPAQ_3: minutes per week of low physical activity according to the short IPAQ questionnaire
- x_6: the total score of the Mini-BES test

In the short IPAQ questionnaire used to create the Human Balance Evaluation database, the vigorous physical activities are defined as: heavy lifting, digging, aerobics, or fast bicycling. The moderate ones, instead are considered as: carrying light loads, bicycling at a regular pace, or doubles tennis. Finally, the low physical activities include: walking at work and at home, walking to travel from place to place, and any other walking that is done solely for recreation, sport, exercise or leisure.

As concerns the value for IPAQ_1 for a subject in our database, this is computed starting from the subject's answers to short IPAQ questions 1a (days per week of high-level physical activity) and 1b (hours per day of high-level physical activity through: $IPAQ\_1 = IPAQ\_1a \cdot IPAQ\_1b$. The same mechanism holds true for the computation of IPAQ_2 and IPAQ_3.

The value of the score for the Mini-BES test is computed through the answers of the subject to 14 questions, each of which can be assigned a value equal to 0, 1, or 2, the higher the better. Therefore, the value of the Mini-BES test score can range within 0 and 28, where a higher value means that the subject has a lower falling risk.

Moreover, we have divided the subjects in the database into three groups:

- *healthy*: they are the subjects with no disease at all. This has resulted in a number of 56 individuals;
- *metabolic diseases*: this group contains all the individuals who declared problems related to hyper - or hypo-thyroidism, hyper- or hypo-glicemia, and so on. This group contains 32 subjects;
- *cardiovascular diseases*: this group is composed by all the individuals with hyper- or hypo-tension, cardiovascular problems, or diabetes. There are 41 people in this group.

It should be pointed out that we excluded from the groups 48 subjects who were not healthy, yet they suffered from diseases other than those reported in the above two groups. As examples, some of them suffered from melanoma, breast cancer, hepatitis, Parkinson, arthrosis, asthma, dermatitis, rhinitis, gastritis, kidney stones, sickle cell anemia,tendinitis, and so on. Moreover, there are 13 people in the database who suffer from both endocrinological and cardiovascular diseases. These have been assigned to both groups.

4 STATISTICAL ANALYSIS

For each of the three groups of subjects described in the previous section we have performed a correlation analysis among the chosen database parameters. By doing so, we have been able to obtain the correlation value for each pair of parameters. Let's recall here that a correlation value between two parameters is in the range [-1.0, 1.0], where positive values represent direct correlations and negative values inverse correlations, and the higher the absolute value the stronger the correlation.

Moreover, for each of these pairs we have created a figure, in which we report the raw data, and have computed and drawn the best line for the linear regression that best fits the data, and have also reported the related R-squared (R^2) value. R-squared is a statistical measure of how close the data are to the fit-

Table 1: Correlation values between pairs of parameters for healthy subjects.

	age	BMI	IPAQ_1	IPAQ_2	IPAQ_3	Mini-BES
age	1.00					
BMI	0.45	1.00				
IPAQ_1	0.56	0.29	1.00			
IPAQ_2	0.30	-0.08	0.20	1.00		
IPAQ_3	-0.05	-0.02	-0.06	0.21	1.00	
Mini-BES	-0.30	-0.24	-0.14	-0.06	0.05	1.00

ted regression line. A value of 0 for R^2 indicates that the model explains none of the variability of the response data around its mean, whereas an R^2 of 1 indicates that the regression line perfectly fits the data. These regression lines and their R^2 values are very useful because from them fruitful information can be obtained. In the next three subsections all these findings are shown for the three groups, respectively.

4.1 Healthy Subjects

Table 1 reports the correlation values for all of the considered parameters.

In it the generic cell (i, j) contains the correlation value between the pair of parameters i and j. Very high values (≥ 0.50) and very low ones (≤ -0.50) are shown in dark grey. Moderate values, lying in [-0.49, 0.30] and [0.30, 0.49], are highlighted in light grey. All the pairs in which the Mini-BES test score appears have been considered for further analysis. For each of them the corresponding figures are shown, which contain information about the linear regression too.

A first remark that can be made concerns the pairs of parameters for which the correlation values are high or moderate, i.e. those for which the values in the tables are shown in dark grey or light grey, respectively.

As concerns the healthy subjects, the only strong correlation is between the age and the IPAQ_1, i.e. the vigorous activity, and it a positive correlation. Basically, this says that as long as healthy people get old, they go on exercising vigorously. Also quite high is the moderate direct correlation between age and BMI, meaning that the older a healthy subject, the more obese she/he is. Moreover, a moderate direct correlation is shown between age and IPAQ_2, similar to that between age and IPAQ_1, but with reference to moderate physical activities. Furthermore, a moderate inverse correlation exists also between age and Mini-BES. This suggests that for healthy subjects the higher the age the lower the value of the Mini-BES test score, hence the more probable the subject will be prone to falls.

Fig. 1 shows that this group is mainly composed by young adults. In fact the average age is 31.32 years

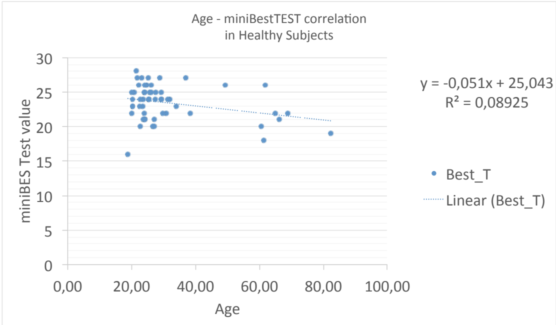

Figure 1: Analysis of parameters age and Mini-BES Test score for healthy subjects.

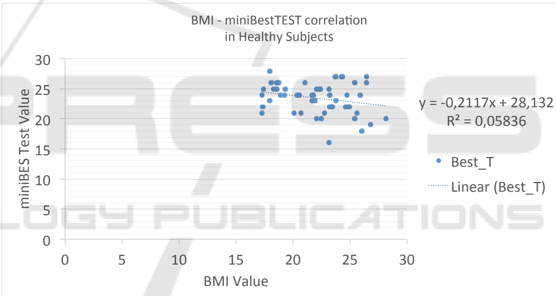

Figure 2: Analysis of parameters BMI and Mini-BES Test score for healthy subjects.

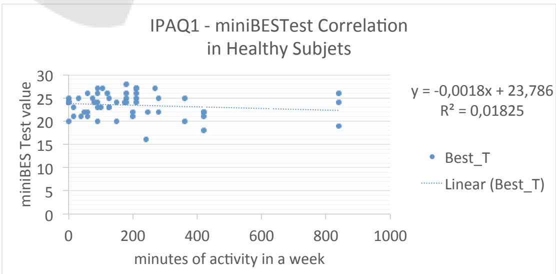

Figure 3: Analysis of parameters IPAQ_1 and Mini-BES Test score for healthy subjects.

± 14.90. Moreover, the average value for the Mini-BES test score is 23.44 ± 2.54, which is quite a high value suggesting that healthy people have a scarce fall risk.

A closer examination of Figures 1, 2, 3, 4, and 5 provides more precise information about the relation-

Table 2: Correlation values between pairs of parameters for metabolic subjects.

	age	BMI	IPAQ_1	IPAQ_2	IPAQ_3	Mini-BES
age	1.00					
BMI	0.52	1.00				
IPAQ_1	0.04	-0.17	1.00			
IPAQ_2	0.13	0.08	0.09	1.00		
IPAQ_3	0.08	0.26	-0.01	0.03	1.00	
Mini-BES	-0.78	-0.54	-0.06	-0.03	-0.25	1.00

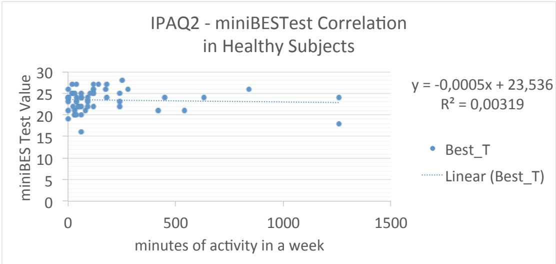

Figure 4: Analysis of parameters IPAQ_2 and Mini-BES Test score for healthy subjects.

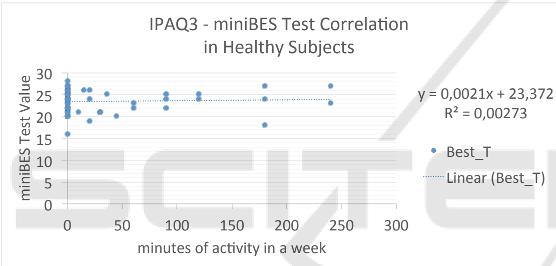

Figure 5: Analysis of parameters IPAQ_3 and Mini-BES Test score for healthy subjects.

ship between the Mini-BES test score and each of the other parameters considered in this study. Namely, the precise form of their relationship, under a linear hypothesis, is shown.

The slope of the line drawn in each figure provides intuitive visual understanding of the relationship: a down-bound line means an inverse linear relationship, an up-bound one a direct dependence, and the more inclined the line the higher the amount of this relationship. Consequently, lines that are almost horizontal imply a substantial independence between the two parameters. As an example, this is the case shown in Fig. 5.

4.2 Subjects with Metabolic Diseases

Table 2 reports the correlation values for all of the considered parameters.

As it has been for the healthy group, here too the generic cell (i, j) contains the correlation value between the pair of parameters i and j. The same convention used for that group applies also in this case to highlight some specific cells in the table. Similarly to the previous case, here too all the pairs in which the Mini-BES test score appears have been considered for further analysis. For each of them the corresponding figures are shown, which contain information about the linear regression too.

As far as the metabolic patients are taken into account, three parameter pairs have high correlation values, namely age-BMI, age-Mini-BES, and BMI-MiniBES. The first is a direct correlation, meaning that as the age increases so does BMI, as it is quite frequent in humans, be they healthy or suffering from some disease. Of higher interest for our purposes are the other two correlations. Age and Mini-BES test score are strongly and inversely correlated, which means that as the age of these diseased subjects increases the Mini-BES test score decreases, so older subjects suffering from metabolic diseases are more prone to falls. Moreover, also BMI and Mini-BES test score are strongly and inversely correlated, meaning that the more obese a metabolic subject, the higher probability she/he has of falling.

In this case, as Fig. 6 reveals, the age of this group is quite higher than that for healthy subjects. In fact, the average is 62.80 years ± 17.91. The average value for the Mini-BES test score for these subjects, instead, is 19.67 ± 4.10, i.e. about four points worse that that for healthy people.

By looking at Figures 6, 7, 8, 9, and 10, it can be visually understood that for people suffering from metabolic diseases changes in IPAQ_2 and IPAQ_3 almost do not affect the Mini-BES test score, while the opposite is true for the age, BMI, and IPAQ_1. In particular, the R^2 value for the correlation between age and Mini-BES test score is equal to 0.60908, so we are confident that the regression line well fits the data.

4.3 Subjects with Cardiovascular Diseases

Table 3 reports the correlation values for all of the considered parameters.

Also for this group, the generic cell (i, j) in the table reports the correlation value between the pair of parameters i and j. The cells in this table have

Table 3: Correlation values between pairs of parameters for cardiovascular subjects.

	age	BMI	IPAQ_1	IPAQ_2	IPAQ_3	Mini-BES
age	1.00					
BMI	-0.08	1.00				
IPAQ_1	-0.10	-0.29	1.00			
IPAQ_2	-0.34	-0.18	0.15	1.00		
IPAQ_3	-0.08	0.17	-0.03	0.03	1.00	
Mini-BES	-0.39	0.01	-0.07	0.17	0.22	1.00

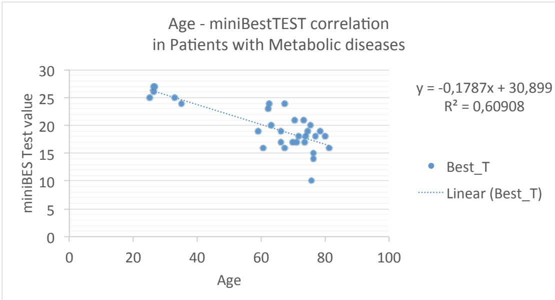

Figure 6: Analysis of parameters age and Mini-BES Test score for metabolic subjects.

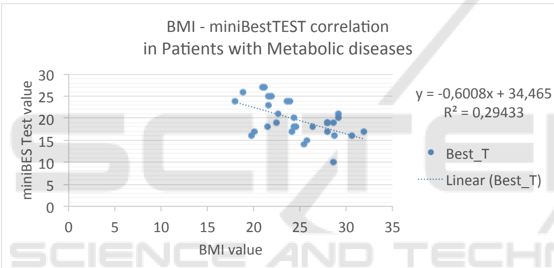

Figure 7: Analysis of parameters BMI and Mini-BES Test score for metabolic subjects.

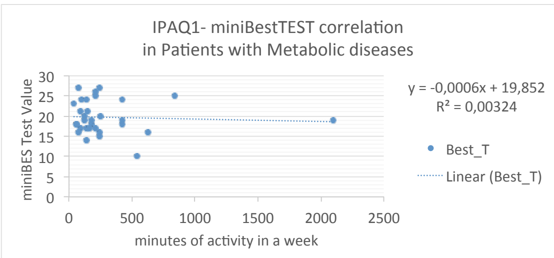

Figure 8: Analysis of parameters IPAQ_1 and Mini-BES Test score for metabolic subjects.

been highlighted by using the same convention as done for the two previous groups. Similarly to the two above described cases, also for this group all the pairs in which the Mini-BES test score appears have been considered for further analysis. For each of them the corresponding figures are shown, which contain information about the linear regression too.

Finally, when the cardiovascular subjects are considered, no correlation can be defined as strong, the

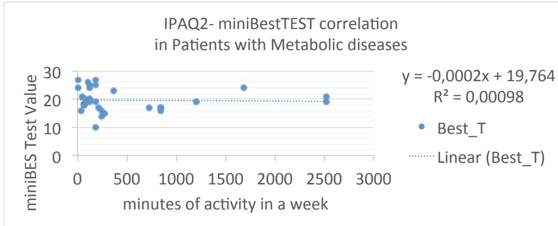

Figure 9: Analysis of parameters IPAQ_2 and Mini-BES Test score for metabolic subjects.

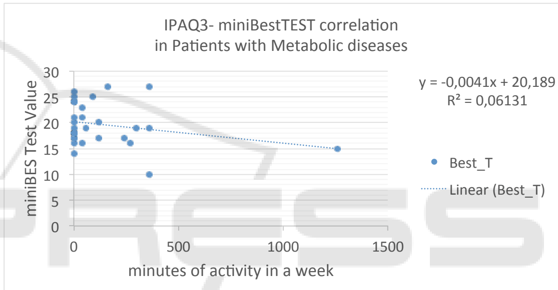

Figure 10: Analysis of parameters IPAQ_3 and Mini-BES Test score for metabolic subjects.

highest one being a moderate inverse correlation between age and Mini-BES test score. This is quite similar to that already seen for the metabolic subjects, although with a lower tie between the two parameters. Also, age and IPAQ_2 show a moderate inverse correlation, that is the opposite as that for healthy subjects: healthy people tend to exercise when they get older, whereas cardiovascular ones tend to not work out.

Also for the cardiovascular subjects, as it was for the metabolic ones, the average age is quite higher than that for the healthy subjects. In fact, as shown in Fig. 11, it is equal to 72.27 $\pm$6.61, which is higher than that of metabolic people too. As for the average score of the Mini-BES test for this group, it results to be equal to 18.02 ± 3.81, i.e. even worse that that of the metabolic subjects.

For this group the Figures 11, 12, 13, 14, and 15 do not show any particularly strong correlation, nor do they report any sufficiently high value for R^2, apart from, possibly, the case of age and Mini-Best test score.

In conclusion, the main result from this statisti-

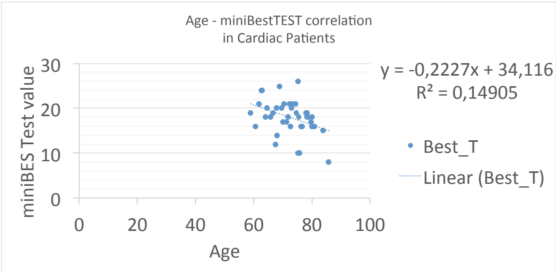

Figure 11: Analysis of parameters age and Mini-BES Test score for cardiovascular subjects.

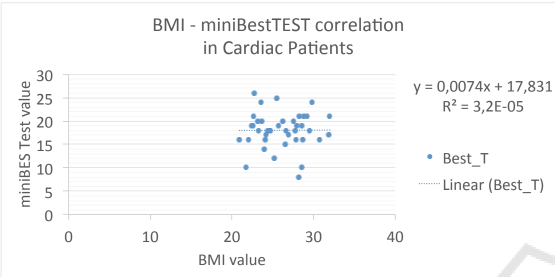

Figure 12: Analysis of parameters BMI and Mini-BES Test score for cardiovascular subjects.

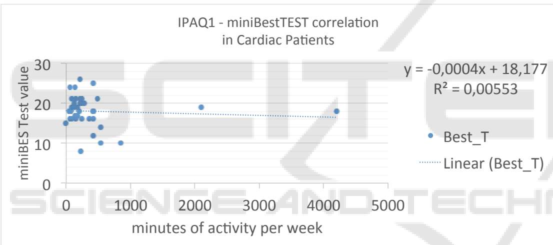

Figure 13: Analysis of parameters IPAQ_1 and Mini-BES Test score for cardiovascular subjects.

cal analysis is that, when a subject suffers from a metabolic disease, she/he has a probability of falling that is higher than that of an equally aged cardiovascular subject, and much higher than that of a healthy peer.

5 USE OF THE STATISTICAL ANALYSIS RESULTS IN A MONITORING SENSOR-BASED SYSTEM

The statistical analysis made in this preliminary study has shown that, even though moderate, a correlation exists between the risk of falling (the mini-BES test score) and the personal and lifestyle indicators.

These results mean that it is imaginable to realize a monitoring system in order to give specific rec-

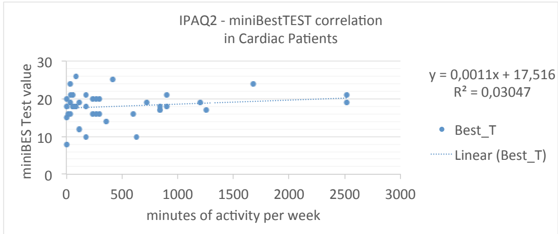

Figure 14: Analysis of parameters IPAQ_2 and Mini-BES Test score for cardiovascular subjects.

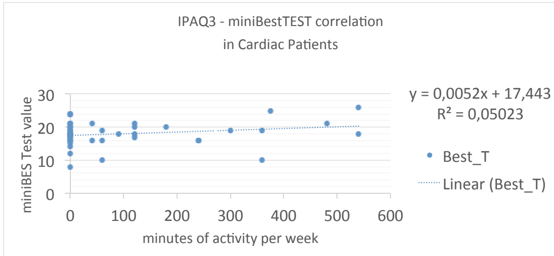

Figure 15: Analysis of parameters IPAQ_3 and Mini-BES Test score for cardiovascular subjects.

ommendations about the diet and the amount and the type of physical activity so as to improve the subject well-being with respect to the risk of falling.

Nowadays, mobile devices, such as smartphones or tablets, wearable devices, such as smartwatches or bands, and wireless healthcare devices, such as smart digital scales, are widely used and it is demonstrated that they are valid tools to monitor body and lifestyles parameters. For these reasons, thanks to these devices, it is possible to collect in real time data about, for example, the weight of a subject or the type and the amount of activity performed during a day or a week.

This collected information could be analyzed in real time on a mobile device in order to give a prompt feedback to the subject about her/his risk of falling and in order to guide the subject to develop new habits to reduce the estimated risk of falling.

As an example, for the subjects with metabolic disease the statistical analysis has shown that there is a strong and inverse correlation between the BMI and the Mini-BES test score, so a wearable sensor-based monitoring system could give specific recommendations in order to not only reduce the obesity, but also to reduce the risk of falling knowing that more obese a metabolic subject, the higher probability she/he has of falling.

Within our laboratory, several mobile applications have been implemented aimed to monitor different kinds of healthcare parameters, as for example (Forastiere et al., 2016; Sannino and De Pietro, 2014). The correlation results found in this study for healthy subjects and cardiac subjects will be easily added into them respectively.

Unfortunately, there is no unique app with the possibility to have a specific knowledge base for each subject in order to suggest different recommendations for the three different groups of subjects.

For this reason, a new mobile health application is under development in order to take into account the different results obtained for the different classes of people examined, e.g. healthy subjects, subjects with metabolic diseases or subjects with cardiac diseases. The app will be able to monitor body indicators, physiological data, and physical activity information by using wearable sensors, be they or not compliant to the Continua Alliance guidelines (Carroll et al., 2007). Of course, some of these sensors will be used for long periods, as e.g. those for physical activity monitoring, therefore they are affected by the typical problems related to battery charge. Other types of sensors, instead, will be employed more rarely, as for example smart digital scales that are typically used just once in a day.

6 CONCLUSIONS AND FUTURE WORK

In this paper the correlation between personal and life-style indicators and the risk of falling has been investigated.

As indicators we have considered here for each subject age, body mass index, and information about physical activity habits, while a subject's risk of falling has been estimated by the Mini-BES test score. Three different groups of subjects have been taken into account, namely healthy, suffering from metabolic diseases and suffering from cardiovascular diseases.

Firstly, explicit linear correlations have been found for any pair of parameters. Secondly, attention has been paid to whether or not these correlations change as the health state of the subjects does.

Finally, some first steps have been moved towards a system, composed by wearable sensors, a mobile device, and an app, that would be able to help people in improving their life-style so as to decrease falling risk.

In the near future we aim at implementing the sensor-based system.

Moreover, due to the fact that the data set from Physionet used in this paper looks highly clustered with little outliers, e.g. most healthy patients are around 20 years old, we plan to start a cooperation phase with the University of Naples "Federico II" in which they will provide us with some volunteers with different ages in order to better balance the database.

Within this cooperation we will supply the system to the volunteers, so as to test its effectiveness and usefulness.

ACKNOWLEDGEMENTS

This work has been supported by the project "eHealthNet: Ecosistema software per la Sanità Elettronica" (PON03PE_00128_1) financed within the P.O.N. "Research and Competitiveness" call of the Italian Ministry for University and Research.

REFERENCES

Carroll, R., Cnossen, R., Schnell, M., and Simons, D. (2007). Continua: An interoperable personal healthcare ecosystem. *IEEE Pervasive Computing*, 6(4):90–94.

Craig, C. L., Marshall, A. L., Sjstrm, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., Pratt, M., Ekelund, U., Yngve, A., Sallis, J. F., and Oja, P. (2003). International physical activity questionnaire: 12-country reliability and validity. *Medicine and science in sports and exercise*, 35(8):13811395.

Faulkner, K. A., Cauley, J. A., Studenski, S. A., Landsittel, D. P., Cummings, S. R., Ensrud, K. E., Donaldson, M., Nevitt, M., of Osteoporotic Fractures Research Group, S., et al. (2009). Lifestyle predicts falls independent of physical risk factors. *Osteoporosis international*, 20(12):2025–2034.

Forastiere, M., De Pietro, G., and Sannino, G. (2016). An mhealth application for a personalized monitoring of ones own wellness: Design and development. In *Innovation in Medicine and Healthcare 2016*, pages 269–278. Springer.

Franchignoni, F., Horak, F., Godi, M., Nardone, A., and Giordano, A. (2010). Using psychometric techniques to improve the balance evaluation systems test: the mini-bestest. *Journal of Rehabilitation Medicine*, 42(4):323–331.

Gardner, M. M., Robertson, M. C., and Campbell, A. J. (2000). Exercise in preventing falls and fall related injuries in older people: a review of randomised controlled trials. *British journal of sports medicine*, 34(1):7–17.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, H. E. (2000). Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals. *Circulation*, 101(23):e215–e220.

Hue, O., Simoneau, M., Marcotte, J., Berrigan, F., Doré, J., Marceau, P., Marceau, S., Tremblay, A., and Teasdale, N. (2007). Body weight is a strong predictor of postural stability. *Gait & posture*, 26(1):32–38.

Kempen, G. I., Yardley, L., Van Haastregt, J. C., Zijlstra, G. R., Beyer, N., Hauer, K., and Todd, C. (2008). The short fes-i: a shortened version of the falls efficacy scale-international to assess fear of falling. *Age and ageing*, 37(1):45–50.

Ku, P., Osman, N. A., Yusof, A., and Abas, W. W. (2012). Biomechanical evaluation of the relationship between postural control and body mass index. *Journal of biomechanics*, 45(9):1638–1642.

Mozumdar, A. and Liguori, G. (2011). Persistent increase of prevalence of metabolic syndrome among us adults: Nhanes iii to nhanes 1999–2006. *Diabetes care*, 34(1):216–219.

Pereira, C. L., Baptista, F., and Infante, P. (2014). Role of physical activity in the occurrence of falls and fall-related injuries in community-dwelling adults over 50 years old. *Disability and rehabilitation*, 36(2):117–124.

Sannino, G., De Falco, I., and De Pietro, G. (2015). A supervised approach to automatically extract a set of rules to support fall detection in an mhealth system. *Applied Soft Computing*, 34:205–216.

Sannino, G. and De Pietro, G. (2014). A mobile system for real-time context-aware monitoring of patients health and fainting. *International journal of data mining and bioinformatics*, 10(4):407–423.

Santos, D. A. and Duarte, M. (2016). A public data set of human balance evaluations. *PeerJ*, 4:e2648.

Shahudin, N. N., Yusof, S. M., Razak, F. A., Sariman, M. H., Azam, M. Z. M., and Norman, W. M. N. W. (2016). Effects of age on physical activity level, strength and balance towards fall risk index among women aged 20–73 years. In *Proceedings of the 2nd International Colloquium on Sports Science, Exercise, Engineering and Technology 2015 (ICoSSEET 2015)*, pages 25–34. Springer.

Shekharappa, K., Smilee, J. S., Mallikarjuna, P. T., Vedavathi, K. J., and Jayarajan, M. P. (2011). Correlation between body mass index and cardiovascular parameters in obese and non obese in different age groups. *International Journal of Biological & Medical Research*, 2(2):551–555.

World Health Organization . Ageing and Life Course Unit (2008). *WHO global report on falls prevention in older age*. World Health Organization.

World Health Organization and others (2005). Preventing chronic diseases: a vital investment: Who global report.