Setting the Criteria for the *MATHOV + QAVS* Tool
Qualitative and Quantitative Aspects for Wearable Fall Prediction

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Abstract: For the first time in history, the world shows a clear trend towards aging. This poses an intrinsic hazard for the ever growing population, which becomes more vulnerable to common age-related illnesses and conditions. One of the most serious risks elders face is falling, as it is responsible for countless admissions to geriatric care institutions and thousands of deaths each year. In an effort to improve elders' safety and quality of life many groups have address the fall prevention issue, coming to several different results as of what variables are the most important to consider in a fall prediction tool. These variables range from qualitative aspects (history of falls, dementia, use of medication, etc.) to quantitative ones (total walked distance per day, walking cadence, center of mass, etc.), but none of them *per se* seems to deliver a definite and complete answer to the problem at hand. The paper herein aims to present a new hybrid approach, which combines both the highest co-related qualitative and quantitative biovariables in a single tool: the *MATHOV + QAVS*, which is proposed as a new fall assessment screening tool and eventually as baseline criteria for a complete elder fall prediction system.

1 INTRODUCTION

The World Health Organization (WHO) defines a fall as "an event which results in a person coming to rest inadvertently on the ground or floor or other lower level" (World Health Organization, 2012). Each year 37.3 million falls are severe enough to require medical attention (424 000 of them fatal) and according to Peel, falls are the leading cause of both fatal and non-fatal unintentional injuries in people older than 65 years —accounting for 40% of all injury-related deaths worldwide (Peel, 2011).

Falling also implies a huge financial burden in health care services all over the world. Based on Dollar purchasing power parities, Heinreich *et al.* determined in his study that the mean costs per fall victim, per fall and per fall-related hospitalization ranged from \$2044\$ to \$25 955\$; \$1059\$ to \$10 913\$ and \$5654\$ to \$42 840\$ respectively (Heinrich et al., 2010). This is more impressive in terms of Gross Domestic Product (GDP): within the European Union the amount sums up to 0.85%, whereas in a high-cost health care model —such as in the United States—, the total cost of medical care for elderly people has risen from 0.8% of the GDP in 1975 to 2.7% in 2008 —more than half of the US 2013 military budget (Siracuse et al., 2012).

Falling has become an actuality topic because of the worldwide trend towards aging. It is estimated that there will be two thousand million persons over 60 years in the year 2050, and by that time the oldest and most vulnerable segment of population (aged 80 and over) are expected to represent 20% of the total elder population. If preventive measures are not taken in an immediate future, the number of injuries caused by falls is projected to be 100% higher in less than 20 years (World Health Organization, 2007). As stated by the WHO "Population aging is a triumph of humanity, but also a challenge to society"; unfortunately this statement forgets to remark the fact that the aging issue is not only a social and economical challenge, but also a technological one.

Predicting falls in order to prevent them constitutes a serious question for both the health and engineering fields. The former has long tried to evaluate qualitatively factors, aiming to find characteristics that might be precursors to falls and actions or conditions that influence the likeliness of falling (Demura et al., 2012; Grundstrom et al., 2012; Neumann et al., 2013); whereas engineers have just recently picked up the task: their approach is focused on acquiring measurable data (Verghese et al., 2009; Liu

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et al., 2011; Karlsson et al., 2012) for further quantitative analysis using state vector machines (Lai et al., 2008), neural and dynamic Bayesian networks (Giansanti et al., 2008a; Cuaya et al., 2013) and other probabilistic/statistic models.

Fall prediction is very complicated in nature, as it tries to answer what physically-acquirable data is of interest, what quantitative bio-variables can be related to falling and finally which tests are to be conducted to actually gather this information. Moreover, all these aspects only represent an entry level, since the subsequent challenge is what type of algorithms could be used to process this information. The work presented herein addresses the issues regarding the selection of these bio-variables and proposes a set of them in the form of the *MATHOV + QAVS* tool, which is part of the first stage of an on-going project for a complete *wearable* fall *prediction* solution (Espinoza, 2013).

The tool is based on an *hybrid* approach, i.e., uses both qualitative and quantitative methods. Their selection has been through an extensive bibliographical research and uses only bio-variables that have been tested and validated before by large studies with patients. It has been developed in an effort to deliver a promptly and modern solution for improving elders' health security and quality of life issue, either by becoming a standard screen tool for fall risk or by setting the criteria for future fall prediction algorithms.

2 QUALITATIVE & QUANTITATIVE VARIABLES

As previously mentioned, there is still an on-going debate whether a qualitative or quantitative approach is the best way to engage fall prediction. Defining the criteria to separate fallers from non-fallers has proven to be a difficult task, and many researchers have tried —and successfully managed— to come up with viable results. However, a completely hybrid-based solution using wearable devices has not yet been developed (Espinoza, 2013). This new approach holds considerable promise, as both the qualitative and quantitative aspects that the *MATHOV+QAVS* tool takes in consideration have already been proven, tested and validated by different experts in different countries with a considerable number of patients.

2.1 Qualitative Aspects

The tool's name, *MATHOV*, is composed by the first letters of the five qualitative variables that have been identified as the most common in fall assessment studies, and most of the authors seem to agree they have the highest co-relation with falls in the elderly. These variables are *Medication*, *Age*, *Toileting*, *History of falls* and *Vision impairment*.

Of these five variables, *history of falls* has been recurrently noted as the closest variable related to a near future (usually a 12 months period) fall. This should not come as a surprise, since a previous fall means that the patient already presents some level of inability to sustain balance, and it is likely the patient also suffers from an injury caused by any of the previous falls. These previous falls and lesions can limit the patient's mobility, reduce their confidence and negatively contribute to their overall well-being.

Many of the *medication* drugs commonly prescribed to elders —either psychotropics, painkillers or blood pressure control drugs, just to name a few— include side effects such as dizziness and drowsiness, which naturally increase the risk of falling, specially under an unsupervised scenario.

The *Toileting* factor also comes from somewhat the same background as *medication*: the elders' frequently prescribed drugs (specially as with the case of diuretics for treating blood pressure) usually come hand in hand with frequent toileting. There also seems to be a general consensus among the studied authors that frequent toileting is an indicator of a muscular detriment to some degree, which could also translate into lack of strength in the lower limbs and thus incrementing the possibility of falling. Regardless if there is a overlap relationship between *medication* and *toileting*, these two variables have been constantly pointed out in the scientific literature as highly influential factors prior to a fall —according to both statistical approaches and assessment by elder care nurses (Sherrington et al., 2010).

Vision impairment also plays a major role, as seen by the amount of times it was repeatedly reported by the studied authors. Limited vision is a very common condition amongst elders and is natural to assume that any type of limitation or impairment for walking —such as by needing a walking aid, low muscular strength or, as in this case, poor visibility— increases the risk of falling. This can be even worse if the patient walks around without his vision aid (glasses), as this could represent a serious hazard to bump and fall —specially in high-risk environments with lots of furniture, carpets, steps, uneven floors and other common obstacles—, with possible fatal consequences.

Although the *Age* variable was not as recurrent as others on Table 1, it is still considered a serious aggravate, specially by health associations such as the WHO (World Health Organization, 2007) and the Pennsylvania Patient Safety Advisory (Feil and Gardner, 2012). The later found over more than 400 stud-

Table 1: Qualitative Aspects for Fall Assessmet (by author).

Author	Subject Count	Medication	Age	Toileting	Fall History	Vision
(Perry, 1982)	1780	✓				✓
(Oliver et al., 1997)	1780			✓	✓	✓
(Lord et al., 2005)	684				✓	✓
(Neyens et al., 2006)	Bibliographic research	✓			✓	✓
(Gama and Gómez, 2008)	Bibliographic research	✓			✓	✓
(Marschollek et al., 2009)	119			✓	✓	
(Russell et al., 2009)	344				✓	
(Sherrington et al., 2010)	533	✓		✓		
(Muir et al., 2010)	117				✓	
(Deandrea et al., 2010)	Bibliographic research	✓			✓	✓
(Bongue et al., 2011)	1759	✓			✓	
(Fong et al., 2011)	554	✓				
(Grundstrom et al., 2012)	120923	✓			✓	
(Demura et al., 2012)	1122	✓	✓	✓	✓	✓
(Feil and Gardner, 2012)	Bibliographic research	✓	✓	✓	✓	
(Aizen and Zlotver, 2013)	1013	✓				
(Neumann et al., 2013)	4735				✓	

ies a high co-relation between falling and advanced age, and the importance of using this information as a general risk stratification method: the older the patient, the higher the risk of falling.

Perhaps the most important characteristic that all the *MATHOV* variables share is the ease of acquisition. Getting the information can be carried out in very short time, does not require any special instruments or technicians and a simple questionnaire to the patient, a close family member, friend or care provider will suffice.

2.2 Quantitative Aspects

The second part of the tool's name, *QAVS*, stands for *Quantitative Assessment Variable Selection*. As well as with *MATHOV*, it was developed after a state of the art research on fall prediction (Espinoza, 2013).

It is important to note that what is shown on Table 2 are actually the tests that return the variables of interest. For example, the 6 m *walking test (SMWT)* is used to measure the time it takes the patient to walk just over 6 m on a straight line. A non-faller should take less than 5.4 seconds, whereas a recurrent faller (2 or more falls a year) takes on average 5.9 s or more to complete the SMWT (Karlsson et al., 2012).

When the SMWT is accompanied by the *number of steps for the* 6 m *walk*, new classification criteria can be set: recurrent fallers take more than 9.7 steps to complete the SMWT, and since the information of time and number of steps is available, *cadence* can also be obtained and compared with other studies (Menz et al., 2003).

The *timed up and go test (TUGT)* consists in measuring the time it takes for the patient to get up from a rest position (usually sitting) and walking a small straight-forward distance (often 3 m). As its name suggests, the test is timed and then the threshold is set accordingly. Contrary of SMWT, there is no statistical information available in the literature for TUGT based on large scale experiments, as the one by Karlsson *et al.* Furthermore, each of the authors mentioned on Table 2 that have experimented with TUGT have used their own variations, almost turning TUGT into a non-standard test. Nevertheless, the getting-up-and-walking essence of TUGT has been extensively used along the years, and can be easily adapted to unsupervised tests using wearable technologies, thus its incorporation into the *QAVS*.

Other quantitative factors for fall risk, such as *total walked distance per day* and *energy expenditure* have been recently and extensively evaluated by many authors (Marschollek et al., 2008; Narayanan et al., 2010). This features are particularly useful when dealing with elders' own perception on mobility: it is common to see elders reporting their activities of daily living as much more intense and longer than they actually are. Total walked distance and energy expenditure can provide a true value of the patient's activity, and could also be used to extended benefits, such as calculating his right caloric intake according to his lifestyle and activities.

Body mass index (BMI) also seems to play a major role as a variable of interest in fall prediction. Morbid obesity is usually related to reduced life expectancy in part due to several illnesses and conditions associated to it —such as diabetes, hypertension, cholesterol, etc.—, as well as high risk of falling due to the limited mobility obese patients present. This situation seems to aggravate as it usually creates a vicious circle: limited mobility tends to discourage patients to practice exercise, which further reduces their mobil-

Table 2: Quantitative Aspects for Data Gathering (by author).

Author	**Subject Count**	**TUGT**	**SMWT**	**Steps for 6m**
(Menz et al., 2003)	100		✓	✓
(Tiedemann et al., 2008)	362		✓	
(Marschollek et al., 2008)	110	✓	✓	✓
(Gietzelt et al., 2009)	241	✓		
(Verghese et al., 2009)	597		✓	
(Narayanan et al., 2010)	68	✓		
(Greene et al., 2010)	349	✓		
(Liu et al., 2011)	68	✓		
(Shimada et al., 2011)	213	✓	✓	
(Karlsson et al., 2012)	10998		✓	✓

ity, directly affects on the patients' strength and health and increases their risk of falling (Rosengren et al., 2011; Grundstrom et al., 2012).

3 DISCUSSION

After an extensive bibliographical research regarding both the qualitative and quantitative aspects related to falling in the elderly, it seems the conclusion still remains the same as with many other studies: there is no silver bullet to tackle the problem (Espinoza, 2013). No specific factor or test can deliver a complete decisive variable or threshold to be used systematically with the elder population, suggesting that a combination of factors —essence of the *MATHOV + QAVS* tool— could be the best approach.

One of the latest trends in quantitative fall assessment has been the use of wearable technologies (micro-electromechanics) which allow constant monitoring of the patient in an unobtrusive way (Shany et al., 2012a; Shany et al., 2012b). Furthermore, if used accordingly to the proposed methods of this research project, wearable technologies could also avoid the laboratory settings needed for data acquisition, reduce the white coat effect, eliminate the necessity of a supervisor and at the same time give complete freedom and autonomy to the patients to do their activities of daily living.

The *MATHOV + QAVS* tool merges what seem to be the most extensively studied qualitative factors with quantitative variables easily acquirable with micro-electromechanics' technology (MEMs), which are not also increasingly smaller over time and hold a great amount of autonomy —thus, ideal for wearable projects—, but are also capable of acquiring biovariables in an secure, discrete, prolonged and non invasive manner.

Table 3 summarizes the *MATHOV + QAVS* tool's variables. The qualitative variables are extremely easy to assess by simply asking the patient or a close family member. Of course some others —as the amount of medication the patient is taking and the level of visual impairment— can be assessed by other means, i.e., by the patient's physician or medical records. This straightforward form of evaluation is ideal for low-tech and low-cost scenarios —such as with developing countries— or simply for easiness and practicality.

As an example, Figure 1 shows a possible device for biodata gathering for the *MATHOV + QAVS* tool: Kinematix's WalkinSense is an in-shoe sensor array located under the shoe's insole capable of acquiring plantar pressure, walking acceleration, speed, step length, number of steps, tibial angles and their respective times (Kinematix, 2013). Furthermore, due to the plantar pressure measurements, it is possible to determine if the patient is sitting (low plantar pressure) or standing (high plantar pressure), which is extremely convenient for the timed up and go test (TUGT).

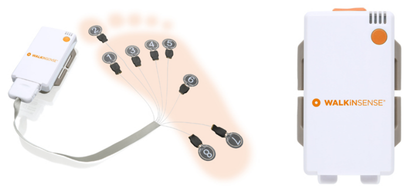

Figure 1: WalkinSense: Example of a device for wearable gait biodata acquisition.

As with the qualitative parameters of the tool, quantitative tests are easy to perform, and the data gathered can be used to calculate several indirect parameters, such as cadence, by using the number of steps for 6 m and dividing them by the time it takes to perform the SMWT. Gait speed can also be calculated —either by integrating the acceleration obtained with the wearable accelerometers or by indirect calculation using the distance and time—, which in return can also be used to obtain the total energy expenditure —using the patient's weight from the data obtained for the body mass index.

Other quantitative parameters known in the liter-

Table 3: *MATHOV + QAVS* Tool's Criteria.

Qualitative	**Quantitative**
Medication	Time: *Timed up and go test (TUGT)*
Age	Time: *Six meter walk test (SMWT)*
Frequent toileting	Number of steps for 6 m
History of falls	Total daily walked distance
Vision impairment	Body mass index
	Walking cadence
	Daily energy expenditure

ature, such as center of mass (McGrath et al., 2012) and gait sway (Stalenhoef et al., 2002; Lord et al., 2005; Giansanti et al., 2008b; Marschollek et al., 2008) have been studied and have returned interesting results, but pose a technological challenge to acquire with wearable and autonomous devices: either due to battery life constrains or the supervised or controlled laboratory environment required. Since the tool's scope is focused on an approach as unstructured and unsupervised as possible, only tests that can be performed completely unmonitored, using microelectromechanics and without any complicated tests —like previously design walking courses or specific researcher-designated trials— have been taken into consideration while designing the tool.

The *MATHOV + QAVS* tool could also be used by clinicians to constantly evaluate a patient's risk of fall and assess if the patient requires preventive or corrective measures —namely, physical therapy—, yielding the opportunity for timely and oriented interventions. Similarly, it could also be used to prescribe walking aids (canes, walkers or wheelchairs) if the falling risk is too high and prophylactic measures should be considered instead.

Some recent studies have shown that what causes most falls among elders is the lack or proprioception and wrong perceptions of their own mobility capabilities (Lafargue et al., 2013; Robinovitch et al., 2013). Both proprioception and self-consciousness of their moving limitations can be boosted by opportunely prescribing the patients with exercise, which would also delivers other benefits like greater energy consumption, a more active living/aging, reduced fatalities due to falls and reduce costs to both healthcare systems and patients.

In summary, the tool's variables were selected due to their gathering simplicity and close relationship with falling, keeping in mind the patient's autonomy, privacy and user-friendliness. The tool intends to conciliate the autonomous, ubiquitous and unobtrusive nature of wearable devices with the unsupervised and unstructured testing methods for data acquisition.

4 CONCLUSIONS

Perhaps what stands as the most interesting question is why hybrid (qualitative with quantitative) approaches had not been tried in the past. The answer could reside with the fact that MEM technology has just recently come into place, as well as the emerging field of biomedical engineering, which tries to address issues converging both the medical an engineering point of view. Technology limitation and absence of an specialized research field may have delayed the launch of a hybrid approach, but it is undoubtedly that these mixed tools will likely replace the one-sided approaches and, consequently, increasingly improve over time.

Furthermore, a great amount of confidence has been deposited in the *MATHOV + QAVS* tool, as its eclectic nature was specifically designed to meet the expectations of clinicians asking for a fall risk screening tool as well as engineers looking for data to feed their fall prediction algorithms. The success of the tool can only be measured after extensive testing, but due to its easy implementation, low cost technology and intrinsic unobtrusive characteristics for the patient its likely and encouraging to anticipate a substantial use of the tool by fall prediction research groups.

Although this tool has not yet been validated, future research and trials will provide the necessary data to conclude whether if it is of use or not. However, taken into consideration the results obtained by other groups with similar qualitative variables, it is tempting to suggest the expected results are at least as good as the ones obtained by such authors, since the presented tool herein should be improved by its quantitative component.

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