

Fall risk in the aging population: fall prevention using smartphones technology and multiscale sample entropy

Yeison Alberto Garcés-Gómez¹, Paula Andrea Duque²,
Angela Viviana Alzate-García³, Nicolás Tóro-García⁴

¹Unidad Académica de Formación en Ciencias Naturales y Matemáticas, Universidad Católica de Manizales, Colombia

²Facultad de Ciencias de la Salud, Universidad Católica de Manizales, Colombia

³Universidad de Caldas, Colombia

⁴Departamento de Ingeniería Eléctrica, Electrónica y Computación,

Universidad Nacional de Colombia–Sede Manizales, Colombia

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ABSTRACT

Falls are an important aspect of older people's health because they trigger major injuries and even death in one-third of fallen patients, making them a major public health problem. Given the risk of physical and psychological injury, if serious injuries occur as a result of a fall, prevention is an important consideration in today's health care landscape, where the population is predominantly adult worldwide. This paper presents the applicability of a simple technique of analysis of gait signals captured by mobile devices with the objective to the generation of early warnings on the risk of falls in older adults, which correlates with subjective scales. The technique is tested in a population of patients showing results of the significant risk of falls in patients that the subjective scales could not detect, demonstrating that mobile devices and signal processing can become important tools in the service of elderly care in fall risk prevention.

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Corresponding Author:

Yeison Alberto Garcés-Gómez,

Unidad Académica de Formación en Ciencias Naturales y Matemáticas,

Universidad Católica de Manizales,

Cra 23 No. 60-63, Manizales, Caldas, Colombia.

Email: ygarces@ucm.edu.co

1. INTRODUCTION

Falls are a major cause of mortality and morbidity in the elderly. Each year, a significant percentage of patients over the age of 65 fall at least once. Falls cause moderate to severe injury, fear of falling, loss of independence and death in one third of these patients. Falls represent the highest rate of all fractures in the elderly [1, 2]. The risk of falling and being injured increases with age, given the conditions of aging of the older adult, such as the stability of walking that deteriorates due to muscle-skeletal changes. The gait is determined by different cycles that correspond to the relative duration of its phases, 60% is the support phase, 40% corresponds to the swing and 20% to the overlap in the double support [3]. As the walking speed decreases, the duration of the double support phase increases [4].

In the older adult the length of the step is easily altered depending on the height, the width of base that is related to the length of the step and the height of the individual, the tall subjects take steps at a slower cadence, while the smaller ones take faster steps. These are modifications in the central and peripheral nervous mechanisms that control the balance of the locomotive system, modifying the normal pattern of walking [3].

Another aspect generating falls is the loss of balance [5], which is the process carried out in the body to control the center of mass with respect to the base of support. The systems that make up the ability to maintain balance are related to the sensory, motor and cognitive systems. In the older adult, due to altered nervous reflexes and diminished senses, the vulnerability to falls is greater.

Age-related diseases such as Parkinson's disease, Alzheimer's disease, stroke and the onset of chronic diseases such as musculoskeletal and lung diseases may be the most common causes associated with falls [6], as they are factors added to the alterations in balance and gait, which become mobility problems and are early indicators of health deterioration and disability. Falls are a common problem, and a devastating risk factor representing the leading cause of morbidity and mortality from physical and psychological injuries. The World Health Organization (WHO) defines fall as the consequence of any event that precipitates a person to the ground against his or her will, which constitutes one of the great geriatric syndromes [7].

The loss of walking ability and balance in the elderly increases with age, causing dependency and generating partial or total immobility, altering the quality of life by triggering loneliness, uncertainty and social abandonment, which increases the conditions of fragility, added to the cost of living. People over 65 years of age suffer a drop in value per year, which rises in those over 75 and 80 years of age [8]. The death rate from falls increases significantly over the years in both sexes, and in all socio-economic strata. Two thirds of the elderly who fall will suffer a new fall in the next six months. The history of falls has shown that they occur in enclosed places, such as the bathroom, bedroom and kitchen, because of the trust that is placed in such places, another place where they often occur is the stairs on the way down, between the first and last steps.

Falls are not only associated with morbidity and mortality in the older population, but are also linked to long-term confinement in care [9], which leads to isolation and abandonment by family and friends, reducing the chances of successful aging. The limitations of mobility [10, 11] alter all the dimensions of life of the older adult, from the physiological, psychological, social and even spiritual by the loss of roles, the deconfiguration of self-concept and self-esteem, increased depression and anxiety [12], reducing access to the free development of everyday life [13] leading to increasingly negative health outcomes [13, 14].

Falls have to be considered as a warning signal that translates into a condition of fragility, so the causes related to both the person and the environment have to be considered. Therefore, a global assessment of the risk of falls in the elderly has to be carried out periodically, with the purpose of estimating the consequences in a timely manner and preventing falls. The above suggests that risk assessments should be accurate by multi-factorial design. The joint commission, as the leading body in hospital safety, suggests that health agencies should manage the risk of falls through the use of interdisciplinary fall prevention interventions, taking advantage of the technologies developed to improve overall functionality [15].

Knowing the above, related to the care of the elderly, the maintenance of independence and autonomy for basic activities of daily living, and how falls interfere with the functional capacity of the elderly. The present study was carried out taking into account the application of technology for the precise measurement of the risk of falls, with the aim of implementing a system of signal acquisition by means of the mobile device that allows the identification of the signals of movement in progress to analyze the risk of falls in the elderly.

2. STATE OF THE ART

2.1. Methods for determining the risk of falls from the nursing station

In nursing, scales validated in different contexts and according to the vulnerability of the older adult are used for clinical assessment of fall risk. For the situation of care in falls it is common to use the Tinetti scale, which evaluates the capacity for balance and walking in older adults to determine the risk of falling by means of the variables of sitting balance, standing up, attempts to get up, immediate balance on getting up (5 seconds), standing balance, pushing, turning 360 degrees, when sitting, start of walking, length and height of the step, symmetry of the step, continuity of the step, route, trunk and posture of the walk. The score given by the Tinetti scale is a maximum of 16 for the balance test and 12 for the gait test, so the total is 28. The higher the final score, the better the patient's functionality and the lower the risk of a fall, considering that below 22 points there is a clear risk of a fall that increases as the score falls.

The studies that enabled the validation of the scale were developed by Tinetti and collaborators [16], Kegelmeyer and Kloos [17], who validated the Tinetti scale for older adults with Parkinson's. Another test, which is often used, is the short physical performance battery test (SPPB), which is an objective assessment tool for evaluating lower extremity function in older people. It was developed by the National Institute on Aging in the USA. The test consists of three tests: balance (in three positions: feet together, semi-tandem and tandem), walking speed, (about 2.4 or 4 meters) and getting up and sitting in a chair five times. The score and assessment of the total SPPB result is the sum of the three sub-tests, and ranges from 0 (worst performance) to 12 (best performance); low SPPB scores have high predictive value for the presence of falls, which constitute health consequences, including disability in activities of daily living to loss of mobility. The reliability of

the SPPB for use with older adults is high and its sensitivity to changes in functional capacity over time has been corroborated [18].

2.2. Technologies

In an aging world, it is essential to maintain good health and independence for as long as possible. Instead of hospitalization or institutionalization, the elderly and disabled can be assisted in their own environment 24 hours a day with many "smart" devices [19]. Solutions are needed to address the care demands of older adults to live independently. Wearable technology is an approach that offers a viable means for ubiquitous, sustainable and scalable monitoring of the health of older adults in typical free-living environments. Wearable devices has been presented as a relevant (bio)marker in ageing studies and pathology studies [20]. Technologies could support important aspects of older people's lives such as safety in the home [21], fall detection for care to elderly people [22], support in emergency conditions [23] and monitoring health condition [24], moreover, with the rise of IoT it is possible to link existing medical resources and provide reliable, effective and intelligent health care services to the elderly [25].

In relation to falls and prevention in older adults, due to the risk of these, different technological methods have been proposed for the study of the risk of falls associated with age from the analysis of signals captured during walking. Within the bibliographic review carried out, it was found that most of the published methods use statistical processes, frequency analysis and artificial intelligence processes. In the review paper of A. Godfrey [20], provides a summary of recent literature on gait assessment using clothing, focusing on the need for a fusion approach to measurement algorithms, culminating in the potential to better detect and classify falls. Bautmans [26] a sample of older adults is taken and compared with a control sample by means of a 3D accelerometer-based gait analysis system finding relationships of functional characteristics with gait variability in older adults at risk of falling.

Senden [27] investigated whether the Tinetti scale, as a subjective measure of fall risk, is associated with objectively measured gait characteristics, determining whether gait parameters are different for groups stratified for fall risk using the Tinetti scale. The study investigated the discriminatory power of gait parameters to classify elderly people according to the Tinetti scale by means of two groups of elderly people with Tinetti scales >24 and ≤ 24 , with an acceleration-based gait analysis using validated algorithms to derive the space-time gait parameters, the harmonic relationship, the stride amplitude variability and the root mean square (RMS) from the accelerometer data. Clear differences in gait between the groups were found. It is concluded that subtle changes in gait that have previously been related to fall risk are not captured by the subjective assessment. Therefore, it is worthwhile to include objective gait assessment in the diagnosis of fall risk.

Benoit [28] showed that several classification algorithms were able to discriminate people from two interest groups, fallen and non-fallen hospitalized, recording limb accelerations during clinical trials with a network of accelerometers distributed throughout the body. Rivolta [29] Several patients and volunteers underwent a full test of Tinetti while wearing a triaxial chest accelerometer. Tinetti scores were evaluated by medical experts and subjects with a score of ≤ 18 were considered to be at high risk. By analyzing the signals obtained by statistical methods and neural networks, it was possible to predict the results of the Tinetti scale. Ferrari *et al.* [30] realized a pilot study to test the feasibility of a motion detection system with wireless sensor in hospitalized older adults to prevent hospital-based falls. They showed that wearable motion sensors, which track and wirelessly transmit body movements, may identify human movement patterns that immediately precede falls.

2.3. Multiscale sample entropy

Shannon entropy can be defined as a measure of divergence of theoretical information [31] which does not require absolute continuity conditions to be satisfied by the probability distribution involved. Entropy is a procedure that allows to distinguish between a clean signal (called clean to a signal with deterministic content) and a distorted one (with high noise content) that does not depend on absolute scales of amplitude or frequency. Shannon proposed the H entropy of a random variable X , with multiple values x_1, \dots, x_n as (1):

$$H(X) = E(I(X)) \quad (1)$$

where E is the expected value and $I(X)$ is the amount of information in X . $I(X)$ is defined as a random variable and defining p as the probability function of X , the entropy (X) [32] of the function can be written as (2):

$$H(X) = \sum_{i=1}^n p(x_i)I(x_i) = \sum_{i=1}^n p(x_i)\log_b p(x_i) \quad (2)$$

For the dynamic dimensional system D , certain moment t_i is determined by its history t_1, t_2, \dots, t_{n-1} , and each new system status brings an additional amount of new information. Kolmogorov-Entropy H_{ks} is an appropriate tool for calculating the average rate of information creation. Other calculations such as the approximate entropy $ApEn$ proposed by Moorman [33] have the advantage of allowing results that are less dependent on the size of the time series as (3):

$$A_p E_n(m, r, N) \cong \frac{1}{N-m} \sum_{i=1}^{N-m} \ln \frac{n_i^m}{n_i^{m+1}} \quad (3)$$

The MSE algorithm is based on the application of $ApEn$ or sample entropy SE [34] for different scales of the same process. AE and SE are measures of regularity (order) in serial data and are based on two input parameters: the length of the sequence m and the tolerance level r . The output of these rhythms from something provides a measure of probability that two sequences within tolerance level r will remain close at the next point. The smallest values of entropy correspond to perfectly regular sequences. AE and SE increase as r decreases, as the sequence matching criterion becomes more stringent [33].

Entropy can be defined as a theory that quantifies the "regularity" and "complexity" of a system from its operation, when you have short data and noisy time series such as those related to biological systems. The calculation of MSE is done in discrete series $\{x_1, \dots, x_i, \dots, x_N\}$ divided into windows of constant length and not overlapping in size η , each window averages the data resulting in a new time series with a scale factor η , as follows:

$$y_k^\eta = \frac{1}{\eta} \sum_{i=(k-1)\eta+1}^{k\eta} x_i, 1 \leq k \leq N/\eta \quad (4)$$

MSE results are used to compare the relative complexity of standardized time series, which can be a differentiating measure in signals of biological origin [35-39]. Therefore, MSE is proposed as a feasible solution for the study of walking signals that may be associated with the risk of falling, showing in different aspects that entropy is higher in biological measurements of healthy individuals and representatively low in those with medical conditions.

3. MATERIALS AND METHODS

The experimental study was developed in three different phases: first, a literature review of the analysis of risk of falls in older adults, as a movement disorder and the existing diagnostic methods for this. Then, a measurement system is designed for the acquisition of the walking signals that is located above the ankle in older adults who are previously tested with the Tinetti scale. The captured signals have been processed with Fourier series and then the MSE technique is applied.

The analysis was performed on the X-axis of movement, since it is the one that presents the most similar results in all patients in terms of frequency. The results of the patients' walking signal are shown in Figure 1 where one of the signals has been highlighted from the rest to show its shape over time. In each of the patients' signals, the transients at the beginning and end of the gait have been suppressed to leave only the harmonic part collected during execution. The signals processed at frequency are shown in Figure 2. It can be seen that the signals are rated on a cycle per second or Hz scale with two prevalent frequencies around 0.9 Hz and 1.8 Hz for the 37 subjects under test. Fourier analysis is performed by means of the discrete Fourier transform as follows:

$$Y(k) = \sum_{j=1}^n X(j) W_n^{(j-1)(k-1)} \quad (5)$$

Finally, the third stage was carried out by installing the electronic device for acquiring signals related to the physiological behaviour of the subjects under study, which would allow the classification of the level of risk of falls. The procedure was standardized for bias control in the experiment: a wide field was organized for walking, the mobile device for signal recording was adapted to the older adult in the back of the, on the right ankle capturing the signals in an equal distance for all the subjects.

The population and sample were made up of 37 older adults from a vulnerable community in the city of Manizales, who showed no risk of falling according to the risk assessment scales provided. The inclusion criteria were: older adults with age-appropriate gait, age over 60 years. Older adults who had presented falls in the last 2 months due to possible recovery, which could alter the gait, and those who presented cognitive alteration due to difficulties in following the guidelines to carry out the experiment were excluded.

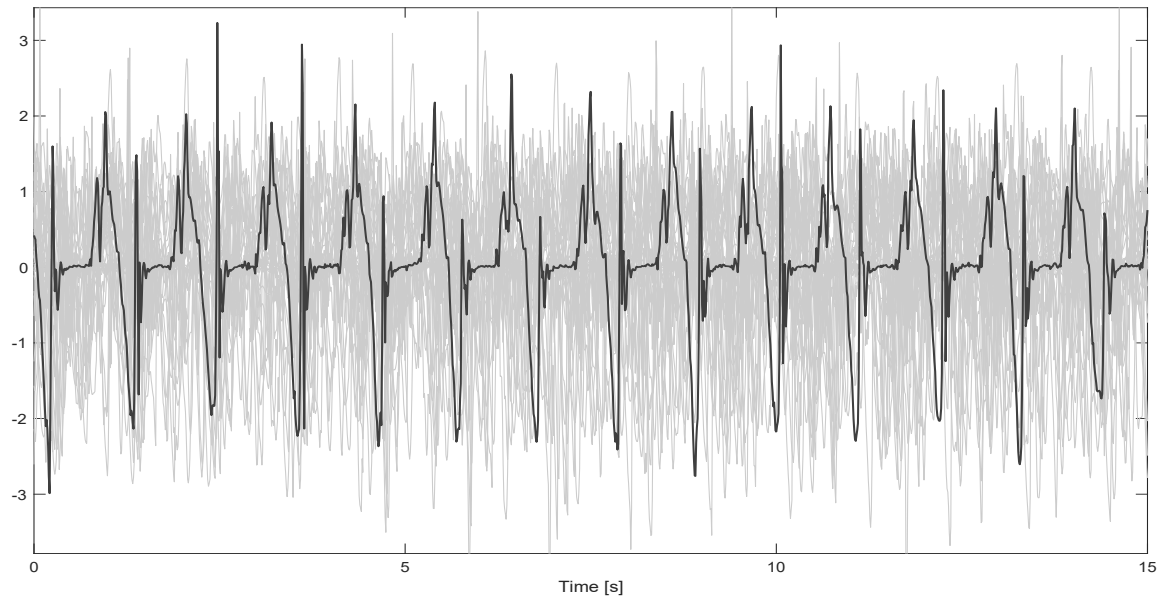


Figure 1. Signals captured in time for 15 seconds for all patients (one of the signals is highlighted to see its periodicity)

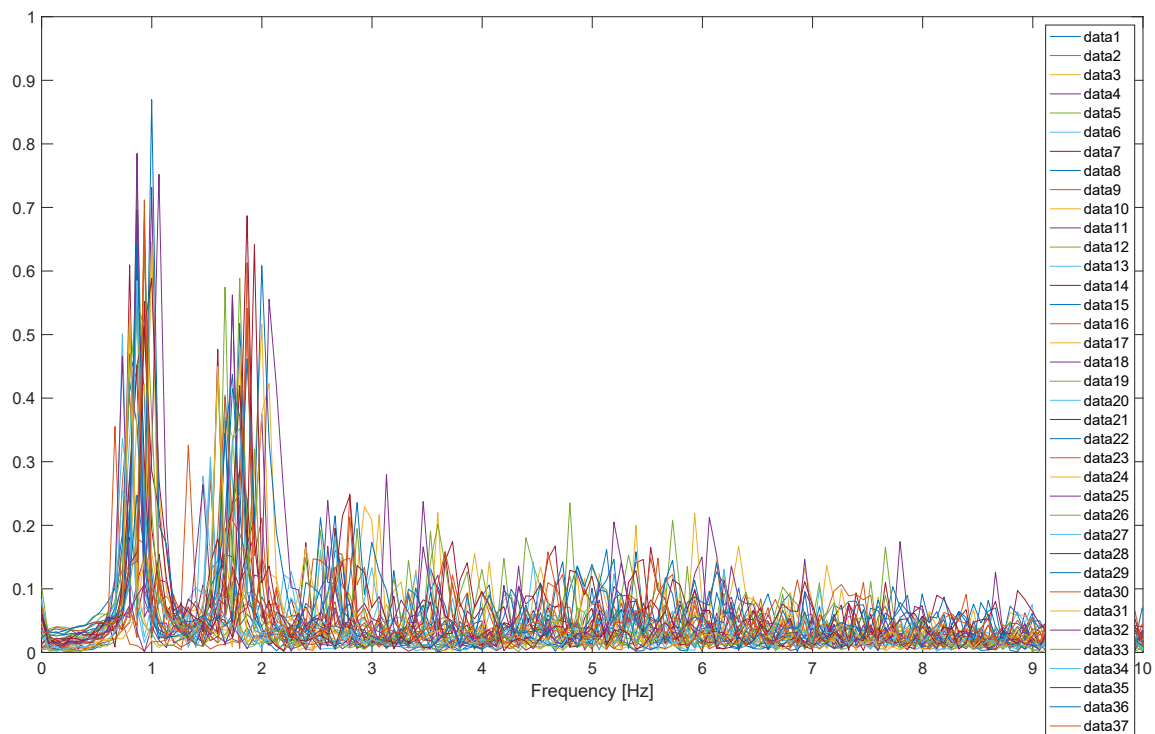


Figure 2. Frequency analysis of the data taken for the 37 individuals, shows the main frequency components grouped in the first three frequencies

4. RESULTS

Figure 3 presents the results for 20 MSE scales (vertical axis) of the data at the frequency for the 37 individuals under normal probability distributions for each scale (assumption that was previously corroborated by testing for normality of the sample data). With regard to person 24 it can be said that Tinetti test was performed giving a result without risk of falling. The results in Figure 3 show that person 24 is outside of statistical normality for almost all MSE scales.

In the SPPB test with person 24, an effective response was evident in each of the positions. The score obtained was 11 points in total, which clinically indicates low risk of falling. In relation to the Tinetti scale, which consists of a balance and gait test for the functional evaluation of the older adult, the maximum score corresponding to 28 points was found, which means low risk of falling. For the rest of the people in the sample, the risk of falling was found to be low according to the subjective scale applied (Tinetti and SPPB), however, after the study was completed, several people in the group reported falling. When analyzing the data obtained, it is found that the three people with reported falls are in the lowest points of the MSE scale (patients 9, 25 and 28) in Figure 4.

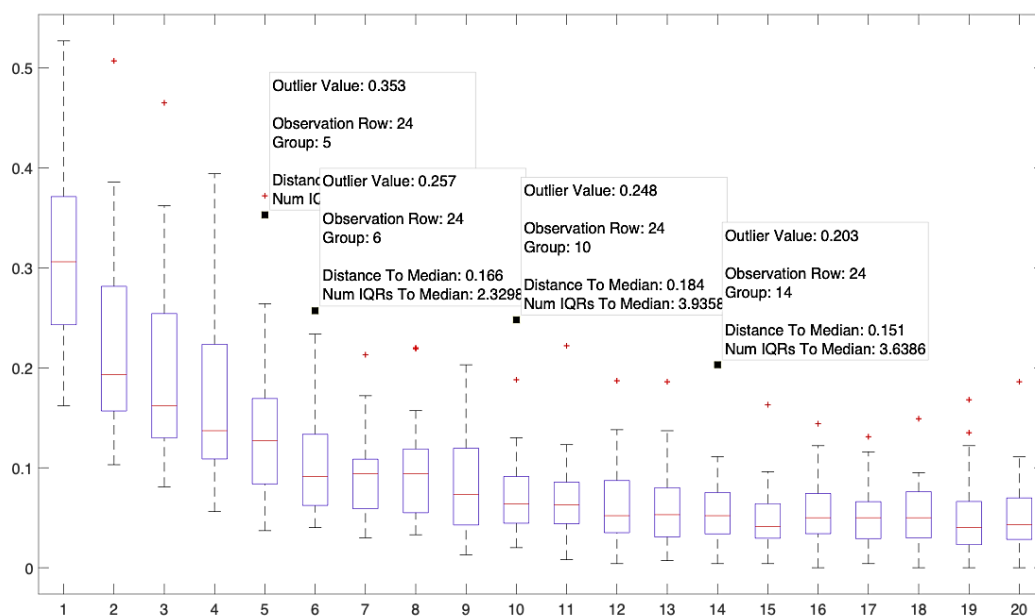


Figure 3. The data that are outside the distribution are analyzed by statistical method and it is determined that they belong to the person number 24

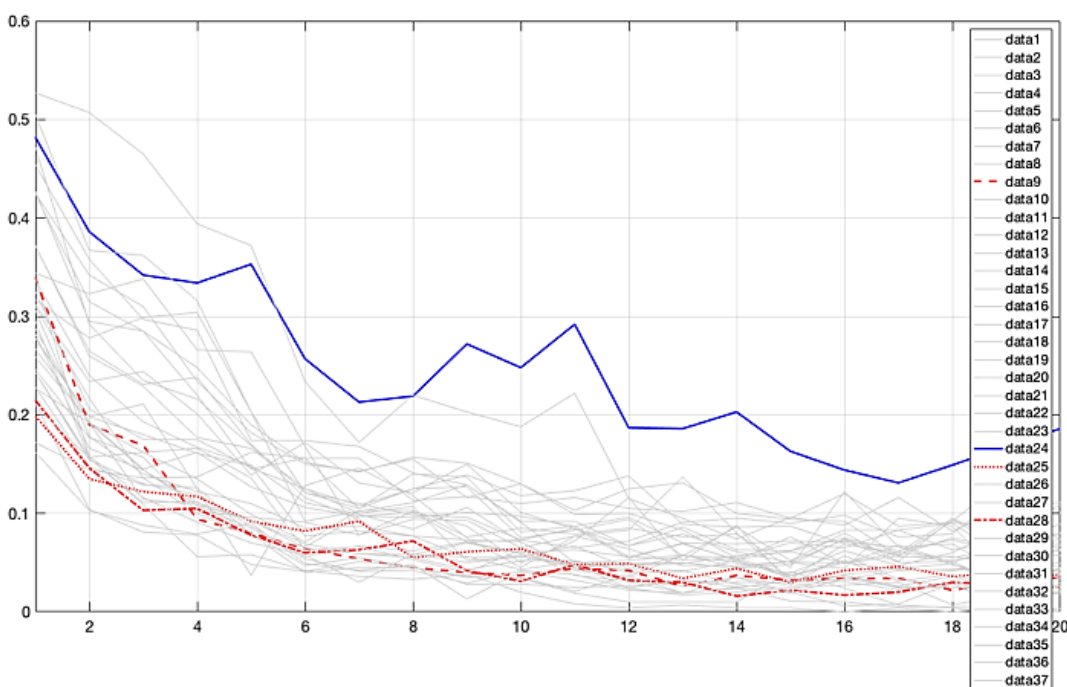


Figure 4. Comparison of the MSE scale for the 37 individuals where the result with the least risk of falling is highlighted (individual 24) and the people who have reported falling after the study (9, 25 and 28)

5. CONCLUSION

The mobile device, present in most people's lives today, can play an active role in the independent living of older adults by providing alerts during free living that are clinically relevant (bio) markers of fall risk. In addition, more accurate automated fall detection could improve living space and reduce the risk of falls. There is a need to consolidate the use of electronic devices and objective algorithms in the prevention and care of older adults, improving the quality of life and enabling timely and less costly care through prevention. This will allow the decentralization of medical care from hospital to home.

RESEARCH DATA FOR THIS ARTICLE

Due to the sensitive nature of the questions asked in this study, survey respondents were assured raw data would remain confidential and would not be shared. The data obtained with the app can be requested by e-mail to ygarces@ucm.edu.co for research purposes.

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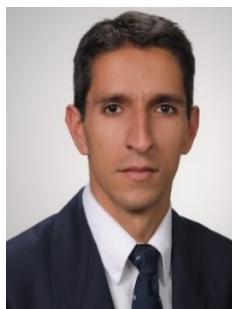
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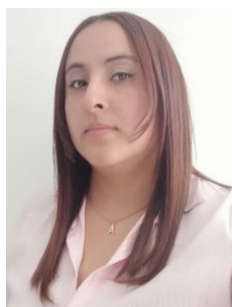
BIOGRAPHIES OF AUTHORS



Yeison Alberto Garcés-Gómez-Electronic Engineer, M. Sc (Eng) Industrial Automation, Ph.D. on Engineering. Associated Professor, UAFCNM, Universidad Católica de Manizales, Manizales, Colombia. E-mail: ygarces@ucm.edu.co. His research interests include applied technologies to healthcare and education, power definitions under no sinusoidal conditions, power quality analysis, and power electronic applications. He is member of the Research Group on Technological and Environmental Development GIDTA and Education and Educators Training EFE. <http://orcid.org/0000-0002-9409-3652>



Paula Andrea Duque-Nurse. M.Sc education and human development. Associated Professor. Universidad Católica de Manizales, Manizales, Colombia. E-mail: paduque@ucm.edu.co her research interests include to advances in innovation for the improvement of quality life. She is member of the Research Group of nursing GRIEN <https://orcid.org/0000-0001-7237-6195>.



Angela Viviana Alzate-García-Physical Engineer, M. Sc. (Eng) Physical Instrumentation. Instructor Proffesor, UAFCNM, Universidad Católica de Manizales, Manizales, Colombia. E-mail: angalzate@ucm.edu.co. Her interests contribute to technological applications based on physical properties that help in people's quality of life. <https://orcid.org/0000-0002-1987-1418>



Nicolás Toro received a B.S. in electrical engineering and Ph.D. in automatics from Universidad Nacional de Colombia, Manizales in 1983 and 2012, respectively, as well as an M.S. in production automatic systems from Universidad Tecnológica de Pereira, Colombia in 2000. He is currently an Associate Professor in the Department of Electrical Engineering, Electronics, and Computer Science, Universidad Nacional de Colombia, Sede de Manizales. His research interests include nonlinear control, nonlinear dynamics of nonsmooth systems, and power electronic converters. He is a member of the reasearch group in power resources GIRE (Código colombiano de registro: COL0144229), at Universidad Nacional de Colombia. <https://orcid.org/0000-0001-8317-4126>