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Fall Detection System by Machine Learning Framework for Public Health

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Abstract

The elderly population is growing every year in Brazil. Consequently, health risks in elderly is a concern for public health system. During the aging process, the mobility is affected, and falls are more frequent causing injuries and even death, whose causes can be prevented, with reduction of financial costs. Therefore, a low-cost inertial sensor-based system is a tool to fulfill the need for detecting falls in elderly. In this paper, we present our system as a proof of concept for the study of fall and we propose a low cost and more accessible system for fall detection using inertial sensors. The inertial sensor collects data, identifies and detect four different "fall states". The aim is to use this system in public health. In real-time, it will advise any person around the elder about the fall. Different machine learning classifiers are tested in the train dataset, and the best one was used for training the sensor data. Then, the model was compared with unknown sensor data (captured and from available datasets) to guess at which state the person is. We found out that there were only 15 wrong observations from all trials, thus, the system has potential to be used to detect falls.

Keywords: Fall; Machine Learning; Wearable devices; Inertial sensors; Public health

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1. Introduction

Fall detection technologies enable fast detection and intervention for individuals who have experienced a fall. This ability could reduce the physical and mental damage caused not only by the fall but time after the incident. These technologies can help to reassure those at a risk of falling, as well as their caregivers and family. In the future, these systems will help physiotherapist and other clinicians to clearly understand not only when the person experienced the fall, but also circumstances surrounding the fall, allowing for better treatment of the individual in question [1].

In addition, exaggerated spending on hospitalizations could be reduced if there were cheaper alternatives to falls surveillance. Therefore, this work investigated low-cost fall detectors to feed the need of the public health system to reduce costs and improve the quality of life of the elderly. Based on these factors, the chosen technology was inertial sensors, which are electronic devices that measure and report on an object's velocity, acceleration, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes and sometimes magnetometers [2].

Hence, the aim of this work is to propose a low-cost inertial sensor-based fall detection system of elderly population in Brazil by applying machine learning classifiers. The next section introduces machine learning concepts and techniques applied.

2. Machine Learning

Machine learning is the domain of science that explores the ability of machines to understand the data. It involves developing algorithms that would enable computers to learn complex patterns and make intelligent decisions based on that. Learning itself covers a broad range of processes that are hard to define [3]. It is possible to produce, quickly and automatically, frameworks that allow to analyze larger and more complex data and deliver faster, more accurate results - even on a very large scale. Therefore, machine learning forecasts can lead to better intelligent decisions and actions in real time without human intervention.

In the context of learning, the amount of data required by the learning algorithm in addition to time and space efficiency are important. Learning algorithms can solve many problems that can be easily applied to a broad class of learning processes, such as fall detection. Machine learning algorithm can model each problem differently based on the input data, so before getting into algorithms, it is important to analyze several learning classifiers broadly used. This way of organizing algorithms helps to choose the right algorithm to tackle a given problem based on the available input dataset and model preparation process and achieve efficient results. Machine learning algorithms can be divided into three different groups based on their learning style: Supervised learning; Unsupervised learning; and Reinforcement learning [4].

The present work is concerned with the supervised learning, which is one of the most important methodology in machine learning and it also has a central importance in the processing of multimedia data. It is a technique for deducing a function from training data. The training data consists of input and desired output data vectors. After the training data process, the machine framework is expected to find patterns in the data and relate it to the corresponding outputs. Therefore, one of the first decisions to be made is the choice of a machine learning algorithm. This involves a comparison of performance of different algorithms on a given data set. Then based on results such as accuracy of classification, time taken to build the model, and complexity of the algorithm, the most suitable algorithm depending on the requirements can be selected [3].

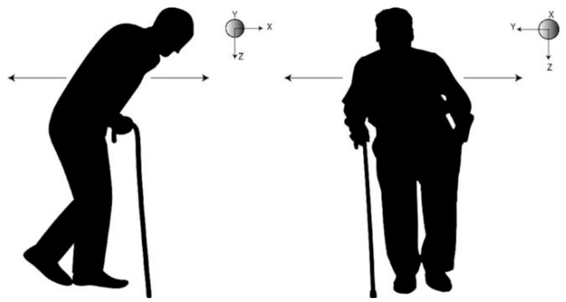
One of the most important things in supervised learning is the quality of the training data. If the machine is expected to perform well for unseen situations, then the training data must be exhaustive and accurate enough to enable the machine to build an appropriate model [4]. If the training data does not include the entire gamut of real-world situations, then the resulting model after supervised learning is prone to overfitting, e.g. it is not generalized enough and thus performs very good on the seen data, but poorly on the unseen one [3,4]. Another factor in supervised learning is classification, which is a part of supervised learning model where the algorithm predicts the class under which the new data fits. In this paper, we dealt with k-Nearest Neighbor. The k-Nearest Neighbor (kNN) algorithm is one of the most widely used classification algorithm due to its simplicity and easy implementation [5]. kNN is a type of lazy learning method because we do not need to train the algorithm but during the classification phase it goes through all the training data to calculate the Euclidian distance between them and input data and predicts the class of input data [6]. The advantages in this model are: training is very fast; simple and easy to learn; robust to noisy training data; and effective if training data is large. The disadvantages are biased by value of k; computation complexity; memory limitation; being a supervised learning lazy algorithm e.g. runs slowly; and easily fooled by irrelevant attributes [5,6]. Because we trained the model with offline data, these disadvantages are not an issue to this study.

3. Anatomy of the fall and incidence in the elderly population

The term fall can be defined as an unintentional event in which the body moves from its initial position to a lower level, with incapacity for immediate correction, and destabilizing the individual. The fall, as well as its resulting lesions, is now considered a public health problem, promoting social impact on countries with advanced aging population. In human anatomy conditions, a fall normally happens along one of two planes, called sagittal and coronal planes. Fig. 1(a) presents the sagittal plane, that is an X-Z imaginary plane that travels vertically from the top to the bottom of the body, dividing it into left and right sections. In this case a fall along the sagittal plane can happen forward or backward. Fig. 1(b) presents the coronal Y-Z plane, which isolates the body into dorsal and ventral (back and front) sections [7]. A loss in balance is indicated by toppling. Fig. 2(a) presents the body from a kinematic perspective [8]. At the point when the vertical line through the focal point of gravity lies outside the base of support the body begins toppling [8]. The body falls on the ground in case of no response to the loss of balance [8, 9].

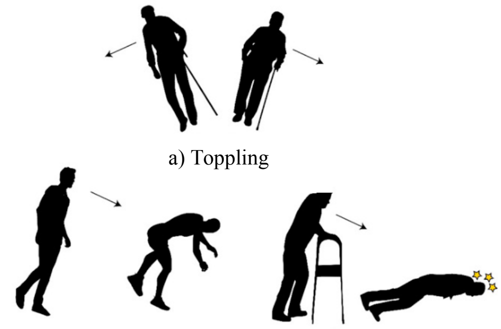
According to [8], the fall of a body from a stationary position is considered at stature h = H. At first the body has a potential energy mgh which is changed into kinetic energy amid the fall with the highest value just before the impact on the floor (h = 0). Amid the impact the energy is completely consumed by the body and, after the effect, both potential and kinetic energy are equivalent to zero. If the person is conscious the energy can be consumed by his muscles. [8] uses as an example using the arms (see Fig. 2(b)) and it is sufficient to cause injuries in elderly people, whereas if the person is unconscious it can induce to sever injuries (see Fig. 2(c)). Once the fall and in this way the impact on the floor happen, the person rests for a few seconds or even hours and after that tries to recuperate independent from anyone else or with the assistance of another person. Just before the impact, the body of the subject is in a free-fall, the gravitational acceleration is equal to its acceleration. Consequently, it is conceivable to distinguish five stages as de-tailed in Fig. 3: 1. Activity of daily living; 2. Unpredictable event 3. Free-fall; 4. Impact; 5. Recovery or unconscious state [8,9].

In Brazil, between 2012 and 2016, the elderly population (aged 60 and over) grew 16%, reaching 29.6 million [10]. This accelerated growth of the elderly population is occurring in several parts of the world, resulting in an increase in the prevalence of chronic-degenerative diseases, especially of "the great geriatric syndromes", among which are the falls [11]. Fall accidents involving older people become more recurrent. In reviewing the recent literature, [12] states that about 30% of the elderly with 65 years of age or more suffer one or more falls per year, which account for two-thirds of the dental deaths suffered by the elderly. [13] found a prevalence of falls in 37.2% of the cases studied. Most falls result from the interaction of factors related to the individual (intrinsic) and environmental (extrinsic) factors. Intrinsic factors include: age, previous falls, visual acuity reduction, dizziness, balance and gait disturbances, nervous system injuries, locomotor disorders, compromise of blood pressure regulating mechanisms (baroreceptors), which predispose orthostatic hypotension, cognitive disturbance, depression, and sleep disorders. Extrinsic factors are related to the conditions of floors, lighting, stairs, chairs, tables, beds, bathrooms, shoes, improper orthotics, physical barriers and use of more than four types of medications. The risk of falls is also higher in individuals after hospital admission, mainly in the first month after discharge [13].



a) Along sagittal plane b) Along coronal plane

Fig. 1. Fall directions.



a) Toppling

b) Conscious fall c) Unconscious fall

Fig. 2 Kinematic analysis of a fall.

a) Daily activity b) Unpredictable event c) Free-fall d) Impact e) Recovery

Fig. 3. Anatomy of a fall.

3.1. Costs and hospitalizations arising from falls

Falls are responsible for high costs, not only for their care, but also for later treatment of the consequences caused [14]. The Unified Health System (SUS), the public health system of Brazil, annually registers more than 51 million Reais (Brazilian currency) spent on treatment of fractures due to falls [15]. A report from the Brazilian Government [13] found results of the total number of hospital admissions due to falls in Brazilian hospital units under SUS, between 2005 and 2010, was 399,681 hospitalizations. Of these, 40,228% (160,747) occurred in males and 59.78% (238,934) in female patients, and the total number of female admissions remained higher than male admissions during the whole period analyzed.

When analyzing the costs of hospital admissions due to elderly population, it has been found that these are becoming higher, corresponding to R$ 464,874,275.91 between 2005 and 2010 [14].

Regarding the services offered by SUS, there is no hypothesis that the costs of the procedures performed on the elderly are more expensive than those of the younger ages [16]. The increase in health expenditures of the elderly is not explained by the increase in the costs of the procedures and, rather, by the frequency of hospitalizations [17]. Public health measures aimed at improving the quality of elderly health care, while not necessarily increasing expenditures, should prioritize a reduction in the number of hospitalizations [13,18]. Some alternatives are programs of fall prevention and fall detection systems.

3.2. Technological approaches for fall detection

According to [8], there are three primary classifications of systems in motion capture that are used to detect fall: Vision-based; environmental; and wearable.

A Vision-based approach utilizes immovable cameras that frequently record the movement of the patients. The information is submitted to image algorithms that can perceive the pattern of a fall to generate an alert. Vision-based methodologies can be restricted to inactivity identification, e.g., the patient lies on the floor without moving after the fall and body shape change analysis, e.g. in view of the difference in pose after the fall. Finally, 3D head movement investigation, e.g. in view of the observing the position and velocity of the head. Using this visual based system to capture motion offers some advantages, for example, it is possible to identify the details of complex movements and low latency (close to real-time). However, the problems of this approach are the time and installation cost, the constrained space of use (just where there are the cameras), and privacy violation.

The utilization of environmental devices is an approach that sensors are installed in the places to be monitored [8]. When people interact with the environment, infrared or pressure sensors on the floor can identify a fall. The problem here is the existence of false negatives, for example, a fall that happens on a table is not detected. Both Visual-based and Environmental device approaches lack a pre-built infrastructure, and this allows their use in hospitals and houses, and the primary disadvantage is the difficulty to use the system outdoor [8].

In the Wearable approach, at least one wearable device is used by the patient. They are normally outfitted with movement sensors, for example, accelerometers and gyro-scopes, whose data are transmitted by means of radio and investigated [8,19]. This solution offers points of interest, for example, low installation cost (indoor and outdoor), small size, long battery duration, and offers the possibility to also collect physiological information (pulse, ECG, EEG and so on.). In the marketplace, there are wide range of wearable sensors that can be used to monitor the human motion activity, which can be classify as mechanical, magnetic or inertial.

The mechanical motion capture sensors are typically exoskeleton structures wireless and directly track body joint angles, they are also known as suits, some of them can provide haptic feedback, there is no interference from lights and magnetic field, however, the sensors make noises and the price compare to the others wearable sensors is relatively expensive [20]. The magnetic sensors capture the orientation and position by the relative magnetic flux of three orthogonal coils on both the transmitter and each receiver [21], the advantages are the positions and rotations captured are absolute and relatively cheaper than the vision-based approach, the main draw-backs are the magnetic distortion and the system are susceptible to others magnetic fields. The inertial motion capture sensors use inertial measurement units (IMUs) containing a combination of gyroscope, magnetometer, and accelerometer, to measure rotational rates. These rotations can be translated to a skeleton structure. The inertial motion capture technology is cheaper compare to the others motion capture systems [22].

Thus, this project is using the inertial motion sensor technology due the fact of the advantage of low installation cost, the freedom to use the sensors indoor and outdoor and for the small size.

4. Materials and Methods

This section deals with materials and methods applied in this study. The aim of this project is to apply a classification protocol with a train dataset from an IMU sensor using machine learning techniques and fall detection alert as output, as it is showed in the block diagram in Fig 4.

Data were collected from participants as they completed the movement of walking, crouch, lie down and then get up 10 times. These repetitions were recorded using an Inertial Measurement Unit (IMU) sensor from Shimmer Company. To process the dataset, we used MATLAB platform. Data from a Shimmer IMU were collected in healthy participants after signing in-formation and consent forms. A pilot study was used to determine an appropriate sampling rate and the ranges for the IMU sensor. The Shimmer sensor was configured to stream tri-axial accelerometer, magnetometer and gyroscope data. A multi-function MATLAB script was developed to perform the following capture protocol: sampling frequency of all sensors was defined to be 52Hz; internal configuration of each IMU; synchronization between the sensors; start/stop IMU system data capture. Pseudo code for this algorithm is provided in Fig.6. The testing protocol was explained to the participants which was, to walk a short distance, lie down and stand up 10 times each participant, following this, the IMU was secure placed on them between the 5th lumbar vertebra and sacrum per Fig. 5. After that, they completed a 5-minute practice exercise and then the actual experiment started.

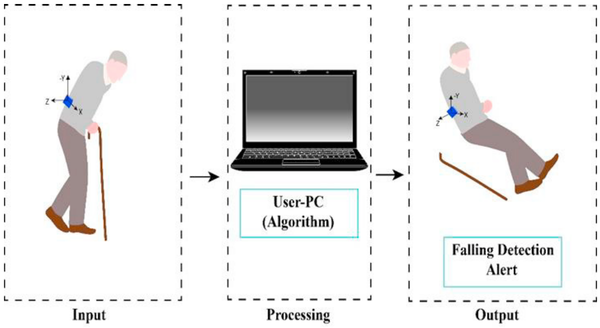


Fig.4. Block Diagram of the system.

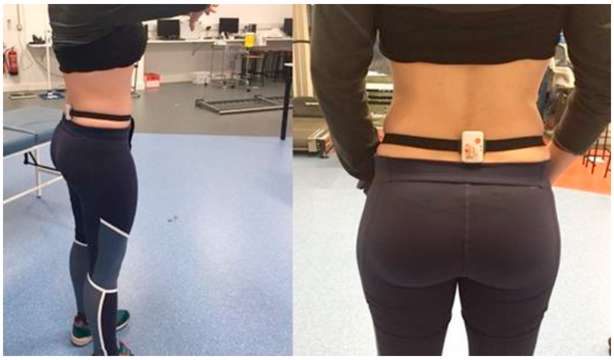


Fig. 5. Sensor placement.

Algorithm 1: Multi IMU Streamer

```
function MultiShimmer(comPorts, jointNames, captureTime)
Input: comPorts (one for each IMU), joint names, and capture time
Output: The .csv files containing each IMU data
        if all sensors are connected through BT protocol then
            Define IMU Handle Class instance;
            Define sample rate;
            Set internal board to 9DOF;
            Enable Shimmer internal sensors (Acc, Gyro, Mag);
            if Shimmers are ready to capture then
                Start assessment
                Audio alert
            while elapsedTime < captureTime do
                Write data in CSV file
                Generate orientation
            end while
            Stop assessment and capture
            Audio alert
        Write the percentage of received packets to detect any lost information
        end
        Disconnect Shimmers
    end
end
```

. Fig. 6. Algorithm for synchronization between sensors.

The Machine Learning framework from MATLAB provides classification algorithms, including support vector machines (SVMs), boosted and bagged decision trees, k-nearest neighbour, k-mean, hidden Markov models and others. In this experiment, the framework investigated each of those algorithms and the algorithm with best accuracy was selected. 2416 observations from all trials using wearable inertial sensor were captured. In the training dataset, 6 predictors were obtained from tri-axial accelerometer (Acc_{xyz}) and triaxial Gyroscope ($Gyro_{xyz}$) and were classified in 1-4 depending on state of the trials (1: Standing, 2: Bed, 3: Fall, 4: Unconscious state) These states were defined for being the indicatives of the falling process.

5. Results and Discussion

After testing the dataset against several models, we selected the fine k-Nearest Neighbor algorithm (kNN) due to its higher accuracy against other models per Table. 1. The fine kNN algorithm had accuracy of 99.4% and training time of 13.6s. From the confusion matrix (Fig. 7), it is possible to see mean 98.75% of total true positive rate, which means the system can alert falling when it really happened. It is important to highlight that we had a small number of false negative, when the patient falls but the system cannot predict correctly.

Table 1. Model 1.4 KNN results

1.1 ☆Tree Last change: Complex Tree	Accuracy: 98.3% 6/6 features
1.2 ☆Tree Last change: Medium Tree	Accuracy: 98.3% 6/6 features
1.3 ☆Tree Last change: Simple Tree	Accuracy: 93.4% 6/6 features
1.4 ★KNN Last change: Fine KNN	Accuracy: **99.4%** 6/6 features
1.5 ☆KNN Last change: Medium KNN	Accuracy: 98.4% 6/6 features
1.6 ☆KNN Last change: Coarse KNN	Accuracy: 90.3% 6/6 features
1.7 ☆KNN Last change: Cosine KNN	Accuracy: 98.6% 6/6 features
1.8 ☆KNN Last change: Cubic KNN	Accuracy: 98.3% 6/6 features
1.9 ☆KNN Last change: Weighted KNN	Accuracy: 98.5% 6/6 features
2 ☆KNN Last change: Medium KNN	[Draft] 6/6 features

Fig. 7. Confusion Matrix model 1.4 Fine KNN.

To test the trained model, we have selected unknown data from different trials from inertial sensor following same experimental protocol. In this dataset, 1519 observations of unclassified data were tested. Confusion matrix in Table 2 shows the number of misclassified observations. 15 observations were classified as 3 – Fall but they were 4 – Unconscious. Those mistaken predictions are not a drawback of our system because even with an unconscious prediction, the system will alert, and the person can be aided.

Table 2. Confusion Matrix for the classifier in unknown data

Activity	1	2	3	4
1 = Standing	713	0	0	0
2 = Bed	0	458	0	0
3 = Fall	0	0	52	15
4 = Unconscious	0	0	0	281

6. Conclusion

In summary, falls represent a serious public health problem, the dimension of which has been a problem that cannot be overlooked by the Brazilian society and government. In addition, falls are, in fact, multifactorial morbid events, causing injuries, emotional disturbances, functional and death, whose causes can be diagnosed and prevented, with consequent reduction of morbidity, mortality and financial costs. To increase this prevention, it is necessary to educate the community, to train professionals, and to apply validated protocols for assessment and intervention at the primary health care level by appropriately trained teams [11].

This work presented a review of fall in Brazilian public health and proposed a wearable detection approach using Machine Learning classifiers. We have trained a model with acceleration and gyroscope data from an inertial measurement unit and tested the model with unknown data. Our results have demonstrated the utility of using or detection system in public health with a few 15 false positives. Based on these results, many potential use cases of the fall detection system can be proposed. The system is cheaper, easy to be set up, is easily portable and can be used in any environment. Future work will include the use of this system for refined detection and use in real time of falling detection that can be applied towards benefit of Brazilian Public Health System.

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References

[1] Chaudhuri S, Thompson H, Demiris G (2014) Fall Detection Devices and Their Use with Older Adults. Journal of Geriatric Physical Therapy 37:178–196

[2] Kempe V (2011) Inertial MEMS: principles and practice. Cambridge Univ. Press, Cambridge

[3] Choi Y, Ralhan AS, Ko S (2011) A Study on Machine Learning Algorithms for Fall Detection and Movement Classification. 2011 International Conference on Information Science and Applications. doi: 10.1109/icisa.2011.5772404

[4] Subbu, Ramesh: Brief Study of Classification Algorithms in Machine Learning. CUNY Academic Works (2017).

[5] Bhatia, Nitin: Survey of Nearest Neighbor Techniques. (IJCSIS) International Journal of Computer Science and Information Security, Vol. 8, No. 2 (2010).

[6] Li L, Zhang Y, Zhao Y (2008) k-Nearest Neighbors for automated classification of celestial objects. Science in China Series G: Physics, Mechanics and Astronomy 51:916–922

[7] Tako K.V.: Profile and prevalence of falls in elderly. J Nurs UFPE on line., 11(Suppl. 11):4687-91, (2017).

[8] Abbate S.: Monitoring of Human Movements for Fall Detection and Activities Recognition in Elderly Care Using Wireless Sensor Network: a Survey, Wireless Sensor Networks: Application - Centric Design, Yen Kheng Tan (Ed.) (2010).

[9] Chapman, A.: Biomechanical Analysis of Fundamental Human Movements. 1st edn. Human Kinetics. United States (2008).

[10] Barroso M IBGE | Agência de Notícias | PNAD 2016: população idosa cresce 16,0% frente a 2012 e chega a 29,6 milhões. In: IBGE - Agência de Notícias. https://agenciadenoticias.ibge.gov.br/agencia-noticias/2013-agencia-de-noticias/releases/18263-pnad-2016-populacao-idosa-cresce-16-0-frente-a-2012-e-chega-a-29-6-milhoes.html. Accessed 10 Apr 2018

[11] Maciel, A.: Falls in the elderly: a public health problem unknown by the community and neglected by many health professionals and by Brazilian health authorities. Rev Med Minas Gerais. 20(4): 554-557. (2010).

[12] Almeida, L. P. D., Brites, M. D. F..: Quedas em idosos: fatores de risco. vol. 8, pp. 384-391 Rbceh (2011).

[13] Quedas. In: brasil.gov.br. http://www.brasil.gov.br/saude/2012/04/quedas. Accessed 10 Apr 2018

[14] Ferreira DCDO, Yoshitome AY (2010) Prevalência e caraterísticas das quedas de idosos institucionalizados. Revista Brasileira de Enfermagem 63:991–997

[15] Carvalho, A. M..: Demência como fator de risco para fraturas graves em idosos. Revista Saude Publica, 448-454 (2002).

[16] Barros, I.F.O.de.: Hospitalizations due to falls among elderly Brazilians and related costs under the Public Health System. Revista Kairós Gerontologia, 18(4), 63-80 (2015).

[17] Laurenti, R.: Doença isquêmica do coração Internações, tempo de permanência e gastos Brasil, 1993 a 1997. Arquivos Brasileiros de Cardiologia, 74(6), 483-487 (2000).

[18] Iunes, R.F.: Impacto econômico das causas externas no Brasil: um esforço de mensuração. Revista de Saude Publica, 38-46 (2007).

[19] (2018) Review of Wearable Device Technology and Its Applications to the Mining Industry. Energies 11:547

[20] Gmiterko A, Lipták T. Motion capture of human for interaction with service robot. American Journal of Mechanical Engineering. 2013;1(7):212-6.

[21] Fourati H, Manamanni N, Afilal L, Handrich Y. Complementary observer for body segments motion capturing by inertial and magnetic sensors. IEEE/ASME Transactions on Mechatronics. 2014 Feb;19(1):149-57.

[22] Alberts JL, Hirsch JR, Koop MM, Schindler DD, Kana DE, Linder SM, Campbell S, Thota AK. Using accelerometer and gyroscopic measures to quantify postural stability. Journal of athletic training. 2015 Jun;50(6):578-88.