Nyon: A Ubiquitous Fall Detection Device for Elders

Cassandra Sofia dos Santos Jesus[1][0000-0003-2649-9375], Ana Rafaela Rosa[1][0000-0002-9472-1954]
and Rogério Pais Dionísio[1,2][0000-0002-6810-2447]

[1] Polytechnic Institute of Castelo Branco, 6000-084 Castelo Branco, Portugal
[2] DiSAC – Digital Services, Applications and Contents, 6000-767 Castelo Branco, Portugal
`rdionisio@ipcb.pt`

Abstract. Falls are one of the main causes of mortality and morbidity in the elderly worldwide. This had let to the research and development of electronic fall-detection systems. We propose a complete fall-detection system, that combines a wearable device (called Nyon) and a message microservice (for email and SMS) to alert caregiver every time a fall occurs. The wearable uses a simple threshold method and has the capability of search and switch between Wi-Fi and Bluetooth, using the available communication technology when a fall occurs. The results have shown that the wearable autonomy is adequate for a daily use and the server microservices are reliable and deliver a message to the caregiver every time a fall alert occurs. Several improvements are planned to increase the autonomy and range of the wearable device.

Keywords: Wi-Fi, Bluetooth, MQTT, Fall detection algorithm, Threshold detection, ROC.

1 Introduction

1.1 Scope

The topic of aging in populations has gained prominence around the world, particularly in more developed countries, such as in Europe, where the highest rates of aging are recorded worldwide.

In 2021, Portugal ranked 4th in the list of the oldest countries in Europe, only surpassed by Italy, Greece, and Finland [1], with an aging index of 182.1 [2]. This scenario poses a set of challenges to which Portuguese society must respond effectively.

Aging is a natural, continuous and inevitable process, guided by numerous biopsychosocial changes, which can represent losses and/or gains [3] and lead to a functional decline, making the elderly more vulnerable, which, in turn, increases the probability of developing pathologies, and consequently increases the risk of falling [4].

Falls are one of the main causes of mortality and morbidity in the elderly worldwide and can be defined as an unexpected event, in which the individual moves, unintentionally, from the level where he is or from a higher level to a lower one [5]. It is estimated that in the European Union, the need for health services that respond to falls and consequent hip fracture can cost approximately 37 billion euros, which in Portugal can reach 216 million Euros [6]. In the population over 65 years of age, falls can be the cause of numerous hospitalizations, institutionalization, and premature death, which contributes to the loss of functional capacity, increased consumption of health resources and, above all, loss of quality of life [7]. In Portugal, the prevalence of injuries from falls rises to 76 % in the 65-74 age group, reaching 90 % in the group of people aged 75 and over [8].

The pandemic caused by the Sars-Cov-2 virus has increased the loneliness and isolation of elderly people, particularly those living in rural areas, two of the most important risk factors for falls in this population [9].

It is in this context, and given the fact that the Castelo Branco district has one of the highest aging rates in the interior of Portugal (213.7) [10] and where 1,826 elderly people living isolated or in a vulnerable situation in the district were counted by the National Security Police [11], that the technological revolution can make a great contribution to improving and facilitating aging in the community, in the sense that they can support the performance of Activities of Daily Living (ADLs), the monitoring of vital parameters while improving safety, mobility, communication and monitoring of the elderly [12]. There are authors who argue that a quick response after a fall considerably reduces the number of consequences inherent to it [13].

1.2 State of the Art

The Internet of Things (IoT) allows a pervasive a seamless interaction between objects, sensors, and computing devices. An important part of the IoT ecosystem are the embedded systems, combining wireless communications and fall-detection sensors.

Recently, many articles have been focusing on the development and testing of fall-detection wearable devices. In [14], the authors review the main hardware and software components involved in a fall-detection system for elderly.

There are two approaches to fall detection using wearable sensors—threshold-based systems and machine learning-based systems. Threshold-based algorithms are typically designed to minimize computational overhead [16]. Most fall detection studies trained their models in an offline mode with a single sensor on personal computers. In studies that used wearable devices, most of them applied wireless methods, such as Bluetooth, which allowed the subject to move unrestricted.

Other research studies have included Electroencephalogram (EEG) in fall detection devices [15]. But there is still much work to do, as EEG systems are normally bulky, mainly used in hospital for seizure detection, which is not portable at all.

Many new and important developments have been made to tackle the best detection algorithm and process for early fall-detection in elderly, but still, wore work must be done to improve the feasibility and reliability of fall-detection devices in real scenarios, especially when elder people are still capable of moving in and out of their house. From a point-of-view of wireless communication ubiquity and battery autonomy, most of the recent works do not include additional input on that question, as mentioned in [17].

1.3 Objectives

With this paper, we propose to combine several wireless technologies into a single fall-detection device, using a 3-axis acceleration sensor and a common algorithm that requires very low energy consumption to detect falls with adequate reliability, and that transmit alerts using the available wireless communication system (indoor or outdoor) when the fall is detected.

The present work is divided into 5 sections: the introduction section presents a brief review of what has been done and developed in recent years, regarding fall detection devices and operation and the objectives of this work; then the methodology used in the development of the Nyon wearable device is described, followed by the description of a ubiquitous prototype in terms of communication technology, implemented with a low consumption device. Finally, the results and respective discussion will be presented, and we finalize with the main conclusions.

2 Fall-detection Methodology

The fall-detection methodology was divided into two distinct processes. First, we execute several trials with an accelerometer and measuring devices to create a proprietary dataset (not describe in this paper). Then, we implement a fall-detection and alert system, including the design and production of a wearable device incorporating the same accelerometer from the one used in the dataset construction, with information on three independent acceleration axes: x, y and z.

2.1 Fall Detection Features

Fall-detection algorithms can be classified into two types: Simple threshold method or Machine Learning (ML) methods. In the simple threshold method, threshold values of specific parameters calculated from sensor data, such as 3-axial acceleration or gyroscope, are used to detect a fall event [18]. They have low computational requirements and are simple to implement on a wearable device. The ML method is more complex and leads to better detection rates compared to simple threshold methods. however, it is difficult to implement the ML approach in battery powered wearable devices due to the heavy computational and energy resource requirements [19].

To detect a fall event, Nyon wearable uses a simple threshold-based fall detection feature called Differential Sum Vector Magnitude (A_{DSVM}) [20], computed using the following equation,

$$A_{DSVM}(n) = \sqrt{(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2 + (z_n - z_{n-1})^2} \tag{1}$$

where x, y and z are the three independent variables from the acceleration axes and n denotes the sample number.

From a proprietary dataset, several scenarios with fall-event sequences were realized using a common accelerometer sensor and a measurement system (not descried in this paper). Data sequences were collected and stored as a csv file, with x, y, z acceleration measured in g (gravity acceleration) and timestamp measured in second. Fig. 1 shows the computed A_{DSVM} of one the sequences with three predefined (black line) fall-events. Mean duration of a fall-event takes 0.45 seconds.

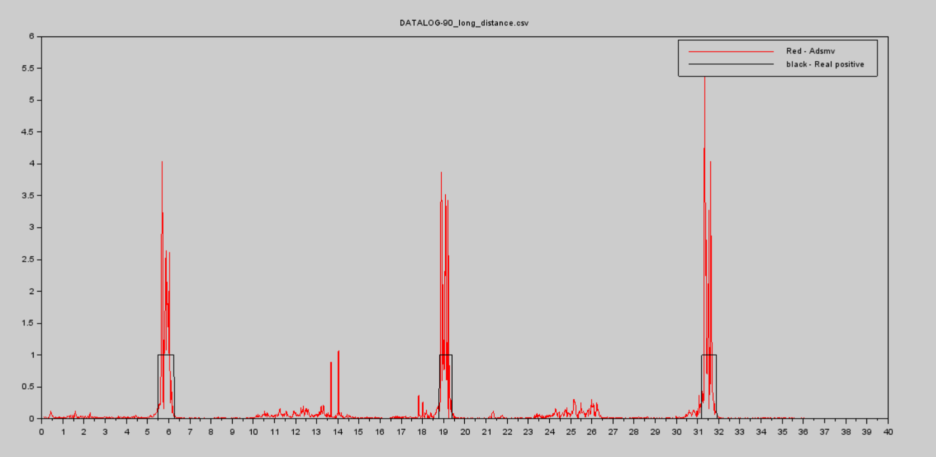

Fig. 1. A_{DSVM} results from one of the time sequences of the dataset, with three fall events: black: True Positive (1) and True Negative (0); red: A_{DSVM} computation.

2.2 Receiver Operating Characteristics Curve

The receiver operating characteristics (ROC) curve shown in Fig. 2.

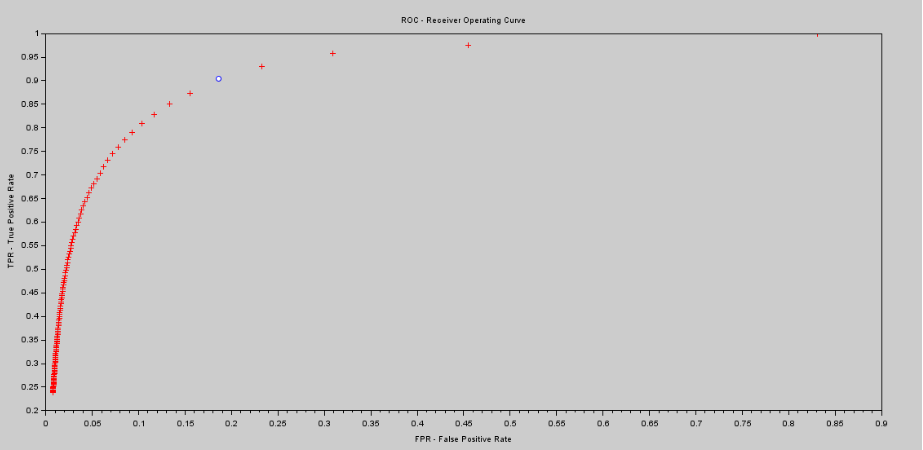

Fig. 2. Receiver operating curve of the fall detection device.

The ROC curve is generated from True positive Rate (TPR) and False Positive Rate (FPR) vectors, calculated for all A_{DSVM} values,

$$TPR = \frac{TP}{TP+FN} \tag{2}$$

$$FPR = \frac{FP}{FP+TN} \tag{3}$$

where TP stands for True Positive, FN is False Negative, FP is False Positive, and TN mean True Negative.

The best threshold is determined from the ROC curve, when the amplitude between TPR and FPR is maximum, as represented by the code snippet from Fig. 3.

```
ampl = TPR-FPR;
best_ampl = find(ampl==max(ampl));
best_th = vect_th(best_ampl);
```

Fig. 3. Pseudo-code of the threshold computation.

The white dot visible in Fig. 2. is the optimal threshold (0.35), when TPR = 90 % and FPR = 22 %.

2.3 Algorithm

The fall-feature parameters are applied to the simple threshold method to determine whether the computed A_{DSVM} parameter is above a certain threshold (0.35) within a time interval (0,45 s). If any parameter is above a threshold, the sample is determined to be a possible fall indicating a subject fall event or ADL like a fall event. The fall-detection algorithm programmed in the Nyon wearable device is shown in Fig. 4.

```
if $A_{DSVM}$ value > threshold value
    if elapsed time < Fall interval
        count++
        if count > N_Samples
            count=0
            return fall detection
    else
        reset elapsed time
else
    return no fall detection (ADL)
```

Fig. 4. Pseudo-code of the fall detection algorithm.

3 Implementation

3.1 System architecture

The proposed System is based on a cloud architecture. The wearable sensor device has two different communications technologies, Wi-Fi and Bluetooth and will switch between them automatically when one of them is unavailable. When a known Wi-Fi access point (AP) is nearby and available, the fall detection device will first try to connect through it to a cloud server, using MQTT protocol. On the other side, when the elder is outside his home, in the garden or farm, and not in reach of a Wi-Fi AP, the fall detection device will try the connection from the elder's mobile phone using a Bluetooth connection. In either case, the Cloud server will send an alert to the caregiver using SMS messages or an e-mail. A diagram of the proposed system is depicted in Fig. 5.

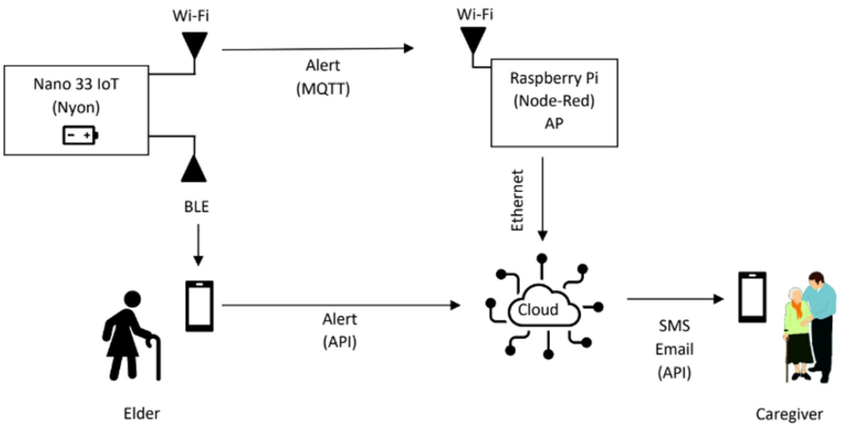

Fig. 5. Diagram of the proposed system for the fall detection device

3.2 Hardware and Software Description

The Nyon fall-detection system consists of an Arduino Nano 33 IoT board, that incorporates a ±4 g triaxial accelerometer (LSM6DS3) and a wireless communication module (NINA-W102) to enable Bluetooth and Wi-Fi connectivity; The wearable system is small enough to be weared as a bracelet, a collar, incorporated into hat or clothes. A gateway (Raspberry Pi 3) collects information from one or multiple wireless wearable devices, and a Cloud server (LAMP) send SMS and e-mails to the caregivers. The wearable sensor node is powered by two 12 V batteries (MN21), as shown in Fig. 6.

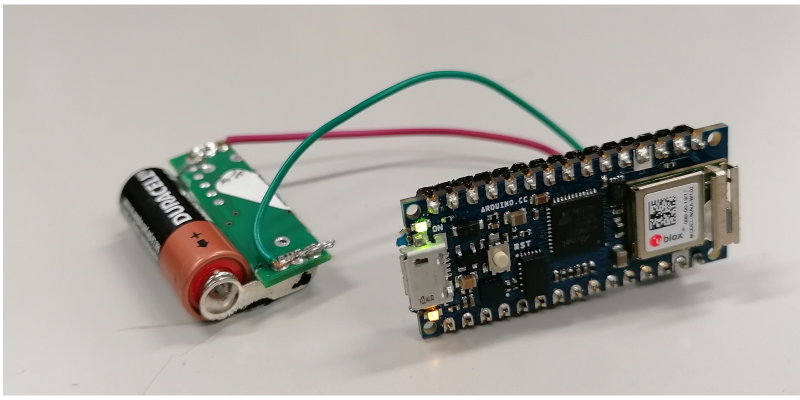

Fig. 6. Nyon wearable device prototype.

The wearable sensor node was programmed using C language form Arduino IDE, including all the necessary libraries. The server-side application was programmed using Node-Red. The Android App was created with pfodDesignerV3 (V3.0.3774+), to generate the general purpose BLE connection for the Nyon wearable device, when Wi-Fi is not available.

4 Experimental Results

4.1 Autonomy

Table 1 shows the instantaneous current measurements from different operation modes of the wearable fall-detection sensor and the computed autonomy when the device is powered with two 12 V battery, each with 60 mAh of stored energy.

Considering that the fall detection algorithm running on the wearable device continuously pools the accelerometer sensor, the baseline instantaneous current is 7 mA and the autonomy is approximately 17 hours. This value could be increased using a timer interrupt-based approach to measure acceleration, reducing the power consumption of the device, and keeping it periodically in sleep mode between measurements.

Table 1. Current and autonomy for each operating mode of the wearable device

Operation Mode	Current (mA)	Autonomy (hours)
Wi-Fi and Bluetooth disconnected	7	17,14
Connecting to Wi-Fi AP	45	2,67
Connected to Wi-Fi AP	22	5,45
Connecting to Bluetooth (SCAN)	56	2,14
Connected to Bluetooth	10	12,00

The worst case is present when the wearable device searches for a Wi-Fi AP or a mobile phone using BLE to connect. After being connected, either through Wi-Fi or Bluetooth, the device will stay in that operation mode only the time necessary time to send the alert, then returns in a lower power consumption mode. Thus, in general, the wearable must be recharged every day to be kept operational.

4.2 Email and Text Message Microservices

Several microservices were created in the cloud server to receive alerts and send SMS and email messages. The software running the microservices on the cloud server is Node-RED. Fig. 7 shows the flow running the microservice that is responsible to receive fall-detection messages from the wearable device, by subscribing to the topic *arduino/fall*. Every time the wearable device publishes a message with the same topic, the MQTT broker (running on the Cloud server) will distribute the information to all the subscribers of that topic.

To use Google Gmail (www.gmail.com) for sending email or Vonage (www.vonage.com) for sending SMS, we have created an account with each of them.

When creating an account, we get various credentials needed to configure both nodes (*Send SMS* and *email*) for the first time. Both services are proven being reliable and have delivered the messages in all cases.

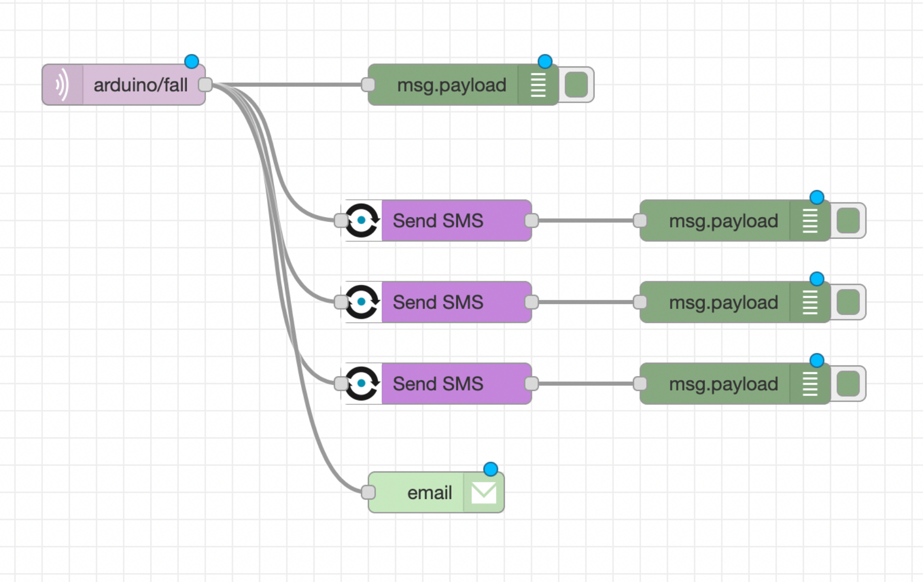

Fig. 7. Node-Red flow for receiving alerts from MQTT and to send SMS and emails.

5 Conclusions

We propose a complete system to detect fall in elder people. The system combines a simple threshold method with a 3-axis accelerometer. Because the proposed algorithm is simple, it can be into an embedded system such as the Arduino Nano 33 IoT.

The proposed wearable device can seamlessly switch between Wi-Fi and Bluetooth, using the communication technology that is available when the fall occurs.

One of the limitations of this work is that the wearable device in continuously pooling data from the accelerometer, draining energy from the batteries, and reducing the autonomy of the device. Further research is required to improve the performance of the proposed wearable device, using an interrupt-based approach to sense fall with the accelerometer. A wireless charging module could also benefit the elder when recharging the device.

Another line of research is to add LoRa communication technology into the wearable device, and increase the possibility of an alert being received by caregiver, when the elder does not have a mobile phone with him and the fall occurs outdoor, or in places out of reach of a Wi-Fi AP.

References

1. EUROSTAT. (2021). Archive: Estrutura populacional e envelhecimento. EUROSTAT. https://ec.europa.eu/eurostat/statisticsexplained/index.php?title=Population_structure_and_ageing/pt&oldid=510113 , last accessed 2021/12/20.
2. PORDATA. (2021). Indicadores de envelhecimento segundo os Censos. PORDATA. https://www.pordata.pt/Portugal/Indicadores+de+envelhecimento+segundo+os+Censos++-525 , last accessed 2022/06/20.
3. Berger, L., & Mailloux-Poirier, D. (1995). Pessoas Idosas: Uma abordagem global. (Edição revista e corrigida). Lusodidacta
4. Silva, L., Oliveira, F., Martins, I., Martins, F., Garcia, T., & Sousa, A. (2019). Avaliação da funcionalidade e mobilidade de idosos comunitários na atenção primária à saúde. Revista Brasileira de Geriatria e Gerontologia, 22(5), 1-10. http://dx.doi.org/10.1590/1981-22562019022.190086
5. World Health Organization. 2018. Falls. WHO. https://www.who.int/news-room/fact-sheets/detail/falls
6. Venâncio, B., Almeida, A., & Filipe, M. (2019). O impacto económico da prevenção de quedas em idosos: uma análise custo-utilidade à intervenção das Equipas de Cuidados Continuados Integrados. Jornal Brasileiro de Economia da Saúde, 11(1), 34-41. https://docs.bvsalud.org/biblioref/2019/07/1005698/jbes-111-art-05.pdf
7. Santos, J., Arreguy-Sena, C., Pinto, P., Pereira, E., Alves, M., & Loures, F. (2017). Social representation of elderly people on falls: structural analysis and in the light of Neuman. Rev Bras Enferm, 71(suppl 2), 851-859. http://dx.doi.org/10.1590/0034-7167-2017-0258
8. Coimbra, V., Marques, E., & Chaves, C. (2019). Prevalência de Quedas em Idosos Residentes numa Comunidade Rural. Millenium, 2(3), 109-116. https://doi.org/10.29352/mill0203e.09.00218
9. Zeytinoglu, M., Wroblewski, K., Vokes T., Huisingh-Scheetz M., Hawkley L., & Huang E. (2021). Association of Loneliness With Falls: A Study of Older US Adults Using the National Social Life, Health, and Aging Project. Gerontolology Geriatric Medicine, (7), 1–7. https://doi.org/10.1177/2333721421989217
10. PORDATA. (2020). Índice de Envelhecimento: Onde há mais e menos idosos por 100 jovens?. Disponível em https://www.pordata.pt/Municipios/%C3%8Dndice+de+envelhecimento-458, last accessed 2022/06/20.
11. Guarda Nacional Republicana. (2021). Operação Censos Sénior 2021 – Balanço. GNR. https://www.gnr.pt/comunicado.aspx?linha=4625, last accessed 2022/06/20.
12. Peek, S., Luijkx, K., Vrijhoef, H., Nieboer, M., Aarts, M., van der Voort, C., Rijnaard, M., & Wouters, E. (2019). Understanding changes and stability in the long-term use of technologies by seniors who are aging in place: a dynamical framework. BMC Geriatr 19(236), 1-13. https://doi.org/10.1186/s12877-019-1241-9
13. Luna-Perejón, F., Muñoz-Saavedra, L., Civit-Masot, J., Civit, A. & Domínguez-Morales, M. (2021). AnkFall – Falls, Falling Risks and Daily-Life Activities Dataset with an Ankle-Placed Accelerometer and Training Using Recurrent Neural Networks. Sensors, 21(5). doi: https://doi.org/10.3390/s21051889
14. Wang, X., Ellul, J., & Azzopardi, G. (2020). Elderly fall detection systems: A literature survey. *Frontiers in Robotics and AI*, *7*, 71.
15. Wang, Z., Ramamoorthy, V., Gal, U., & Guez, A. (2020). Possible life saver: A review on human fall detection technology. *Robotics*, *9*(3), 55.
16. Ramachandran, A., & Karuppiah, A. (2020). A survey on recent advances in wearable fall detection systems. *BioMed research international*, *2020.*

17. Bet, P., Castro, P. C., & Ponti, M. A. (2019). Fall detection and fall risk assessment in older person using wearable sensors: A systematic review. *International journal of medical informatics*, *130*, 103946
18. Li, Q., Stankovic, J. A., Hanson, M. A., Barth, A. T., Lach, J., & Zhou, G. (2009, June). Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In *2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks* (pp. 138-143). IEEE.
19. Igual, R., Medrano, C., & Plaza, I. (2013). Challenges, issues and trends in fall detection systems. *Biomedical engineering online*, *12*(1), 1-24.
20. Kim, N. H., & Yu, Y. S. (2013). Fall recognition algorithm using gravity-weighted 3-axis accelerometer data. *Journal of the Institute of Electronics and Information Engineers*, *50*(6), 254-259.