Elderly Fall Monitoring in Smart Homes Using Wearable Device

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ABSTRACT

The constant progress of technology, especially in the area of health, brings numerous benefits, one of which is the increase in human life expectancy. However, problems that occur recurrently among the elderly age group are now on the radar of studies that also seek to improve the quality of life of these people. The number of cases of falls among elderly people is worrying, even more so as this is a portion of the population that tends to live alone. In the context of smart homes, several solutions have emerged for monitoring elderly people to increase safety and provide faster assistance, if necessary. One of these solutions is the use of wearable devices responsible for identifying the person's movements. This work presents the study and development of a wearable device capable of detecting falls and, if they occur, automatically notifying the necessary people through alert messages via the Telegram application so that they can help the person who has suffered a fall. In this work, a Wi-Fi network, MQTT protocol, accelerometer and gyroscope inertial sensors and an ESP32 board programmed using the Arduino IDE were used. Preliminary tests indicated good performance in recognizing falls, based on tilt angle analysis, gyroscope readings and accelerometer readings. The proof of concept and preliminary tests carried out demonstrate the potential for using low-cost technologies for wearable resources for application in smart homes and monitoring the health of elderly people.

KEYWORDS

fall detection, wearable technologies, accelerometer and gyroscope, alert messages

1 INTRODUCTION

With the encouragement of innovation and technology as an important pillar to improve people's quality of life, there is also an increase in life expectancy and the aging rate of the world's population. In Brazil, according to the 2022 IBGE census, the population over 60 years of age reached 32,113,490 (15.6%) [9]. The best thermometer to measure an elderly person's health is checking their functional capacity, which is a person's real ability to carry out the daily activities possible to live independently and self-sufficiently, which tends to reduce with aging. There are scales that measure this functional capacity, such as the Barthel scale, the Katz scale, the Lawton and Brody scale, the Pfeffer scale, among others [12], which assess the independence of the elderly in basic activities of daily living: eating, personal hygiene, getting dressed, using the toilet, moving from bed to chair and vice versa, cooking, managing medications, shopping, washing clothes, cleaning the house, using the telephone, remembering appointments, among others. Risks such as falling further increase the concern of family members and people close to elderly people, as they reduce functional capacity [28].

A smart home has devices connected to the Internet that allow remote monitoring and control of appliances and systems such as lighting and heating, as well as other types of sensors, using the internet of things (IoT)[13]. Furthermore, there may be wearable sensors that allow the implementation of *Human Activity Recognition (HAR)* systems in smart homes, helping to improve people's quality of life with autonomy and safety [7] , [23]. In this context, a solution to alleviate the consequences of these difficulties in the lives of elderly people, while rescuing independence in daily activities and reassuring people close to them, consists of installing monitoring systems in the home, in order to guarantee assistance if an incident occurs such as: a fire, fainting, fall or even illness caused by changes in vital signs. There are different types of emergency alert devices that have been developed for dependent people, including children, people with disabilities, the sick and the elderly. Most of them send an alarm only when help is needed, but some are developed to monitor the health of sick patients, such as blood pressure, heart rate, among others [17]. Monitoring an environment means using different devices that obtain desired data, such as a camera, motion sensor, temperature, humidity or brightness, among others, so that from this data it is possible to make decisions in order to achieve the objectives of monitoring.

The problem addressed in this work is how to identify that an elderly person who is alone in their home has suffered a fall and, in addition to identifying, use this information to alert people nearby through warning messages [11]. Therefore, an effective, portable solution is sought, with integration with the internet network, to maintain connectivity and provide warnings when necessary. One of the ways to monitor situations that happen to human beings is by "wearing" sensors and devices capable of identifying variations and

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communicating important information in such a way that readings and data collection are not harmed and are useful for the necessary analysis.

The main objective of this work is the design and implementation of a wearable device prototype for fall monitoring, using accelerometer and gyroscope sensors, and connecting this monitoring devices to a smart home ecosystem using the Node-RED platform to manage warnings when a fall has been detected. To achieve this objective, it was necessary to research and understand the technologies involved in existing wearable devices and, from this, choose the best and most affordable ones to implement in a real prototype. Then, an accelerometer and a gyroscope were integrated with the ESP32 module to build the wearable device. Finally, software was developed in a smart home environment capable of reliably collecting sensor data and interpreting it to identify different movements that determine a fall and manage alerts sent over the internet to registered people.

Section 2 presents the references about elderly falls and domestic accidents, wearable devices, Node-RED and related work. Section 3 describes the methodology adopted to build the prototype and defines the test cases studied, as well as the standard followed to carry out these tests. Section 4 presents all the results obtained with the developed solution and, finally, Section 5 deals with the conclusions about the prototype and implemented solution and indicates development opportunities to improve the project.

2 THEORICAL REFERENCE

2.1 Elderly falls and domestic accidents

A fall is defined as *"inadvertently coming to rest on the ground or at another lower level, excluding intentional changes of position to lean on furniture, walls or other objects"* [16]. As this is an increasingly present problem in the lives of families around the world, the World Health Organization (WHO), which defines the age group of elderly people as 60 years or older, publishes global reports aimed at preventing falls in old age. The frequency of falls increases with age and level of frailty. Approximately 28% to 35% of people over 65 years of age suffer falls each year, and the proportion rises from 32% to 42% for people over 70 years of age [16].

Falls can occur due to factors such as: decreased muscle strength; osteoporosis; walking abnormalities; change in blood pressure; depression; senility; osteoarthritis, hip fragility or balance changes; neurological changes (stroke, Parkinson's disease, multiple sclerosis and Alzheimer's disease); decreased vision and/or hearing; among others. There are also factors related to the environment such as: poorly lit environments; poorly planned houses; inadequate arrangement of furniture that hinders movement; slippery objects scattered around the house; among others [5].

Furthermore, a higher frequency of falls has been reported in nursing homes, in some cases including recurrent falls. It is possible to conclude, then, that even if nursing homes are adapted to the reality of the elderly's tasks, they are still not out of danger. Therefore, the implementation of integrated solutions for these people's homes is increasingly being studied so that assistance can be provided quickly if falls occur, such as the development of intelligent surveillance systems for monitoring, since the medical consequences of accidents like this depend on much of the rescue response time [18].

2.2 Wearable devices

Wearable devices are technologies developed to be used directly in contact with the body, whether as sensors embedded in clothing, as accessories to wear on the head, badges or even as wrist accessories. Several brands already have so-called "smartwatches", which are watches with the functions of well-known smartphones and which increasingly have applications that are interesting for monitoring the health of the individual who uses them. There are "smartwhatches" which are capable of measuring body temperature, blood glucose or oxygen concentration, blood pH and blood pressure through biometric sensors [24].

The benefits of this type of technology are very interesting from the point of view of people's quality of life, especially the elderly population.

In the specific case of fall detection, as discussed in [1], there is also a study on the best location for the wearable device considering two main factors: the accuracy of the sensors and the need to be comfortable for the person using it. Among the places available to attach them, there are waist, head, wrist, front of the waist, thigh, chest, ankle and arm. According to [8] and [1], the best places to guarantee correct analysis of sensor data are the chest, ankle and waist, however these are strongly linked to the stigma of using a medical device and, combined with the fact needing to be used 24 hours a day, they can be uncomfortable and less accepted [8].

The most comfortable place from the user's point of view is the wrist, however solutions based on wearable devices attached to the wrist have the worst accuracy results, with values lower than 90%, greatly increasing the level of complexity of the analysis and calculations involving the data obtained. For devices used in this location, a more in-depth study on the use of this data ends up being necessary. Some studies include, for example, machine learning applications as a resource to increase the precision and quality of analyzes [8].

Accelerometers and gyroscopes are inertial sensors used to monitor movements that can be attached as wearables [26]. The accelerometer measures the acceleration of a body in relation to gravity, that is, it measures the acceleration exerted on certain objects, performing some type of action depending on the movement performed on it. The gyroscope uses the force of gravity to indicate the position of a given object in space, being able to identify whether something is rotating on its own axis or whether it is pointing up or down. When the objective is to accurately determine the movement of an object or user, it may be necessary to combine the signals from sensors accelerometers and gyroscopes, because accelerometers present as an output signal the linear acceleration of the object and gyroscopes the angular velocity. The combination of these signals results in more complete information about the movement and allows for more assertive analysis.

2.3 Node-RED

In order to connect and implement IoT devices, it is possible to find some tools that facilitate activities at the code and programming levels. Node-Red is a programming tool, created by IBM Emerging

Technology, based on flow, used to integrate electronic components with applications of different natures, making it possible to develop programs quickly and intuitively. It is open source and is based on *nodes*, blocks of pre-defined functions available in a platform tab called *palette*. It is possible to build the desired flow just by dragging the blocks to the provided workspace and making the desired connections and interactions between blocks [21].

To make it possible to assess whether the constructed flow is performing the functions as determined, the platform also has a "debug" tab, where messages and actions appear synchronously with the functioning of the developed system. Node-RED has been used in the scenario of developing IoT and connectivity solutions as it proves to be a very useful and practical platform [3].

2.4 Related works

Gupta et al. [14] presents an IoT-based fall detection monitoring system for the elderly using only a 3-axis accelerometer. Torres [26] uses two sensors (accelerometer and 3-axis gyroscope), attached to the user's chest. A threshold analysis algorithm uses the data generated by these sensors to detect falls. This approach is the same as that used in this work. However, in the work of [26] Node-Red was not used as a tool to integrate devices with the network and a smart home system.

Quadros et al. [8] show the development and evaluation of a fall detection solution with the implementation of machine learning to improve results. The developed solution is worn on the wrist, as it is considered the most comfortable place, and uses an accelerometer, gyroscope and magnetometer to calculate acceleration, speed and displacement which, implemented in methods based on machine learning, can define the best approach for detecting a fall. The results are based on data acquired from falling and non-falling movements of 22 volunteers demonstrating the approach used for testing with real users. The authors of [20] applied the methodology, focusing on precision and effectiveness, to evaluate the KNN, Decision Tree and MLP algorithms applied to accelerometer data to detect falls. Other works also applied machine learning algorithms and [2] and deep learning [4], [15] and [19].

The works of [18] and [27] make a comprehensive survey of different devices, fall detection systems and the algorithms implemented in each one. Three categories of approaches are identified: solutions based on wearable devices, devices placed in the environment and solutions using cameras. The analysis on wearable devices deals with the same sensors used in this work and the approach is very close considering algorithms and location of the wearable device. The analyzes of other approaches are interesting, as they demonstrate alternatives that, if linked to wearable devices, add even more reliability to monitoring in smart homes, especially in the problem of elderly people falling.

In the work of [25], wearable devices based on inertial sensors and insoles that were developed for applications related to falls are analyzed, identifying key points, including spatio-temporal parameters, biomechanical parameters of gait, physical activities and methods data analysis relating to developed systems.

The assessment of confidence in the functioning of a ubiquitous system that uses a microphone and accelerometer and magnetometer sensors to detect and alert falls called fAlert is presented in the works [10] and [11]. Software quality measures such as precision, sensitivity, availability, specificity, performance, accuracy, among others, are used.

This work presents a wearable device (on the chest) that collects and analyzes movement data from elderly people wherever they are in a smart home ecosystem. An alert is sent to the responsible personnel in real time via Telegram in a cell phone, speeding up the rescue process.

3 METHODOLOGY

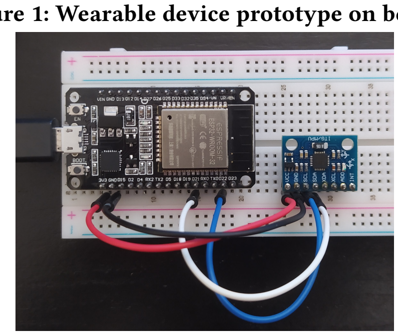
The wearable device for monitoring falls proposed in this work is based on two sensors, the accelerometer and the gyroscope, to find movement patterns that determine a fall and then alert family members of elderly people. The MPU6050 module was chosen because it has the two sensors mentioned integrated in order to facilitate the use of its output data when carrying out the tests. This module was connected to the ESP32 development module, which has a small size and built-in support for WiFi and Bluetooth networks, as well as integrated flash memory.

To develop the project's programming, the integrated development environment created to program microcontrollers from the Arduino family (Arduino IDE) was used, but which can also be used for compatible modules, such as the ESP32. The IDE's programming language is C++, with the installation of specific libraries that already have ready-made functions for reading and processing sensor data, in addition to libraries that assist in the use of the ESP32 module's WiFi connectivity (WiFi, Ethernet, Wire and PubSubClient).

3.1 Construction of the wearable device

The construction of the prototype began with the assembly of the components on a bench to carry out basic functional tests, with the sole objective of reading sensor data in a satisfactory manner, implementing communication with other clients using the MQTT protocol (*Message Queue Telemetry Transport*) and implement the complementary filter in order to increase data reliability [26]. Figure 1 depicts the arrangement of the prototype components in the first stage of construction without considering sensor reading axes.

Figure 1: Wearable device prototype on bench.



Source: From the author (2024).

To build the wearable device prototype, the chest was considered as the best place to attach the components, aiming for more reliable data and better performance. Based on this determination,

Figure 2: Wearable device.

Source: From the author (2024).

a comfortable and safe way to use the device was sought, as shown in Figure 2. The ESP32 is powered at this stage by a 9V battery.

3.2 Algorithm

The algorithm implemented in Arduino IDE for the ESP32 module is schematized in the flowchart in Figure 3. ESP32 stablish connection with Wi-fi to access the MQTT broker and activate the MPU6050 module composed by accelerometer and gyroscope. ESP32 remains in a loop taking sensor readings, converting values of gyroscope to degrees/second and accelerometer to degrees. After that, the complementary filter is used. The results are analyzed to identify falls and the alerts are sent.

3.3 Test Cases

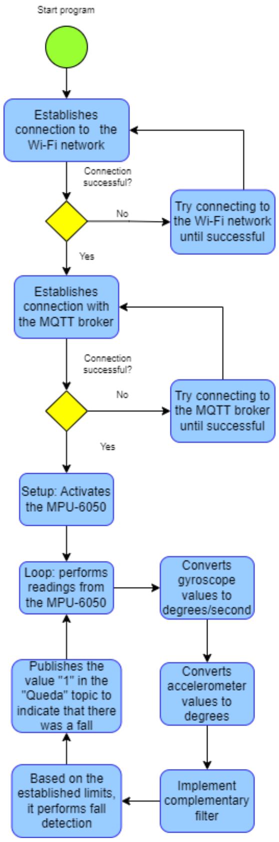
Considering the age range of the elderly, it is possible to identify some scenarios that could result in a fall: falls when walking or standing, falls when standing on supports (e.g. stairs, benches, etc.), falls when lying down or getting out of bed or falling when sitting on a chair [18]. Therefore, to carry out the tests, three non-falling movements and four falling movements were determined for analysis. The non-falling movements are walking, standing and sitting, and the falling movements are forwards, backwards and to the left and right sides. Movement variations occur based on the initialization and stationary values of the MPU6050 module sensors. In this way, the device is always initialized in the sitting position in order to reproduce a scenario where the user puts on the device in the morning before getting up, thus maintaining value references with the smallest possible variations and improving results. Other voluntary movements of lying down are considered normal and do not generate alerts.

3.4 Testing methodology

To carry out tests, the following methodology was defined:

(1) The person responsible for using the wearable device prototype must place it on the body, adjusting the straps so that it is coupled and fixed to the chest, but still in a comfortable way that does not impede movement. The device must be turned off.

Figure 3: Flowchart of the program developed for ESP32.



Source: From author (2024).

(2) Once adjusted and dressed properly, the user must sit in a chair with an upright posture and turn on the device.
(3) All tests must last two minutes to better visualize the plotted data and be carried out in a location with a stable Wi-Fi connection and by the same user.
(4) For non-fall tests, data can be collected as soon as the device is turned on, however for fall data the user must get up and go to the testing location and wait at least thirty seconds until the data is collected and stabilized for better visualization in graphs that are plotted simultaneously.
(5) After carrying out the falling movement, wait again for at least thirty seconds for the data to stabilize.
(6) At the end of the desired data collection, the user must turn off the device so that the data plotting stops and the graphs can be saved with the recent data.
(7) Ideally, the tests should be repeated three to four times for data comparison and coherence.

4 RESULTS

Obtaining the results begins with reading the data from the MPU6050 module. The raw values read by the sensors can be obtained using the Wire library, however it is necessary to process these data, as the values found do not correspond to any physical quantity and therefore it is necessary to convert them. In the case of the gyroscope, the values are converted to degrees per second (°/s) and represent the position variations in an angular velocity quantity. As for the accelerometer, the raw data is used to find an inclination angle, but for the result of the values obtained to be a more accurate value, it is necessary to use a relationship between the three axes, making a conversion according to equations (1) to (3) implemented in the code.

$$\rho = \arctan\left(\frac{A_x}{\sqrt{A_y^2 + A_z^2}}\right); \tag{1}$$

$$\phi = \arctan\left(\frac{A_y}{\sqrt{A_x^2 + A_z^2}}\right); \tag{2}$$

$$\theta = \arctan\left(\frac{\sqrt{A_x^2 + A_y^2}}{A_z}\right) \tag{3}$$

In the equations ρ represents the rotation around the Y axis, ϕ the rotation around the X axis and θ the rotation around the Z axis, "arctan" refers to finding the arc tangent, the inverse function of the tangent, and the values A_x, A_y and A_z represent the readings obtained with the MPU-6050 module on the X, Y and Z axes, respectively.

After the sensor data reading provides treated values with known units, the implementation of the complementary filter is included with the function of reducing noise in the measurements by integrating gyroscope data with the angles obtained from the accelerometer readings. The complementary filter uses two constants in the calculations, α (alpha) and Δt (sampling rate). α is determined by a relationship between a time constant and the sampling rate. For the calculations in this article, a time constant equal to 1 and a sampling rate of 0.04 are used, values obtained through the specifications of the chosen sensor module, resulting in an alpha value equal to 0.96. In this way, the filtered angle is found through the equation (4).

$$Angle = \alpha * (AngGiroscopy) + (1 - \alpha) * (AngAccelerometer) \tag{4}$$

With all readings occurring correctly, the aim is to develop the fall detection algorithm based on values obtained for previously determined falling and non-falling movements.

A dashboard was developed using the Node-RED platform capable of synchronously plotting the values obtained with the device. Data readings are published in topics and in the flow built in Node-RED, these topics are subscribed to nodes called "`mqtt in`", this is possible because both the ESP32 development module and the node are connected to the same broker, according to server and client concepts, using the MQTT protocol. These nodes responsible for receiving the reading values are connected to "`chart`" nodes capable of plotting graphs on the dashboard. This way the data is posted at the same time as the readings take place. The constructed flow is demonstrated in Figure 10, where subscription nodes in the topics where sensor values are posted in Node-RED.

From the built dashboard it is possible to monitor the values of the desired readings for subsequent analysis and definition of limits for each type of fall determined. The graphs present the tests following the methodology described previously, first for non-fall values (sitting, standing and walking) and are demonstrated in Figures 4 and 5. In Figure 4, it can be seen that the tilt angle in the Y axis increases, while in the X axis it decreases when the person stands up, but in the Z axis the change is small due to the position of the body where the wearable is located. The person leans forward to stand, so the values of X and Y vary more. These variations are visualized in the gyroscope and accelerometer readings. When the person is walking (Figure 5), the variations in the X and Y readings are greater, as the person varies the position of their body.

Figures 6, 7, 8 and 9 present data on falling movements (forward, backward, right side and left side).

In all plotted graphs, the X axis presents the last two minutes of sensor readings in HH:MM format. The Y axis for the "Accelerometer Readings" graph presents the angle variations in degrees, for the "Gyroscope Readings" graph it presents the angular velocity in degrees per second (°/s) and, for the " Tilt angle" the Y axis presents the angles in degrees. The values presented were analyzed to verify coherence and are samples chosen from four others for each movement.

It is possible to infer from the graphs generated that non-falling movements will not be confused with falling movements, since the values obtained for angular velocity for both the movement of getting up from a chair and movements for walking are not greater than 80 or less than -40, whereas for falling movements the values obtained from the gyroscope reading exceed these limits. The angular velocity is very important for determining the limits, as the speed of falling movements is clearly greater than that of everyday movements. It was expected that in the accelerometer readings the Z axis and the Y axis would present greater variation in degrees for forward and backward falling movements, since these movements occur by rotating the axes around the X axis. The falling movements to the right and left sides, the X and Y axes are those that show the greatest variations, as the movements occur by rotating the axes around the Z axis. Finally, the inclination angle values, mainly on the Y axis, are also very specific and clearly incorporate the critical components of the accelerometer and gyroscope.

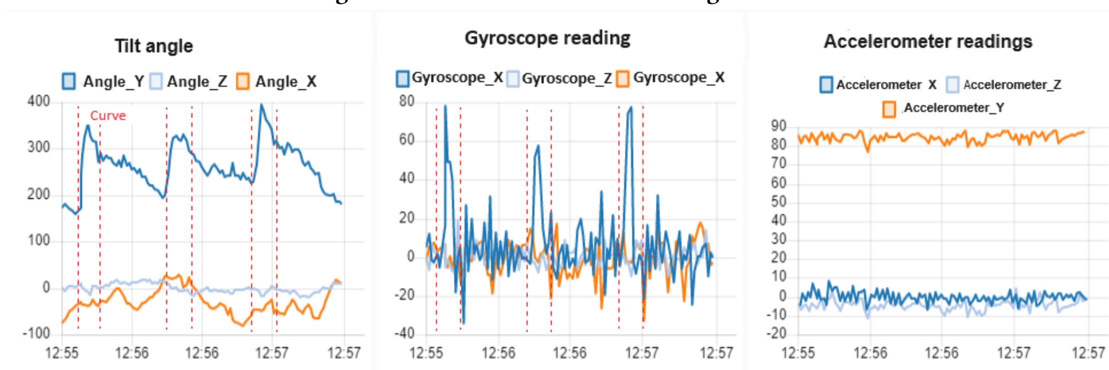
After analyzing and identifying limits for each component of the tests: accelerometer, gyroscope and tilt angle readings, these limits are implemented in conditional structures in the code to ensure that all cases are understood. Each case of an outage is published in a single topic called "`Outage`" and this topic must be accessed on Node-RED, where messages are sent to the people registered for this purpose.

With the implementation of all cases of failure in the developed algorithm, integration with Node-RED can be carried out. A flow was built with a node subscribed to the topic "`Queda`" which, upon receiving the value "`1`" indicating that there was a fall, activates a trigger that sends a message through the Telegram application. To implement the sending of messages via Node-RED, it is necessary to create a chat bot on Telegram, that is, a specific programmed conversation window for sending outage alert messages. The creation of the chat bot can be easily done through the application itself by chatting with another bot developed for this purpose. It is necessary to search for "`BotFather`" within the Telegram application and send the "`newbot`" command. With this, it is possible choose the bot's name and username, but the username must be

Figure 4: Values obtained for user testing initially sitting and then standing.

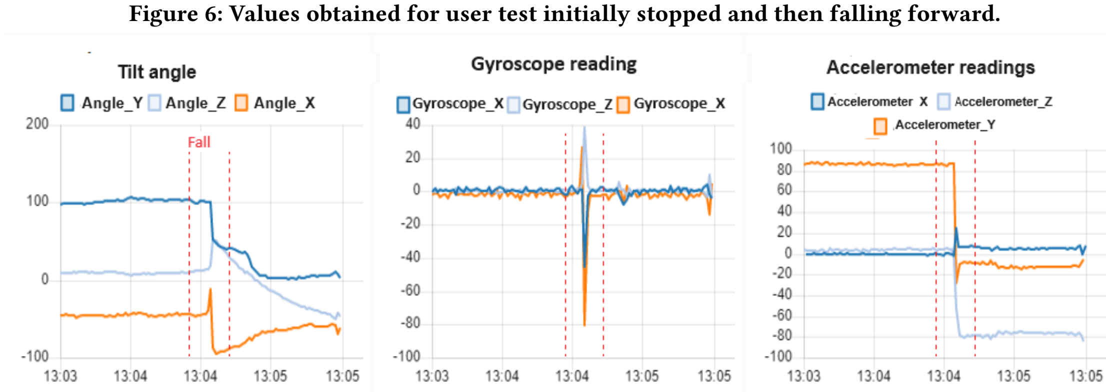
Source: From author (2024).

Figure 5: Values obtained for walking user test.



Source: From author (2024).

Figure 6: Values obtained for user test initially stopped and then falling forward.



Source: From author (2024).

unique. For this work, a bot named "`Monitoramento e saúde`" with username "`monitoramento-saudebot`" was created.

When creating a bot with "`BotFather`" a token code is provided to access the HTTP API. Node-RED has an extension that directly accesses Telegram named "`telegrambot`", generating five new nodes. One of these is the "`sender`" node responsible for sending a message to the registered chat when activated. To execute the sending action, a "`mqtt in`" node is used to receive the message posted by ESP32 when a fall movement occurs and this event is enough to start the flow.

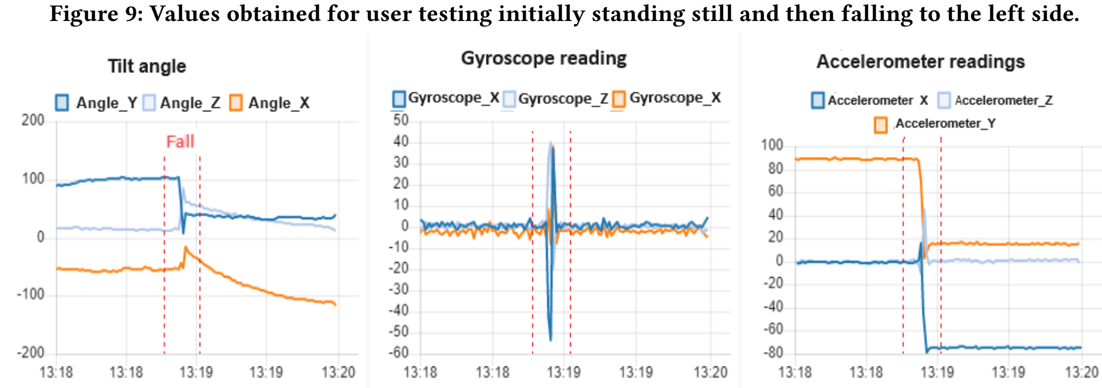
Figure 7: Values obtained for user testing initially standing still and then falling backwards.

Source: From author (2024).

Figure 8: Values obtained for user testing initially standing still and then falling to the right side.

Source: From author (2024).

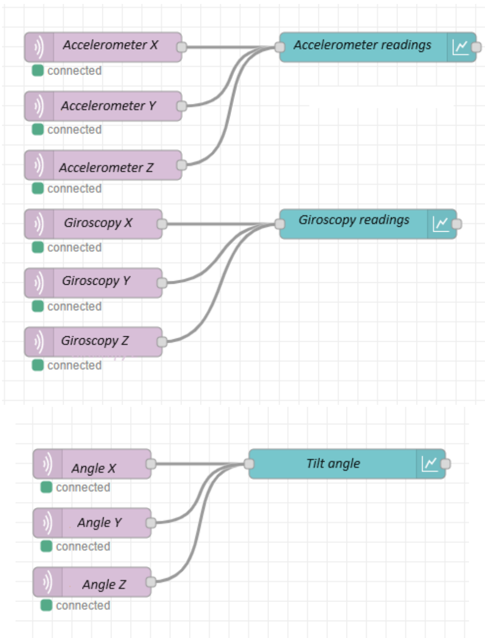
Figure 9: Values obtained for user testing initially standing still and then falling to the left side.



Source: From author (2024).

One message that will be sent with each fall alert can also be configured using nodes in Node-RED. The fall alert message is written in the "`funcion`" block and connected to the "`mqtt in`" block with the `chatID` number specific to the destination Telegram. The `chatId` is provided by the Telegram application searching for "`Get My ID`" in the search field of the Telegram application itself and after starting the conversation, the number will be provided automatically. The "`sender`" node must be filled in with the `chatId` provided and the message configured to indicate which chat bot the message is intended for.

Figure 10: Subscription nodes in the topics where sensor values are posted.

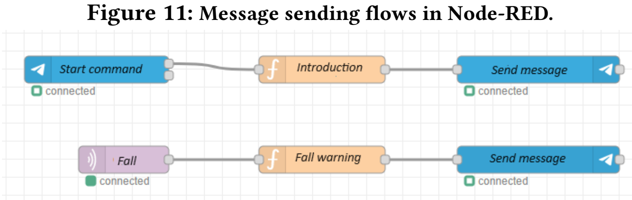


For the person interested in monitoring falls to receive messages via Telegram on their cell phone, they must search for the name of the chat bot in the application's search field and start the conversation, which corresponds to sending a "`start`" command to the bot. An introduction message is also configured for when a person signs up for the conversation. Using the "`receiver`" node, it is possible to trigger a new process when a message is received by the chat bot. From the "`start`" received, a trigger is activated that sends an introduction message. The settings are the same as the fall alert flow. The constructed flows are represented in Figure 11. The message sent by Node-RED to Telegram from the person responsible translate from Portuguese to English is:

`"Hello! I'm Mr. José's falls monitoring assistant. I'm here to warn you if an accident happens.`

`WARNING: Mr. José may have suffered a fall. Try to get in touch as soon as possible".`

Figure 11: Message sending flows in Node-RED.



Source: From author (2024).

5 FINAL CONSIDERATIONS

The main problem addressed in this work is how to identify that an elderly person who is alone in their home has suffered a fall. When identifying that there has been a fall, it is necessary to alert people nearby through warning messages.

The objective of this project was to implement a wearable device prototype for fall monitoring, using accelerometer and gyroscope sensors, and connect this monitoring to a smart home ecosystem using the Node-RED platform to manage warnings if a fall movement is detected.

The wearable prototype developed in this work is a suitable solution for monitoring movements, more specifically for detecting falls. It has been proven that wearable devices developed with inertial sensors are suitable for this type of problem and can be used to reduce rescue time if accidents occur with elderly people, while increasing the independence and safety of this age group in their own houses.

Even if low-cost modules with limited computational capacity are chosen, it is possible to implement data treatments such as the complementary filter to increase the precision of the values obtained and still develop reliable solutions. The approach used in this work to develop the algorithm responsible for determining falling movements was based on the limits found in coherent tests, however there is room for implementing more complex computational analyzes using machine learning. These are currently topics with great emphasis in the context of assistive technologies and can bring more performance to solutions such as the one developed.

Finally, more and more investment is being made in smart home applications, and the integration of several of them results in more complete, reliable and comfortable controls. That said, a solution like the one developed combined with other systems will guarantee greater performance and reliability in your activities. Other systems that have the potential to be integrated may be based on different sensors, networks, communications protocols and algorithms. In this work, a Wi-Fi network, MQTT protocol, accelerometer and gyroscope inertial sensors and an ESP32 board programmed through the Arduino IDE were used, but there are more possibilities such as bluetooth connection, cameras, presence and light sensors, HTTP protocol and other development boards such as Arduino, Raspberry Pi, among others.

As future work, we intend to carry out usability testing of the wearable in a smart home environment and with elderly people, aiming to further improve the prototype. Other real-world scenarios can be also used in tests. Fall movements can be analyzed along with movements performed during the person's daily routine. Historical data generated by sensors associated with machine learning techniques can be used to more accurately identify fall situations. Another possibility is to use other forms of fall detection, such as analyzing images from monitoring cameras, as discussed by [6] and *deep learning* [22].

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REFERENCES

[1] Ibukun Awolusi, Eric Marks, and Matthew Hallowell. 2018. Wearable technology for personalized construction safety monitoring and trending: Review of applicable devices. *Automation in Construction* 85 (2018).

[2] Sejal Badgujar and Anju S. Pillai. 2020. Fall Detection for Elderly People using Machine Learning. In *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*. 1–4. https://doi.org/10.1109/ICCCNT49239.2020.9225494

[3] Shirley Basílio. 2021. O que é Node-RED? Conhecendo e instalando. Disponível em: https://blogmasterwalkershop.com.br/outros/o-que-e-node-red-conhecendo-e-instalando, Acesso em: ago de 2022.

[4] Tingting Chen, Zhenglong Ding, and Biao Li. 2022. Elderly Fall Detection Based on Improved YOLOv5s Network. *IEEE Access* 10 (2022), 91273–91282. https://doi.org/10.1109/ACCESS.2022.3202293

[5] Ministério da Saúde. 2009. Quedas de idosos. Disponível em: https://bvsms.saude.gov.br/quedas-de-idosos. Acesso em: junho, 2024.

[6] Koldo De Miguel, Alberto Brunete, Miguel Hernando, and Ernesto Gambao. 2017. Home Camera-Based Fall Detection System for the Elderly. *Sensors* 17, 12 (2017). https://doi.org/10.3390/s17122864

[7] Luciana De Nardin, Kamila RH Rodrigues, Larissa C Zimmermann, Brunela DM Orlandi, and Maria da Graça C. Pimentel. 2020. Recognition of human activities via wearable sensors: variables identified in a systematic mapping. In *Proceedings of the Brazilian Symposium on Multimedia and the Web*. 49–56.

[8] Thiago de Quadros, André Eugenio Lazzaretti, and Fábio Kürt Schneider. 2018. A Movement Decomposition and Machine Learning-Based Fall Detection System Using Wrist Wearable Device. *IEEE SENSORS* 18, 12 (2018).

[9] Irene Gomes e Vinícius Britto. 2024. Censo 2022: número de pessoas com 65 anos ou mais de idade cresceu 57,4% em 12 anos. Disponível em: https://agenciadenoticias.ibge.gov.br/agencia-detalhe-de-midia.html?view=mediaibge&catid=2101&id=6730, Acesso em: jun. de 2024.

[10] Andressa B Ferreira, Leonardo S Piva, Reinaldo B Braga, and Rossana MC Andrade. 2015. Avaliação da confiança no funcionamento de sistemas de detecção e alerta de quedas. *Revista de Informática Aplicada* 11, 2 (2015).

[11] Andressa Bezerra Ferreira, Leonardo Sabadini Piva, Reinaldo Bezerra Braga, and Rossana Maria de Castro Andrade. 2014. Trust Evaluation in an Android System for Detection and Alert Falls. In *Proceedings of the 20th Brazilian Symposium on Multimedia and the Web*. 111–114.

[12] Ligia FREITAS, Elizabete Viana de; PY. 2016. *Tratado de geriatria e gerontologia.* (4th ed.). Guanabara Koogan. 1651 pages.

[13] Usman M. Daud S. Kabir A. Nawaz Q. Gilani, S.M.M. and O. Judit. 2024. SDN-based multi-level framework for smart home services. (2024), 327–347.

[14] Akash Gupta, Rohini Srivastava, Himanshu Gupta, and Basant Kumar. 2020. IoT Based Fall Detection Monitoring and Alarm System For Elderly. In *2020 IEEE 7th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*. 1–5. https://doi.org/10.1109/UPCON50219.2020.9376569

[15] Sardor Juraev, Akash Ghimire, Jumabek Alikhanov, Vijay Kakani, and Hakil Kim. 2022. Exploring Human Pose Estimation and the Usage of Synthetic Data for Elderly Fall Detection in Real-World Surveillance. *IEEE Access* 10 (2022), 94249–94261. https://doi.org/10.1109/ACCESS.2022.3203174

[16] Alexandre Kalache. 2010. WHO Global Report on Falls Prevention in Older Age. Disponível em: https://www.who.int/ageing/publications/Falls_prevention7March.pdf, Acesso em: jun de 2024.

[17] Suchitporn Lersilp, Supawadee Putthinoi, Peerasak Lerttrakarnnon, and Patima Silsupadol. 2020. Development and Usability Testing of an Emergency Alert Device for Elderly People and People with Disabilities. *e Scientific World Journal* 2020 (2020).

[18] Muhammad Mubashir, Ling Shao, and Luke Seed. 2013. A survey on fall detection: Principles and approaches. *Neurocomputing* 100 (2013).

[19] Md. Jaber Al Nahian, Tapotosh Ghosh, Md. Hasan Al Banna, Mohammed A. Aseeri, Mohammed Nasir Uddin, Muhammad Raisuddin Ahmed, Mufti Mahmud, and M. Shamim Kaiser. 2021. Towards an Accelerometer-Based Elderly Fall Detection System Using Cross-Disciplinary Time Series Features. *IEEE Access* 9 (2021), 39413–39431. https://doi.org/10.1109/ACCESS.2021.3056441

[20] Camila Pereira de Oliveira, Cristiano da Silveira Colombo, and Daniel José Ventorim Nunes. 2024. Machine Learning Applied To Fall Detection in the Elderly. In *Proceedings of the 20th Brazilian Symposium on Information Systems* (<conf-loc>, <city>Juiz de Fora</city>, <country>Brazil</country>, </conf-loc>) *(SBSI '24)*. Association for Computing Machinery, New York, NY, USA, Article 58, 9 pages. https://doi.org/10.1145/3658271.3658330

[21] Guilherme Bruno Araújo Pimenta. 2019. *Uso da Ferramenta Node-RED em Processos de Automatização no Cenário da Quarta Revolução Industrial.* Monografia. Universidade Federal de Lavras, Lavras - MG.

[22] Mahsa T. Pourazad, Anahita Shojaei-Hashemi, Panos Nasiopoulos, Maryam Azimi, Michelle Mak, Jennifer Grace, Doojin Jung, and Taran Bains. 2020. A Non-Intrusive Deep Learning Based Fall Detection Scheme Using Video Cameras. In *2020 International Conference on Information Networking (ICOIN)*. 443–446. https://doi.org/10.1109/ICOIN48656.2020.9016455

[23] Luis GS Rodrigues, Diego RC Dias, Marcelo P Guimarães, Alexandre F Brandão, Leonardo CD Rocha, Rogério L Iope, and José RF Brega. 2021. Upper limb motion tracking and classification: A smartphone approach. In *Proceedings of the Brazilian Symposium on Multimedia and the Web*. 61–64.

[24] Thanos G. Stavropoulos, Asterios Papastergiou, Lampros Mpaltadoros, Spiros Nikolopoulos, and Ioannis Kompatsiaris. 2020. IoT Wearable Sensors and Devices in Elderly Care: A Literature Review. *Sensors* 20 (2020).

[25] Deen MJ. Subramaniam S, Faisal AI. 2022. Wearable Sensor Systems for Fall Risk Assessment: A Review. Front Digit Health.

[26] Guilherme Gerzson Torres. 2018. *Tecnologia Assistiva para Detecção de Quedas: Desenvolvimento de Sensor Vestível Integrado ao Sistema de Casa Inteligente.* Dissertação de mestrado. Universidade Federal do Rio Grande do Sul, Porto Alegre - RS. Disponível em: http://hdl.handle.net/10183/180824.

[27] Xueyi Wang, Joshua Ellul, and George Azzopardi. 2020. Elderly Fall Detection Systems: A Literature Survey. *Frontiers in Robotics and AI* 7 (2020). https://doi.org/10.3389/frobt.2020.00071

[28] Jing Zhang, Jia Li, and Weibing Wang. 2021. A Class-Imbalanced Deep Learning Fall Detection Algorithm Using Wearable Sensors. *Sensors* 21, 19 (2021). https://doi.org/10.3390/s21196511