IoT-Based Human Fall Detection System

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1. Introduction

Human falls can occur at all ages, provoked by the loss of balance or the inability to regain balance.According to [5], falls can be classified according to their cause, as being accidental falls, unpredictable physiological falls, and predictable physiological falls. Accidental falls are unpredictable falls that result from external factors that affect people with no risk of falling. Unpredictable physiological falls represent about 8% of falls and affect people with no risk of falling, but they are the result of physiological factors, such as pathological fractures or seizures. Predictable physiological falls are 80% of falls and affect people with a risk of falling, mainly resulting from physiological change. To minimize the negative impact of human falls, it is important to act fast when the fall occurs and to supply the proper warning to health support services. The wearable IoT devices can go with the elderly person and create walking profiles and detect falls in near- or real-time

2. Method of Approach

The problem is appreoched using an IoT device with two classification models, and datasets such as UMAFall, SisFall, DLR, MobiFall, and UP-FALL to detect human falls, one based on Morlet wavelet and another based on Artificial Neural Networks. These models were designed for a distributed architecture that uses a three-computational-layered architecture.

3. Proposed Architecture

The proposed solution is an IoT-based architecture with three computational layers for data filtering and treatment, allowing for scalability and adding new nodes. The solution is organized in a hierarchical tree structure.

The IoT device uses a local buffer to collect data in a time window composed of three events: before, during, and after an off-normal event. The fog-layer classifies events as falls and stores them for human validation. After validation, the events are sent to the cloud-layer for use in training and updating classification models, as well as overall system evolution. The cloud-layer is responsible for updating and evolving the system by using the data sent from the fog-layer to train and improve the classification models.

4. Edge Side Iot-Device

The proposed solution uses an edge-side IoT device for data collection. Two prototypes were developed using different microcontrollers and the same sensors. The first prototype used an Arduino UNO R30s Atmega328 and a USB connection to transmit data to a Python script for processing and fall classification. The second prototype uses an ESP8266 (NodeMCU) microcontroller for data transmission over Wi-Fi and can be updated to

ESP32. The sensors used are an analog sound sensor, an MPU-9250 accelerometer, a GY-521 accelerometer, and an HB-100 Doppler sensor. They are placed in close contact with the floor surface. The sensors are read without delays and the data is transmitted using the MQTT protocol, only off-normal events are transmitted for classification. The off-normal events are detected using level thresholds in each sensor and trigger a time window of around 700 milliseconds with 70 data samples of each sensor for storage and transmission.

5. Classification Models

In this work, two classification models were conceived, developed, and tested. One is based on the mathematical approach of the Morlet wavelet, and the other is based on the artificial intelligence approach of artificial neural networks (ANN). The mathematical approach considers the use of a threshold to evaluate the Morlet wavelet of the accelerometer time series.

The mathematical approach proposed for human fall detection uses the continuous wavelet transform (CWT) to decompose the time series into components of different scales, comparing the decomposition with the wavelet of varied sizes, as

$$c(a,b) = \int f(t)\psi(at+b)dt$$

The CWT is applied to the two profiles of human falls and ADLs to create a mother wave. New event signals are then compared to the mother wave of human falls to evaluate their similarity degree through the calculation of CWT coefficients. The higher the coefficient, the greater the similarity between the new event signal and the mother wave and is represented as

$$CWT_{coeff(a,b)} = \frac{1}{\sqrt{x}} \int_{-\infty}^{+\infty} SV_{candidate}(t)\psi_{fall}\left(\frac{t-b}{a}\right)dt$$

In the proposed classification model, the Morlet wavelet is used to calculate the wavelet transform of the time series D. This wavelet is recommended for geophysical signals analysis, which are similar to the non-stationary signals of accelerometers when used to read floor vibrations. The Morlet wavelet is represented as an equation that includes parameters for oscillations and displacement as

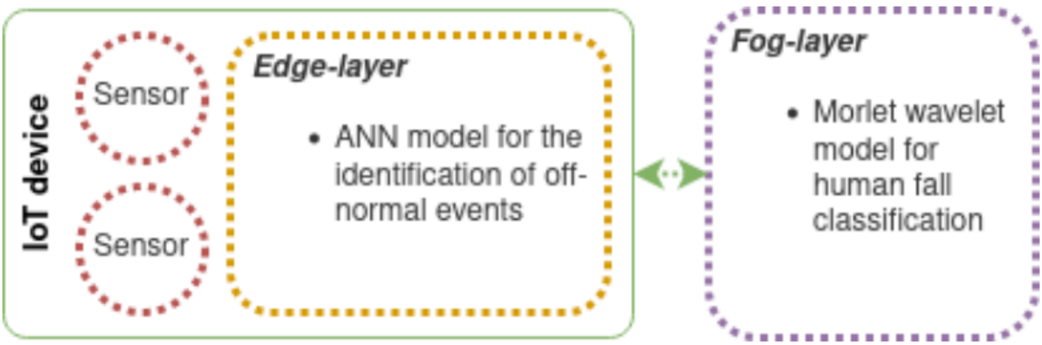
$$\psi_0(\eta) = \pi^{-\frac{1}{4}} e^{iw_0\eta} e^{-\eta^2/2}$$

For the artificial intelligence classification model, a multi-layer ANN with eight input neurons and one output neuron is used. The two hidden layers are composed of 12 and 8 neurons, respectively. The input layer and hidden layers are configured to use the rectified linear activation function (ReLu). The proposed solution uses an Artificial Neural Network (ANN) that is configured using Keras API and TensorFlow platform. The ANN has 8 inputs: x-axis acceleration value, y-axis acceleration value, z-axis acceleration value, x-axis gyroscope value, y-axis gyroscope value, z-axis gyroscope value, sound level, and D value from Equation.

The output layer has only one neuron that indicates if the event is classified as a human fall or an ADL. The ANN uses sigmoid activation function for the last layer and it was trained using a binary cross-entropy loss function. The optimization function used is Adam algorithm and the training used 250 epochs and a batch size of 32 samples. The dataset used to train the ANN model consist of 170 events (40 human-body falls and 130 different ADLs) which were created using the proposed IoT device.

6. Findings

The proposed solution uses both the Morlet wavelet and ANN models to complement each other. The ANN model is used in the IoT device for fast classification and real-time detection, while the Morlet wavelet model is used in the fog-layer for more accurate detection of human falls. This approach improves the accuracy of the system and eliminates false negatives, providing a more reliable fall detection system. The proposed solution also includes a two-step classification process, where the initial classification is done in the IoT device, and a more accurate classification is done in the fog-layer, using the Morlet wavelet model. Overall, the proposed solution is a more robust and reliable system for fall detection, thanks to the integration of both models.



7. Conclusion

In summary, this paper proposes a fall detection solution based on IoT devices that uses a layered architecture for human fall classification. The proposed IoT device uses a low-cost microcontroller with low-cost sensors that can be deployed in residential homes and other facilities, using a non-wearable and non-intrusive approach. The solution uses two classification models, one at the edge-layer using an AI-based model for detecting off-normal events and one at the fog-layer using the Morlet wavelet for accurate classification of human falls. The results showed an accuracy of 92.5% without having false negatives. The authors conclude that the best approach is a combination of wearable and non-wearable solutions to enable continuous operation.