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# Development of an Intelligent Walking Aid for Fall Detection

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**Abstract:** The medical field has made significant improvements over the past decades, leading to an older and healthier population. One of the main core problems being tackled is the detection of falling events. The quick detection of a fall contributes greatly to the fast arrival of help and prevents further damages. Therefore an intelligent crutch was developed with the purpose of detecting a fall and the following call for help if needed, as well as conveying the location of the user to relatives and care givers. The crutch was evaluated in a series of experiments during which all falls were identified correctly and alerting was initiated.

**Keywords:** fall detection, walking aid, crutch

## 1 Introduction

With an older growing population and fewer people working in the health care sector, the need of reliable, yet convenient care and supervision devices arose to make life at home for elderly as well as people with chronicle illnesses as safe as possible. One of the biggest safety hazards in everyday life is the event of falling. As reported by the WHO, falls are with estimated 684.000 individuals the second leading cause of unintentional injury deaths worldwide [1]. At that are approximately 37.3 million falls severe enough to require medical attention each year [1]. A fall can have several consequences, minor issues such as bruises and burn marks, but also severe injuries such as fractures and concussions resulting in a state of immobility on the floor and dependence on being found [1]. Therefore, a quick detection of falls contributes greatly to the fast arrival of help and can help to prevent further injuries.

There have been many achievements in fall detection-related technologies, which can mainly be divided into two methods: vision-based and wearable-based. The vision-based fall detection methods use cameras which recognize the posture of the individuals [2, 3]. However, the vision-based fall detection methods are limited to a single room and, depending on the camera systems, might result in privacy issues [4].

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Wearable-based fall detection methods such as smartphones, smartwatches or dedicated wrist sensors overcome the problem of a limited area where a fall can be detected. The fall detection in wearables is realized through different technologies [5]. The usual method is to capture motion information or patterns with an inertial measurement unit (IMU) and then either analyze the data using a threshold-based method, or evaluate the motion patterns using machine learning techniques. Depending on the method, promising results in detecting falls with an accuracy of 99% have already been reported [6, 7]. Nevertheless, a limitation in using smart wearables for fall detection is the need to regularly, nearly daily, recharge the smartwatches, which can be a hurdle for elderly people. Fall detection integrated in smartphones assumes that the smartphone always remains with the patient, which is rather untypical in the household.

Since many elderly people use crutches as walking aids, these tools can be used for the detection of a fall. We therefore developed an intelligent crutch, able to detect falls and discriminate whether the user fell or only the crutch. In addition a system to locate the individuals, if they also use their tools outside, is integrated.

## 2 Material and methods

### 2.1 Hardware

A standard crutch was used for this study. For faster development, a comprehensive sensor platform was used (M5CORE2, M5Stack Technology Co., Ltd, Shenzhen, China). The M5CORE2 is a battery powered ESP32 IoT Development Kit with out of the box integrated sensors including an inertial measurement unit (IMU) with an accelerometer and a gyroscope, display and speaker. In order to track the location an additional GPS sensor (ATOM GPS Development Kit, M5Stack Technology Co., Ltd, Shenzhen, China) was added to the crutch.

Since there is a possibility that the walking aid falls when leaned against a wall or other furniture, another sensor is necessary, in order to detect whether the walking aid was currently used or not. Therefore a proximity sensor (Adafruit VL6180X, NYC, USA) is applied to the handle. Aforementioned does not require physical touch in order to work. It can measure objects

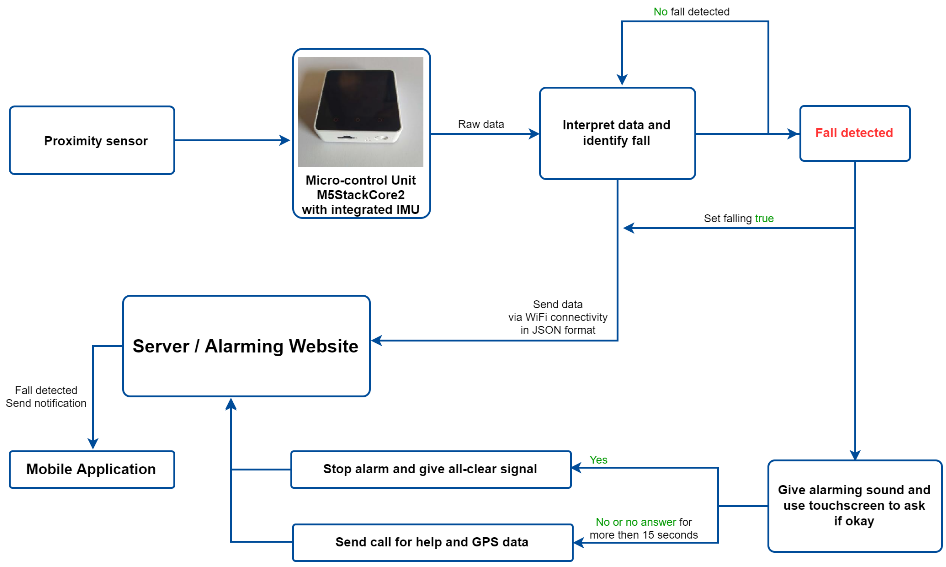


**Fig. 1:** Overview of the fall detection and alarming process

in a distance up to 10 cm and can be installed at the beginning of the handle, focusing only on whether a hand is placed in front of it.

## 2.2 Software

The basic principle of the fall detection system is separated into several steps, as shown in figure 1. In general the IMU in the M5Stack mounted on the walking aid indicates, if the walking aid falls (see section 2.3). To assure, that the fall is not classified as a "user fall" if the crutch falls unattended when not in use and also in order to save battery, a light sleep mode is implemented into the system. The micro-controller enters a sleep mode triggered by the absence of a hand on the handle. The system wakes up again, as soon as the proximity sensor observes a hand on the crutch.

The sensors are connected to the M5Stack Core2 micro-controller, which interprets if the data imply a fall incident and transfers the data in JSON format via the inbuilt WiFi-Module. As soon as the data suggest a fall has occurred, the device communicates the incident with the mobile or web application and starts to make an alarm sound. The interactive touch screen also shows a confirmation message: "I am okay" or "Help". The user can then press "I am okay" to cancel the further process, if the incident was not severe. A message about the incident and that the person feels they are okay is still being transferred. If the user presses "Help" or no answer is received in less than 15 seconds after the reported fall, further steps are initiated. If help is specifically requested by pressing "Help" or the alarm is not stopped, a message and the location of the person needing help is then sent via the application on the server to the stored contact numbers of relatives or caregivers. As power consumption needs to be considered, data will only be sent, if the device interprets the data from the gyroscope and acceleration sensors as a fall.

## 2.3 Threshold identification

To identify the correct patterns of fall with the IMU, a set of data of typical walking patterns with the walking aid, as well as situations simulating falls were collected. For this raw data from the IMU with its three orthogonal positioned acceleration sensors and the three gyroscope sensors was recorded with a frequency of 50Hz. A set of 250 data sets was collected (134 falling events, 116 normal use and fallen state) during a study with seven volunteer students (1 female, 6 male). All data was then analysed offline and the threshold, indicating a fall with the walking aid in use, was determined.
After the specification of the threshold, sensitivity was tested in a series of 20 test falls.

## 2.4 Alarming website

After a fall is detected by the M5Stack mounted on the walking aid, an alarm is sent to an alarming host website via WiFi connectivity. In addition the ID of the device is sent in order to distinguish between the used devices of different patients. The website then notifies caregivers or doctors via a configured alarming channel. Depending on the area where the system is used this can be an automatically generated SMS, Whatsapp or Telegramm message. In the current development stage, no data encryption is implemented, nor an encryption on the website.

# 3 Results

Recorded data was analysed to determine falls with Orange 3.33.0 [8]. In a first step, the collected raw data was labelled as "normal position, "fall detected" and "fallen". The main tool for detecting falls is the aforementioned 3-axis-gyroscope built into the M5Core2, with the acceleration sensor providing additional information. Each gyroscope value can vary between 1 and -1, which then indicates the current position of the crutch. The first one is the upright position in which the crutch remains, when it is not in use, as well as when the patient is standing or walking. Thus smaller impacts on the acceleration and gyro data cannot be considered as falling and need to be classed and labelled as "normal position". The upright position is indicated by the y-value of the gyroscope being close to 1, whereas x- and z-values should be close to 0. As the crutch oscillates while the person is walking, according divergences are considered to avoid false positive alarms. When in use, the x- and z-values usually alternate between 0.2 and -0.2. Consequently the y-value varied between 0.8 and -0.8. To determine the threshold all values above 0.7 and beneath -0.7 were excluded.

Significant changes in the gyroscope and acceleration data indicate a fall and are labelled as "fall detected". "Fall detected" will be considered as harmful and initiates data distribution from the device to the host website, conveying that help might be needed. The data collected from this action shows the vastest variety, as a fall can have different starting angles and the orientation of the crutch will vary greatly depending on the direction as well as the speed of the fall. While falling the orientation of the crutch and thus the device is changing from a vertical to a horizontal position. The y-value of the gyroscope will decrease from about 1 to 0, whilst either the x-value or the z-value will change to 1 or -1, depending on the fall direction. If the crutch falls to the right, the x-value will decrease against -1 or increase to 1 if it falls to the left. A forward fall is indicated by the z-value climbing up to 1, whereas a fast decrease to -1 indicates a backwards fall. Since the y-value indicates the change from the vertical to the horizontal position, these were focused on, when the threshold was identified. To find a suitable threshold we calculated the mean value of all 134 y-values suggesting a fall. The result was 0.46, leading us to decide on a threshold of 0.5. In case a fall has taken place the walking aid is laying on the floor in a still manner. This will be indicated by little to no variation in the acceleration and the gyroscope data, a y-value close to 0 and x and z-value close to 1 or -1.

Figures 2 and 3 visually depict aforementioned. Figure 2 shows how the y-axis and the x-axis of the gyroscope correlate during normal walking patterns and falls. Replacing the x-axis with the z-axis creates a similar picture respectively. Figure 3 shows the data of the x-axis and the z-axis of the gyroscope, depicting how the data indicates different fall directions.

Based on the identified threshold with 0.5 on the y-axis of the gyroscope, 20 falls of volunteer students in the second study showed, that all falls were identified correctly.

# 4 Discussion

Even though the system was tested successfully, some complications need to be considered in future works. The testing group consisted of seven healthy students between the ages of 20 and 26. Their gait pattern is to be differentiated from the pattern of elderly people, who have difficulties walking. In order to adjust the system to the appropriate gait pattern more data with different test subjects needs to be recorded. Also, if the crutch hits an obstacle and remains in a skewed position above threshold, currently, this would not indicate a fall and thus would not initiate the alarming mechanism. In our small study with healthy participants, the direction of the fall was identifiable. If this would also be possible in the target group, the severity of the fall could possibly be predicted and therewith the alarming procedure individually adapted. Generally, more thought should be given to the general design of the intelligent crutch so that the usability is adapted to the habits of the elderly population. This could also include a wireless communication module with GSM/ LTE or 5G connectivity as an alternative to the otherwise obligatory connection to a WiFi network used in this study. Moreover the M5Core2 is a useful tool for research purposes, as it includes a wide range of practical features. However, when it comes to usability for the elderly population it might be considered to make the system more accessible by avoiding a touch screen and replace it with labelled or colour coded buttons and implement everything into the crutch.

As the device is battery powered the need to charge the device arises. Ideally the battery should last long enough that caregivers can recharge the crutch during regular visits, if the person is not able to remember it by themselves. Also a notification if the battery runs low via the alarming website or with indicators on the crutch must be implemented. The falling alarm itself will be send, as mentioned before, as a message on a suitable platform. To increase the success rate of the message

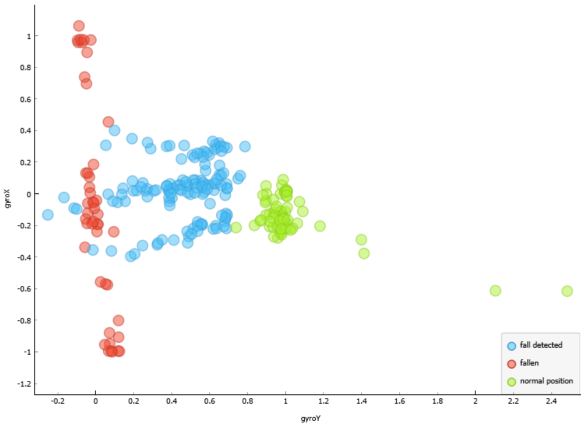


**Fig. 2:** Depiction of exemplary fall detection data considering x-value and y-value of the gyroscope, showing the fall detection process based on the y-value

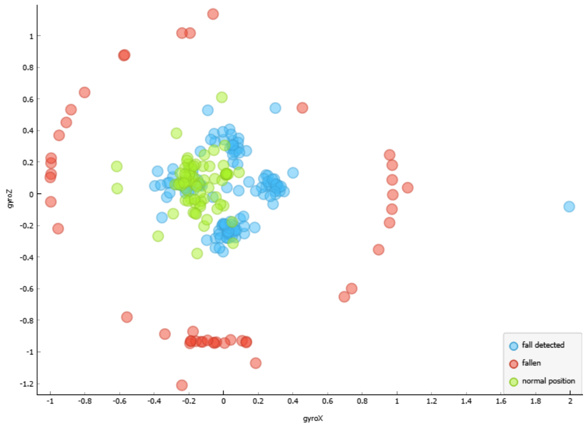


**Fig. 3:** Visual depiction of the fall detection data considering x-value and z-value of the gyroscope, showing the direction of the fall

distribution a chain mechanism should be considered, meaning if the first caregiver does not receive or react to the message it will be send again to the caregiver next in line.

Lastly, currently the fall detection method runs only on the micro-controller, determined by a figured threshold. While this works well, it could be further improved by integrating a machine learning (ML) method, processing all data on the host website. In addition to detecting a fall this could also give more information on the general situation of the tumbled person, and would also provide options for fall forecasting with ML as already done by [9].

# 5 Conclusion

Aim of this project was to develop an intelligent walking aid which includes a fall detection and a locating system. It has been shown that a combination of accelerometer and gyroscope data to detect the violation of thresholds, enables a robust detection of falls. Alerting was implemented using a dedicated web service, but confirmation of the reception of the alert is required for real-world application.

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