A Wearable Fall Detector for Elderly People Based on AHRS and Barometric Sensor

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A Wearable Fall Detector for Elderly People Based on AHRS and Barometric Sensor

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***Abstract*—Falls and their consequences are among the major health care problems affecting functional mobility and quality of life of elderly people. Even for people living independently, falls are common occurrences. In this paper, we present a waist-mounted device useful to detect possible falls in elderly people. Through data coming from a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer and a barometer sensor integrated into our device, we are able to obtain a highly accurate estimation about posture and altitude of the subject. By means of such information we have developed an extremely efficient system for fall detection reaching 100% of sensitivity in commonly adopted testing protocols. Particularly, the algorithm was tested according with three different experimental protocols where volunteers performed several scenarios including various types of falls, falls with recovery and daily living activities frequent in the elderly. Results show that the proper combined use of the four sensors and efficient data fusion algorithms allow to achieve noticeable better performances to those obtained with similar systems proposed in the literature.**

***Index Terms*—Fall detection, Wearable sensors, Inertial sensors, MEMS, Altimeter, Barometer, AHRS.**

I. INTRODUCTION

FALLS are a widespread problem among the elderly, causing significant a amount of injury, mortality and use of health care services [1]. Worldwide the number of elderly (people aged 65 years or older) is growing faster than any other age group; their share was to 12 percent in 2014 and is expected to reach 21 percent by 2050 [2]. Roughly 28-35% of people ages of 65 and 32-42% aged over of 70 fall each year. In addition, the segment of the population aged 80 and over, particularly susceptible to fall, will represent the 20% of the elderly population in 2050 [3].

During a fall an involuntary change in position with or without loss of consciousness occurs, causing the victim to land on ground [4]. Falls and consequent injuries require medical attention and are often the cause of fractures, traumatic brain injuries and lesions in the upper limbs inducing, in many cases, to the loss of independence or death. Often the elderly cannot return to standing position after a fall and there is a close relationship between the delay of the assistance to the injury and the mortality rate [5]. Therefore, a rapid reporting of the fall can enable a fast help and avoid serious consequences.

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Fall detection systems provide for the use either of external sensors or wearable sensors [6]. The first are placed within the surrounding environment of the subject of interest but they are not able to monitor the user when he comes out of the sensors's range of coverage. The seconds, thanks to the development of miniaturized and very cheap sensors, can be worn by the subject removing the previous limitation imposed by the systems based on environmental sensors [7]. Most studies in the literature on this type of wearable sensors use fall detection algorithms based on accelerometer measurements to detect fall-related events.

Kangas *et al.* [8] proposed three different algorithm for fall detection using a triaxial accelerometer attached to the waist, head, or wrist. They subdivided a fall event into several phases through the setting of specific thresholds. Their first algorithm detected a fall if an impact on the ground followed by an horizontal posture occurred. The second algorithm additionally required the detection of a phase preceding the impact when the subject loses the contact with the ground. The third algorithm further required that the velocity before impact was above a proper threshold value. In this study, many volunteers subjects performed both fall events and Activities of Daily Living (ADL). Falls were best recognized with the first algorithm (sensitivity of 97.5% and specificity of 100%) and placing the sensor on the waist or head of the subjects.

Bourke *et al.* [9] tested the performance of 21 algorithms of varying complexity based on a waist-mounted triaxial accelerometer. Ten volunteers simulated fall events and ADL performing either scripted and unscripted activities. The most accurate algorithm was threshold-based and achieved 100% sensitivity and specificity and a false-positives rate of 0.6 FP/day.

Jantaraprim *et al.* [10] and Vallejo *et al.* [11] proposed a fall detection method that used Artificial Neural Networks (ANN), attaching a triaxial accelerometer to the torso and waist respectively. Jantaraprim used a short time Min-Max feature based on the specific signatures of critical phase fall signal and a neural network as a classifier. According to the experimental protocol used, two subject groups of different ages, Group A and Group B, were tested. Results showed that better performance was achieved for Group B (99.4% sensitivity and 100% specificity) than for Group A (98.2% sensitivity and 99.3% specificity). In Vallejo's work, ten volunteers performed 11 different types of falls and the system obtained 98.4% of sensitivity and 98.6% of specificity.

The fall detection systems presented by Kangas [8], Bourke [9], Jantaraprim [10] and Vallejo [11] are rather limited for same aspects. In fact, in their validation tests, they only take into account the fall scenarios in which the trunk of the subject keeps in the horizontal position after the ground impact, as in the case of backward falls, forward falls and lateral falls. In these kinds of falls, an acceleration peak followed by a change in the subject's orientation always occur. Indeed, a class of falls in which the trunk of the subject no gets a significant rotation also exist, as backward falls ending sitting and syncopes. A syncope is defined as a short loss of consciousness and it can lead to a vertical fall in which a person slowly leans againts a wall, slides down on it and ends up sitting. This event must be considered a fall as it may cause injurious consequences such as fractures, lacerations and bruises [12]. The previously mentioned systems do not provide information as to their ability to reveal the last category of falls.

Noury *et al.* [13] proposed a falls detector based on an accelerometer, worn on the belt of the subject. The falls scenarios considered by Noury included backward falls ending sitting and syncopes, in addition to the typical backward, lateral and forward falls. The system, able to recognize several body orientations and detect when the speed of the trunk exceeds a fixed threshold, achieved a sensitivity of 79% and specificity of 83%. The limited results highlight some critical issues such as detections of the syncopes and forward falls with the recovery.

In a previous work [14] we proposed a waist-worn fall detection system which incorporated an Attitude and Heading Reference System (AHRS) combining a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer. The system was compared with Kangas' ones by their revaluation according to the experimental protocol proposed by Noury [15]. Results showed a decrease in the performance of the most accurate Kangas' algorithm if it is tested according to Noury's experimental protocol (i.e. the new values are 76.29% of sensitivity and 98.89% of specificity). Consequently, we can reasonably assume that the performance in [9], [10] and [11] would be significantly lower if they had considered the scenario including falls in which the subject's trunk remains upright. Furthermore, our previous study highlighted that the use of the AHRS allowes better performance (80.74% of sensitivity and 100% of specificity) than Kangas' system that is based on data provided by just one accelerometer. However, the detection of backward falls ending sitting and syncopes has proved to be the main limitation of both the systems.

To overcome these limits, the introduction of a further sensor, such as a barometer, capable of measuring the altitude variation in a fall, is necessary. In fact, during any type of fall, an increase in atmospheric pressure exerted against the device worn by the subject always occurs. Obviously, the related amount depends on the difference of altitude experimented by the device during a fall.

Bianchi *et al.* [16] developed a waist-mounted fall detection system based on a barometric pressure sensor in combination with a triaxial accelerometer sensor. They thought to correlate atmospheric air pressure variations and accelerometer data with possible events of fall. The performances of the three proposed fall detection algorithms were verified by means an experimental protocol that introduces further scenarios compared to those of Noury. Bianchi's experimental protocol is decomposed into three sub-tests called A, B and C. Test A includes simulated indoor ADL and falls, Test B simulated outodoor falls and Test C indoor and outdoor simulation of ADL different from those in Test A. Bianchi's best algorithm evinces accuracy, sensitivity and specificity of 96.9%, 97.5%, and 96.5%, respectively with reference to the Test A, accuracy and sensitivity of 90% and 86.7%, with reference to the Test B. The authors state that the system does not generate false positives in performing the Test C.

Chen *et al.* [17] implemented a real-time werable wireless fall detection system based on an accelerometer and a barometer. The algorithm achieved an overall accuracy of 97.5%, a sensitivity of 95.71% and a specificity of 97.78%. However, the protocol used by Chen does not consider some scenarios provided by Bianchi.

The aim of this paper is the presentation of a novel fall detection system able to recognize every fall events, even those ending in sitting position, improving fall detection performance compared to the previous works. The proposed system is mainly composed of an AHRS and a barometric sensor and incorporates ad-hoc data fusion algorithms in order to provide accurate information about dynamic acceleration, orientation and altitude of the subject wearing the device. Starting from the data measured by the accelerometer, gyroscope and magnetometer, our system is able to get the accurate estimation of the device orientation with respect to a fixed reference system. Therefore, the assessment of changes in orientation of the trunk of the subject is made possible. Altitude values, derived from barometric measurements, are depending on factors such as thermal and quantization noises. For this reason, the raw data provided by the barometer and the values of vertical displacement obtained by AHRS are merged togheter for deriving a more accurate altitude estimation. Thereby, the system is able to detect every type falls including syncopes and backward falls ending sitting. In order to evaluate the performance of the proposed fall detection system, volunteers performed falls and ADL events according to the three experimental protocols adopted by us [14], Chen [17] and Bianchi [16].

II. Design of the fall detection system

In this paper we present a fall detection system consisting in a waist-mounted wireless device usable in everyday life and characterized by its noninvasiveness and able to automatically detect every kind of fall.

The proposed device embeds a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer and a barometer. The first three sensors implement an AHRS able to correctly estimate the orientation of the device. The angular and accelerometer data furnish us the dynamic values of the vertical acceleration. The altitude signal, calculated through raw measurements of pressure and temperature coming from the barometer, contains an amount of noise which makes it unsuitable for immediate use. For this reason, in order to derive an accurate altitude estimation, we fused raw altitude

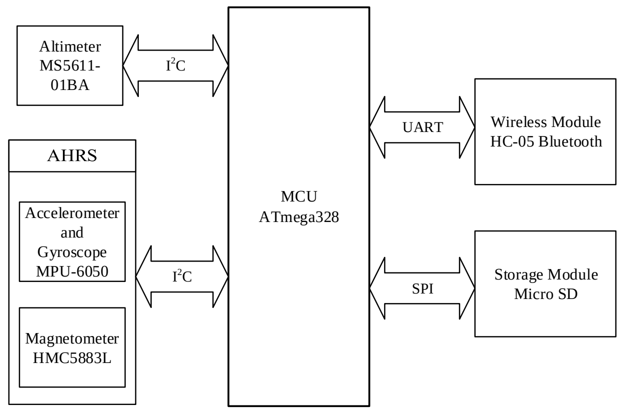

Fig. 1. Block diagram of the wireless sensor node.

values furnished from barometer, and vertical displacements, obtained by the AHRS and the acceleration data, via an ad-hoc complementary filter.

The block diagram of the projected system is shown in Fig. 1 and its components are described in details in the following paragraph.

In particular, the MCU embeds the proposed real time fall detection algorithm that utilizes the orientation data, dynamic acceleration and altitude estimation with a sampling data rate of 50 Hz.

A. AHRS system

A combination of 3-axis magnetometer, gyroscope and accelerometer is required to realize a AHRS system which measures the local magnetic field, acceleration and angular rate in three dimensions.

Accelerometer and Gyroscope sensors: the MPU-6050 (InvenSense Inc., USA) combines a MEMS 3-axis accelerometer and a MEMS 3-axis gyroscope and communicates with the MCU via I2C bus. The gyro is an angular rate sensor with full-scale ranges of ±250, ±500, ±1000, and ±2000dps and a sensitivity up to 131 LSBs/dps. The accelerometer sensor measures the acceleration with configurable full-scale ranges of ±2g, ±4g, ±8g and ±16g.

Magnetometer sensor: the HMC5883L (Honeywell, USA) is a 3-axis digital compass designed to measure the direction and magnitude of Earth's magnetic field. It embeds a 12-bit ADC convertor and achievies a field resolution of 4 mG in the ±8 G range.

B. Barometric sensor

The MS5611-01BA (MEAS, Switzerland) is a MEMS barometric pressure sensor that provides digital temperature and pressure measures with 24-bit resolution. It communicates with the MCU via the SPI and I2C bus interfaces.

C. MCU module

We adopted the ATmega328 (ATMEL, USA) that is a low-power 8-bit microcontroller with 32kB ISP flash memory, I2C and SPI interface, 1kB EEPROM, 2kB SRAM and 32 general purpose I/O lines. The MCU reads the data from the external MARG sensor through I2C bus and processes them in order to implement the orientation filter, fall detection algorithm and alarms management. Data and alarms are sent via the programmable serial USART interface of the MCU. The firmware for ATmega series microcontrollers is easily programmable using the efficient GCC compiler.

D. RF module

The HC-05 component is a small low-power and low-cost Bluetooth module, ideal for embedded applications. It is designed to wirelessly extend the serial interface. Through the UART port, data processed by the MCU are transmitted via the RF module.

E. Mass-storage unit

The MCU memory capabilities are not sufficient to store data from sensors and orientation filter if wireless connectivity is unavailable. We use a microSD card in order to provide the device with mass-storage capability. Communication with microSD card is achieved over SPI interface.

F. Battery

A very slim, extremely light weight battery based on the new Polymer Lithium Ion chemistry is used in order to power the device. This battery includes built-in protection against over voltage, over current, and minimum voltage.

Finally, we have developed a simple Android application for smartphones that allows to receive, via Bluetooth interface, possible fall alarms sent from the device worn by the subject.

III. Orientation estimation

The knowledge about the orientation of a body is very important for systems such as falls detection, human motion analysis and robotics ones. In order to describe the spatial orientation of the human body we adopt a representation through Yaw, Pitch and Roll angles. Starting from these angles, it is possible to describe rotations between two different reference systems, following a Z-Y-X rotation sequence. In our case, the first reference system, called $Sensor\ frame$, is mobile and integral with the device mounted on the waist of the subject and the second, called $Earth\ frame$, is represented by a fixed reference system. In practice, the Yaw, Pitch and Roll angles superimpose the $Sensor\ frame$ to the $Earth\ frame$ and, in our system, they are used to represent the actual orientation of human body. Yaw describes a rotation around the Z-axis of the $Earth\ frame$, Pitch describes a rotation around the Y-axis of the $Earth\ frame$ and Roll describes a rotation around the X-axis of the $Earth\ frame$. The first video frame in Fig.2 shows the orientation of the device worn by a subject during the typical scenario of a simulated backward fall ending sitting.

A single 3-axis accelerometer can define the orientation of a body when used like an inclinometer. In particular, if the accelerometer placed on the waist of a subject is not moving, it is possible to find the direction of the gravitational force

Fig. 2. Orientation of the device worn by a subject during the typical scenario of a simulated backward fall ending sitting.

acting on it in and get its inclination. In this case, only the Pitch and Roll angles can be computed and it is unfeasible to have any information on the Yaw angle. This is due to the fact that, employing only gravity as reference vector, any rotation of the device around the gravity vector does not produce any variation in acceleration. In fact, Yaw is defined as the angle between a fixed heading point (e.g. Earth's North) and the X axis of the device. In addition, this method also suffers from errors caused by external accelerations and vibrations which adding itself gravity, make the accelerometer unreliable for the estimation of the body orientation.

An IMU (Inertial Measurement Unit) sensor combines the features of 3-axis accelerometer and a 3-axis gyroscope in order to provide complete information about acceleration, orientation, speed, position, etc. of a rigid body. Pitch and Roll angles are estimated fusing angular displacements obtained by integration of the gyro and the accelerometer measurements. This solution allows to compensate the problem due to the influence of external vibrations and accelerations on gravity measurements. Again, the Yaw angle is subject to a very small amount of drift since there is no absolute reference point available for the heading.

An accurate estimation of the Yaw angle can be obtained by using an AHRS system that combine an IMU sensor with a 3-axis magnetic sensor. Trough information coming from these sensors, the AHRS implements a filter able to provide an accurate estimation of the device orientation. The drift error introduced by the gyro sensor is compensated by two reference vectors, which are the gravity vector, measured by the accelerometer, and Earths magnetic field vector, measured by the magnetometer.

Mahony *et al.* [18] developed an orientation filter highly efficient but it is generally used into IMU devices. Madgwick *et al.* [19] proposed a new orientation filter designed for both IMU and AHRS devices. The filter includes gyroscope bias drift compensation and magnetic distortion compensation. It reduces the computational load associated with conventional Kalman-based methods, making it particularly well suited for real-time applications where limited processing resources may be available. In order to prevent problems such as gimbal lock, Madgwick's algorithm makes use of a quaternion representation. A quaternion q, is a four-element vector consisting of one real part, q_0, and three complex parts, q_1 q_2 and q_3. The representation of the Yaw, Pitch and Roll angles, starting from the components of a quaternion $\hat{q}$, can be expressed by the following equations:

$$Yaw = atan2\ (2q_2q_3 - 2q_1q_4,\ 2q_1^2 + 2q_2^2 - 1) \quad (1)$$

$$Pitch = -sin^{-1}\ (2q_2q_4 + 2q_1q_3) \quad (2)$$

$$Roll = atan2\ (2q_3q_4 - 2q_1q_2,\ 2q_1^2 + 2q_4^2 - 1). \quad (3)$$

The proposed system implements an AHRS and Madgwick's orientation filter in order to provide a complete estimation of the subject's orientation.

IV. Dynamic acceleration estimation of human body

In many studies a fall is detected by identifying typical changes in acceleration measurements provided by a 3-axis accelerometer attached to the subject's body and in particular by observing the $Signal\ Vector\ Magnitude$ (SVM) of the acceleration.

A fall event can be also identified and valued by analyzing the dynamic acceleration component parallel to the Earth's gravitational field vector, namely dynamic vertical acceleration E_{dz}. In order to compute the dynamic acceleration of the subject, the 3-axes acceleration measurements must be rotate in the $Earth\ frame$ and then can be removed the Earth's gravitational field vector to get the vertical component E_{dz} of the resultant vector [20].

In general, a three dimensional vector $\hat{v}$ can be rotated using the quaternions through the relation:

$$\begin{aligned} E_{\hat{v}_n} &= \ {}^S_E\ \hat{q}_{e,n-1} \otimes S_{\hat{v}_n} \otimes \ {}^S_E\ \hat{q}^*_{e,n-1} = \\ &= \ {}^E_S\ \hat{q}^*_{e,n-1} \otimes S_{\hat{v}_n} \otimes \ {}^E_S\ \hat{q}_{e,n-1} \end{aligned} \quad (4)$$

where $E_{\hat{v}}$ and $S_{\hat{v}}$ represent the same vectors described in E and S frame respectively, $\otimes$ is the quaternion product determined by the Hamilton rule and ${}^S_E\ \hat{q}_{e,n-1}$ is the estimated orientation of the $E\ frame$ relative to the $S\ frame$ at the *(n-1)-th* sample. In the proposed system, the accelerometer readings $S_{\hat{a}}$, referred in the $Sensor\ frame$, have been rotated using equation (4) in order to compute the acceleration vector in the $Earth\ frame$, $E_{\hat{a}}$.

As well as accelerometer measurements, the acceleration vector, $E_{\hat{a}}$ is subject to dynamic and static accelerations expressed in the $Earth\ frame$ as follows:

$$E_{\hat{a}} = E_{\hat{d}} + E_{\hat{g}} \quad (5)$$

where $E_{\hat{d}}$ is the dynamic acceleration due to the movements of the subject and $E_{\hat{g}}$ is the gravity vector both expressed in the $Earth\ frame$. The magnitude and direction of $E_{\hat{g}}$ are known ($E_{\hat{g}}$ = [0, 0, 1]), thus it is possible to compute $E_{\hat{d}}$ as follows:

$$E_{\hat{d}} = E_{\hat{a}} - E_{\hat{g}}. \quad (6)$$

In the proposed system, a possible fall event is revealed by analyzing the vertical component of the dynamic acceleration

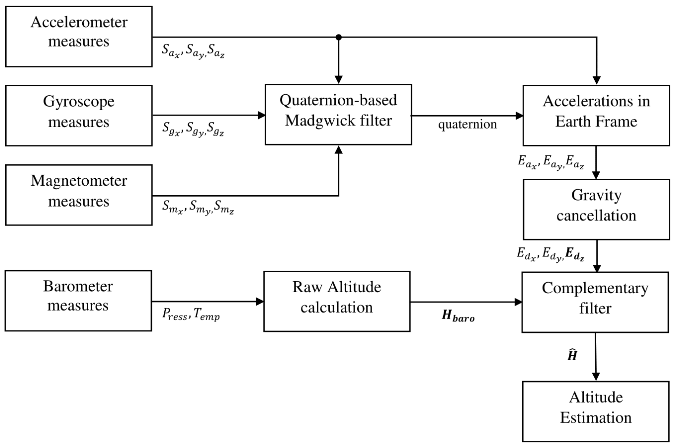

Fig. 3. Block diagram of the sensor fusion method for the estimation of altitude using an altimeter in conjuntion with an AHRS.

in the $Earth\ frame$ and therefore the value of $E_{\hat{d}}$ along z-axis, namely E_{d_z}.

V. ALTITUDE ESTIMATION

The air pressure signal coming from a barometer sensor allows to calculate altitude, H_{baro}, at the measurement site. It can be determined as follows:

$$H_{baro} = \frac{(T + 273.15)}{0.0065}(1 - (P/P_0)^{(0.19)}) \tag{7}$$

where H_{baro} is measured in meters, T is the temperature in $°C$, P is the pressure measured in Pa, P_0 is the pressure at sea level and it is equal to 101.325 kPa in normal conditions. This altitude measurement is affected by thermal noise and quantization noise that cause its wide and rapid fluctuations in the signal.

In order to get a more accurate altitude estimation, we adopt a complementary filter to fuse the raw altitude values, calculated by barometer measurements, and the vertical displacements, obtained by a double integration of the dynamic component of the vertical acceleration in the $Earth\ frame$, E_{d_z}, [20]. Fig. 3 shows the block diagram of the data fusion method implemented to provide an accurate estimation of the altitude.

A complementary filter is commonly applied to combine more noisy measurements of the same signal characterized by complementary spectral characteristics [21]. For example, we can consider a generic signal z furnished by two different measurements $x_1 = z + n_1$ and $x_2 = z + n_2$ where n_1 is mainly low frequency noise and n_2 is mainly high frequency noise. x_1 must be filtered by a high pass filter with transfer function $G_1(s)$ whereas x_2 must be filtered by a low pass filter with transfer function $G_2(s)$, which is complementary to $G_1(s)$. The output of the filter, $\hat{Z}(s)$, is given by:

$$\begin{aligned}\hat{Z}(s) &= G_1(s)x_1(s) + G_2(s)x_2(s) = \\ &= Z(s) + G_1(s)n_1(s) + G_2(s)n_2(s).\end{aligned} \tag{8}$$

In practice, the signal $Z(s)$ is entirely rebuilt after the filtering while $n_1(s)$ and $n_2(s)$ are high and low pass filtered respectively.

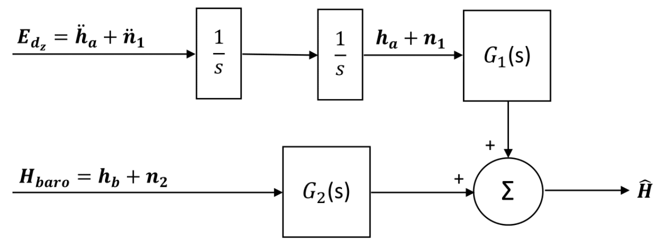

Fig. 4. Block diagram of the complementary filter used for the altitude estimation starting from the measurements altimeter and the dynamic component of the vertical acceleration in the $Earth\ frame$.

In this paper a complementary filter is used to estimate the altitude of the subject who wears the device and the basic scheme of the implemented filter is shown in Fig. 4. In our case, the output of the filter is represented by the estimated altitude $\hat{H}(s)$ while the two noisy measurements are the dynamic component of the vertical acceleration in the $Earth\ frame$, which is equal to $\ddot{h}_a(s) + \ddot{n}_1(s)$, and the altimeter measurements H_{baro}, which is equal to $\ddot{h}_b(s)+\ddot{n}_2(s)$. The vertical displacement derived through a double integration of the dynamic component of the vertical acceleration in the $Earth\ frame$, h_a, is characterized by a noise n_1 that is predominantly at low-frequency. Conversely, H_{baro} is characterized by a high-frequency noise, n_2. Consequently:

$$G_1 = \frac{s^2}{s^2 + as + b} \tag{9}$$

$$G_2 = \frac{as + b}{s^2 + as + b}. \tag{10}$$

where $G_1(s)$ and $G_2(s)$ represent the transfer functions of a second order high pass filter and a low pass filter, respectively.

The estimated altitude $\hat{H}(s)$ obtained by using the complementary filter, can be derived as:

$$\begin{aligned}\hat{H}(s) &= \frac{1}{s^2}G_1(s)E_{d_z}(s) + G_2(s)H_{baro}(s) = \\ &= \frac{1}{s^2}G_1(s)(\ddot{h}_a(s) + \ddot{n}_1(s)) + G_2(s)(h_b(s) + n_2(s)) = \\ &= G_1(s)(h_a(s) + n_1(s)) + G_2(s)(h_b(s) + n_2(s)) = \\ &= h(s) + \frac{s^2}{s^2 + as + b}n_1(s) + \frac{as + b}{s^2 + as + b}n_2(s)\end{aligned} \tag{11}$$

where the design of the constant a and b is derived from a low frequency analysis of the noise superimposed to E_{dz} and a high frequency analysis of the noise characterizing H_{baro}. The choose of the best crossover frequency is a tradeoff between the two measurements. Therefore, according to the previous optimization procedure, we have obtained the better performance of the implemented complementary filter setting a and b to 1 and 0.55, respectively.

Fig. 5 shows a typical trend of the raw altitude signal and the altitude signal from the output of the implemented complementary filter when the device is raised and then returned to the starting position.

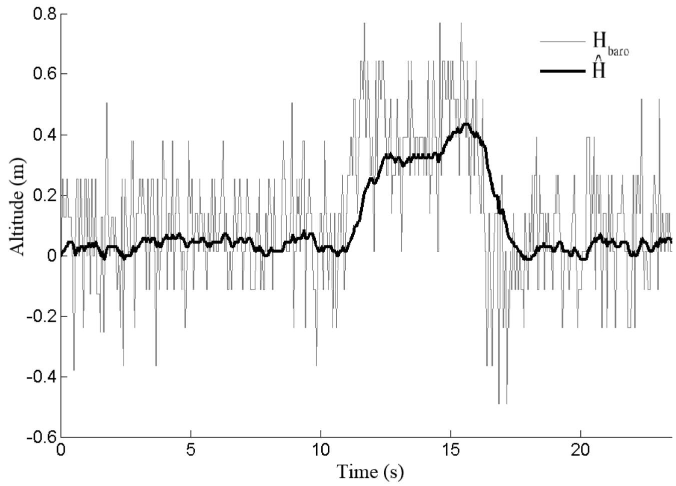

Fig. 5. Comparison between raw altitude data H_{baro} (grey line), and altitude signal coming from the complementary filter $\hat{H}$ (black line).

VI. Fall detection algorithm

In this section is shown how the developed algorithm makes use of acceleration, orientation and estimated altitude data, in order to detect fall events. The algorithm is based on settings of proper thresholds for the detection of different phases characterizing a fall. This method has allowed to obtain excellent performance [8], [9], [14] respect other solutions [10], [11] that may demand too much computational load for real-time system with limited processing resources. In particular, the proposed algorithm is based on the detection of the following phases:

1) $Impact\ phase$: after the loss of contact with the ground and the start of the descent towards the ground, due to the attraction by the gravity force, the subject impacts on the ground or other objects that cause a peak of acceleration;
2) $Aftermath\ phase$: immobilization, or nearly so, to the ground associated with low values of acceleration for a short time;
3) $Posture\ phase$: end posture, dependent on the direction of the trunk of the subject after the fall on the ground.

It has been shown that the impact phase due to a fall event is always characterized by a peak of acceleration [14], [22]. In our algorithm, a possible impact on the ground is classed by evaluating if the E_{dz} value exceeds the threshold At_I (Acceleration threshold for Impact) set to 1.5 g. Whenever is detected the $Impact$ phase, the algorithm calculates the altitude variation of the subject within Tt_{AV} = 2.5 s (Time threshold for Altitude Variation), as follows:

$$\Delta H = \hat{H}^b - \hat{H}^a \tag{12}$$

where $\hat{H}^b$ and $\hat{H}^a$ represent the estimated altitude values 1 s before and 1.5 s after the peak of E_{dz} respectively.

At the same time, the $Aftermath$ phase occurs when E_{dz} value decreases below the threshold At_A (Acceleration threshold for Aftermath) set to 0.35 g within Tt_A = 1 s (Time threshold for Aftermath) after the peak of acceleration due to the Impact phase.

If also the previous condition is verified, changes in Pitch and Roll angles are observed in order to identify the $Posture$ phase. Defining Ot_P as the Orientation threshold for $Posture$, the algorithm verifies if the absolute value of Pitch or Roll angle has exceeded 50° within Tt_P = 1 s (Time threshold for Posture) after the detection of the phase $Aftermath$ (thus within 2 s after exceeding the Impact Acceleration threshold). When the $Posture$ phase is detected, the body of the subject has changed its orientation with respect to the one it had before falling.

In order to indicate that assistance is not required because the subject has raised up, the algorithm checks if the absolute value of both Pitch and Roll angles is back below Ot_{GU} = 40° (Orientation threshold for Get Up) within Tt_{GU} = 30 s (Time threshold for Get Up).

When the $Posture$ phase is not detected, it is possible that the subject is falling vertically. In such cases (as in syncope and falls backward ending up sitting), significant changes in body's orientation during the falls are not registered. For this reason, the introduction of the altimeter sensor allows to classify an event as a possible fall when ΔH value exceeds the threshold At_{FA} (Altitude threshold for Fall Alert) set to 0.52 m. If this occurs, the algorithm evaluates the subject's altitude variation after the fall by computing $\Delta H'$ value, as follows:

$$\Delta H' = \hat{H}^c - \hat{H}^a \tag{13}$$

where $\hat{H}^c$ is the current subject's altitude calculated every second and $\hat{H}^a$ is the altitude estimated 1.5 s after the $Impact$ phase. The subject is considered again standing if the $\Delta H'$ value exceeds the threshold At_{GU} (Altitude threshold for Get Up) set to 0.46 m within Tt_{GU}, and if both the absolute values of Pitch and Roll angles are back below Ot_{GU}.

The impossibility to get up without any help after a fall is a crucial event that must be monitored by the fall detection system. Therefore, this system must also avoid the alarm transmission if the fallen subject has raised up and does not need any assistance. In order to improve the accuracy of the proposed system, the evaluation on the altitude variation of the subject is verified even when the absolute value of both Pitch and Roll angles is back below Ot_{GU} = 40° (Orientation threshold for Get Up) within Tt_{GU}. This additional control allows to obtain better values for the accuracy of the algorithm, as shown in the results section.

The orientation and time thresholds have been derived from our previous study [14], where we obtained 100% average accuracy, sensitivity and specificity considering an experimental protocol that included only fall events in which the trunk of the subject ended orizzontal on the ground. The accelerations and altitude thresholds were calculated using a Support Vector Machine method [23] on experimental data obtained during an accurate training process.

An event that no verify the conditions of the algorithm in the established sequence and within the time thresholds is classified as non-fall. For example, in an ADL like lying on a bed then standing the *Aftermath* and *Posture* phases could be identified but not the *Impact* phase. In fact, in this type of ADL the proposed algorithm does not detect a fall because there is

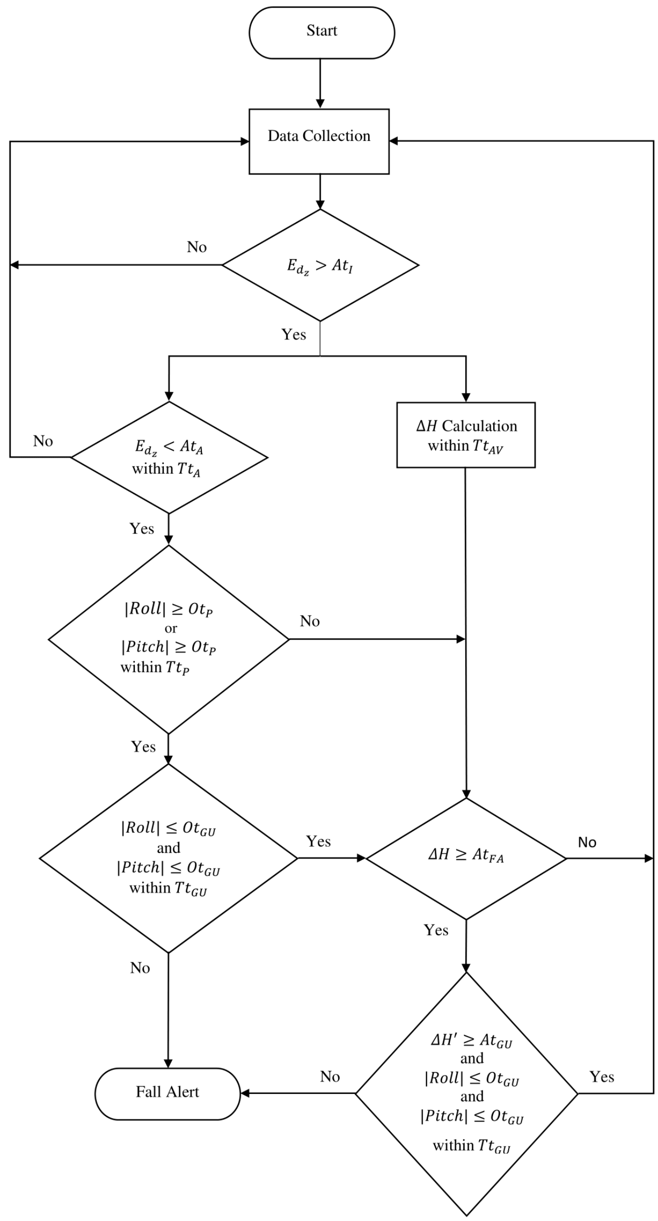

Fig. 6. Flow chart of the proposed fall detection algorithm.

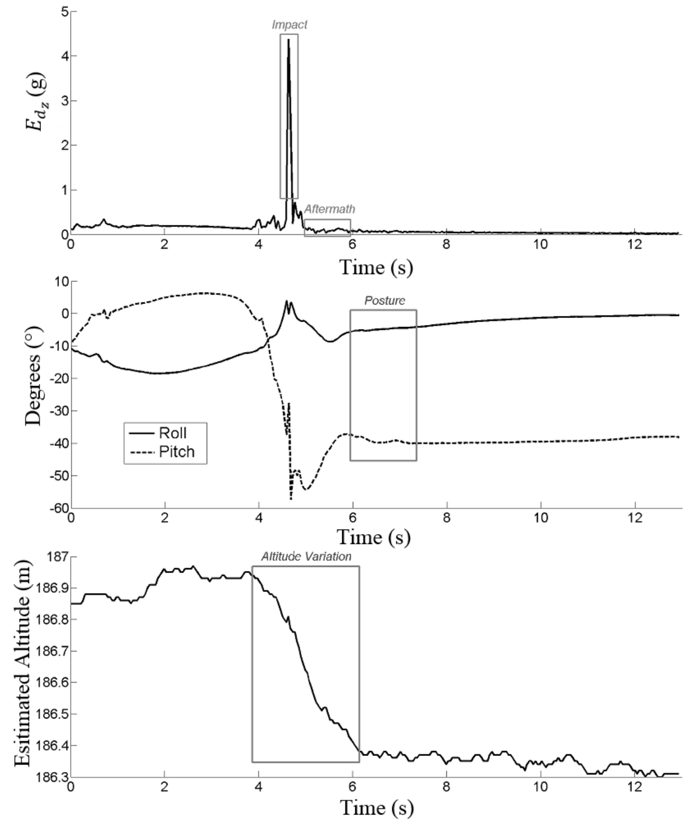

Fig. 7. Acceleration, orientation and estimated altitude obtained during a simulated backward fall ending sitting.

not an E_d peak greater than 1.5 g that should characterize the *Impact* phase.

Typical outputs provided by the four sensors during the execution of a backward fall with the subject remaining sitting (Fig.**??**) are shown in Fig. 7. The acceleration peak of E_{dz} due to the impact (*Impact* phase) is followed by low values of acceleration related to the motionless of the subject (*Aftermath* phase). In this specific event, the fall does not cause considerable Pitch and Roll variations of the subject?s trunk. Conversely, the difference between the altitudes calculated before and after the impact to the ground is enough to detect a fall event.

VII. Experimental protocols

In order to evaluate the performance of our algorithm, it is necessary to adopt an experimental protocol that takes into account all the possible events (falls and ADL) that can occur in everyday life of an elderly.

To date, in the literature does not exist a unique protocol used for the validation of fall detection systems. Past studies report that the consequences of a fall can depend on different factors such as sex and age of the subject [24] together with direction [25] and type of fall [1]. An optimum experimental protocol should take into consideration all these factors, however, the engagement of elderly person to simulate falls could cause them injuries. For this reason the majority of previous studies exclusively employ young persons to perform their fall tests. O'Neill *et al.* [25], have shown that most of falls in elderly people occur in forward, backward or sideway direction. Furthermore, retrospective studies of Rubenstein [1] highlighted that about 13% of occurrence of types of fall among older persons were caused by falls in which the subject is generally able to sit. In order to mimic realistic events that most often occur among elderly people, a reliable experimental protocol for fall detection has to include backward, forward, lateral fall categories and also syncope and falls ending sitting.

The experimental protocols used by Kangas [8], Jantaraprim [10] and Vallejo [11], considered only types of falls provided by O'Neill (falls in forward, backward, and lateral direction) and a limited number of ADL.

Otherwise, in a previous work [14] instead we have tested our algorithm considering a protocol based on the research of Noury [13] in which were also included falls with recovery and falls where the trunk of the subject does not gets a significant rotation (syncope and backward fall ending sitting) but were not considered a sufficiently significative number of ADL.

Chen [17], starting from the protocol proposed by Noury, introduced some indoors and outdoors ADL scenarios not considered in our previous works. In this way, he has carefully checked the system capabilities to generate false alarms.

Finally Bianchi has evaluated his system testing it on three different experimental protocols [16]: Test A comprises indoor simulated movements and falls, Test B includes outdoor simulated falls and Test C integrates indoor and outdoor simulations of normal activities of daily living. Bianchi's experimental protocols added several indoors and outdoors ADL events such as the scenario where subject collapse into a chair that is an event particularly important in order to avoid many false alarms. However, these scenarios do not take into account some dangerous falls, like the one backwards in which the subject remains sitting.

Table I gathers all the fall events and ADL scenarios provided in the experimental protocols used by us in our previous study [14], Chen [17] and Bianchi [16]. In the table is specified for each event, if it has been tested indoor (I), outdoor (O), or both (I/O).

In order to allow an objective evaluation of our fall detector, the proposed algorithm has been tested in same protocols proposed by us in our previous study, Chen and Bianchi. For security reasons, all trials were performed by young subjects simulating falls onto a mattress (thickness 15 cm) and keeping the device attached on the waist. We asked the subjects to remain on the mattress for at least 30 seconds after the fall to simulate a possible lying down period experienced by the elderly. During these trials a possible signaling of fall have been transmitted to the local computer for data storage and display.

In order to test the proposed fall detection algorithm described in Section VI, we engaged 10 volunteers (5 male and 5 female, age 23.2 $\pm$ 2.5 years and height: 1.74 $\pm$ 0.06 m) who mimicked the scenarios of the experimental protocol adopted in [14]. According to [17], the Chen's test involved 10 volunteers (5 male and 5 female, age 23.2 $\pm$ 2.5 years and height: 1.74 $\pm$ 0.05 m) who perform the experimental protocol as in the table I. Similarly, 20 healthy volunteers (10 male and 10 female, age 22.7 $\pm$ 3.2 years and height: 1.73 $\pm$ 0.04 m) performed the Test A and 5 healthy volunteers (2 male and 3 female, age 22.7 $\pm$ 3.1 years and height: 1.71 $\pm$ 0.05 m) performed the Test B and Test C designed by Bianchi [16].

VIII. Results

The performance of the proposed system has been evaluated in terms of sensitivity, specificity and accuracy according to the experimental protocol adopted in [14]. Syncopes and backward falls ending sitting were weak point in our previous work. On the contrary, the improved system correctly assesses the totality of the events envisaged by the experimental protocol, as shown in Tab II. In this case no false negatives and no false positives occurred on a total of 540 tests. The algorithm described in Section VI shows 100% average accuracy, sensitivity and specificity highlighting better performance than our previous fall detection algorithm [14] in the same experimental protocol.

TABLE II
PERFORMANCE OF THE PROPOSED FALL DETECTION ALGORITHM, COMPARED TO OURS PREVIOUS VERSION AND THOSE OF CHEN AND BIANCHI, ACCORDING TO DIFFERENT EXPERIMENTAL PROTOCOLS.

Experimental Protocol	**Algorithm**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
Our previous Test	Proposed	100	100	100
	Our previous	80.74	100	90.37
Chen Test	Proposed	100	98.89	99.69
	Chen	95.71	99.44	97.5
Bianchi Test A	Proposed	100	99	99.38
	Bianchi	97.5	96.5	96.9
Bianchi Test B	Proposed	100	100	100
	Bianchi	86.7	100	90
Bianchi Test C	Proposed	N.A.	100	100
	Bianchi	N.A.	100	100

According to his experimental protocol, Chen has not detected 4 falls ended up with lateral posture and, during ADL events, his device announced 7 times a fall although it has not occurred. Differently, the proposed system has correctly recognized all the fall events, achieving 100% of sensitivity, and the only false alarm generation has occurred when the subject was walking down the stairs in outdoor environment. As shown in Table II, our proposed algorithm reaches 99.69% and 98.89% of accuracy and specificity, respectively.

Similarly, the results of Test A, Test B and Test C, which compose the whole experimental protocol proposed by Bianchi, are shown in Table II. In the first protocol (Test A), the algorithm of Bianchi has misclassified 3 fall events, 2 fall events with recovery and 5 ADL scenarios. Differently, our algorithm has achieved 100% of sensitivity, but it has incorrectly classified for 2 times the ADL scenarios where the subject has collapsed into a chair.

The test B was designed by Bianchi to verify the false negative rate of the system by simulating falls in the outdoor environment. The results obtained by Bianchi during this test shown that, in an outdoor environment, the sensitivity of his algorithm (90%) is lower compared to that obtained in an indoor laboratory environment (97.5%). With our algorithm, two fall events were not detected (forward with attempt to break the fall and slipping against a wall ending up sitting), so reducing the sensitivity to 93.33%.

The last results in the Table II, one test protocol of Bianchi (Test C) was designed to test the false positive rate of the system when subjects are performing long-term ADL scenarios in both indoor and outdoor environments. In this case, both our that his system do not generate false alarms.

TABLE I
EXPERIMENTAL PROTOCOL WITH ENVIRONMENTAL SPECIFICATION OF EACH EVENT: INDOOR (I), OUTDOOR (O), OR BOTH (I/O).

Event			Protocol		
Category	**Type**	**Outcome**	**Previous**	**Chen**	**Bianchi**
Backward fall	Ending up sitting	Positive	I	I	
	Ending in lateral position	Positive	I	I	
	Ending up lying	Positive	I	I	I/O
	Ending up lying with recovery	Negative	I	I	
Forward fall	On the knees then ending lying	Positive	I	I	
	Ending in lateral position	Positive	I	I	
	Ending up lying	Positive	I	I	I/O
	Ending active lying	Positive			I/O
	With attempt to break the fall	Positive			I/O
	Protecting with arm, ending lyng	Positive		I	
	Ending up lying with recovery	Negative	I		I/O
	Ending up lying with recovery and walking	Negative			I/O
Lateral left fall	Ending lateral	Positive		I	
	Ending up lying	Positive	I	I	I/O
	Ending up lying with recovery	Negative	I	I	
Lateral right fall	Ending lateral	Positive		I	
	Ending up lying	Positive	I	I	
	Ending up lying with recovery	Negative	I	I	
Syncope	Slipping against a wall ending up sitting	Positive	I	I	I/O
ADL	Lying on a bed then standing	Negative	I	I	I
	Standing after picking something	Negative	I		I
	Sitting on a chair then stand up	Negative	I	I/O	I
	Walking on the stairs	Negative	I	I/O	I
	Walking	Negative	I	I/O	I
	Running	Negative		I/O	I/O
	Bend down and doing own laces	Negative		I/O	I
	Jumping	Negative		I/O	I
	Squatting then standing up	Negative		I/O	
	Coughing or sneezing	Negative		I/O	
	Taking the lift	Negative		I	I
	Coolapse into a chair	Negative			I
	Opening and closing the door in a room	Negative			I
	Wearing the device after dropping it on the floor	Negative			I
	Wearing the device after going to the toilet	Negative			I
	Dropping the device after going to the toilet	Negative			I
	Walking down four big steps	Negative			O
	Walking up and down a slope	Negative			O
	Driving, parking and leaving the car	Negative			O
	Dropping the device on the car's seat	Negative			O
	Dropping the device on the floor	Negative			O
	Getting into the car	Negative			O
	Wearing the device on the car's seat	Negative			O

IX. Discussion

The obtained results indicate that the combined use of accelerometer, gyroscope, magnetometer and barometer, has determined higher performance compared to the systems currently present in the literature.

The main weakness of fall detectors that include only accelerometer and barometer is represented by the inability to get an accurate estimate of the device orientation and by the imprecision of altitude measurements. In such systems, the Pitch and Roll angles are obtained through accelerometer data and therefore are influenced by external accelerations and vibrations which add up to gravity. Moreover, it is not possible to have any information about the Yaw angle.

Our previous system was able to get high accuracy in the orientation of the device worn by the subject through the combined use of data from accelerometer, gyroscope and magnetometer, but it was unable to detect falls in which the trunk of the subject had not had a significant rotation.

In the proposed system, the ensured precision about the device orientation and the addition of the barometer, have allowed to solve the last problems we noticed in our previous work. In detail, we are referring to the failed detection of those falls characterized by a vertical final position of the subject, as in falls ending sitting and syncope [14]. Indeed, through an accurate estimate of the altitude by means data fusion between the barometer and the AHRS measures, our system is able to proper assess the variation in altitude during a fall.

The main problem recorded by Chen was the unsuccessful detection of falls ending up with lateral posture (these events were not detected 4 times) [17]. Through the estimate of the device orientation, the proposed algorithm is able to evaluate exactly these types of scenarios. According to Chen?s protocol, our system has generated only one false alarm when the subject was coming down the stairs in outdoor environment. Solely in this case, the acceleration and altitude conditions related to a fall detection event have been, even if mistakenly, verified.

In the system proposed by Bianchi, false negative events had occurred during forward falls and when the subject was leaning against the wall and then slips to the floor finishing seated [16]. The author states that in these two cases no change in the pressure measures were observed during the fall. In our algorithm, forward falls are correctly reported through the accurate evaluation of the subject orientation and the altitude variation calculated by the complementary filter. Again, the false positives generated during the Test A are due to the overrun of the thresholds determined for acceleration and altitude. In any case, the number of false positives detected by our system is less than those identified by Chen and Bianchi's systems.

X. Conclusions

The purpose of this work was the development of a wearable fall detector that exceeds the limits of the current systems.

The proposed device embeds a triaxial accelerometer, a triaxial gyroscope, a triaxial magnetometer and a barometer. Through the signals from the first three sensors, it is possible to get an AHRS that provides information about the orientation of the device worn on the waist by the subject. The orientation and acceleration data are used to obtain values of the dynamic vertical acceleration. The altitude signal, calculated by means of measurements coming from the barometer, contains an amount of noise that makes it unsuitable for our application. Consequently, in order to derive an accurate altitude estimation, we fused the raw altitude values, calculated by the barometer, and the vertical displacement data, obtained from the AHRS and the acceleration data, through a complementary filter.

The developed fall detection algorithm is based on the evaluation of dynamic vertical acceleration, orientation and accurate altitude signals coming from the device worn by the subject. The algorithm was evaluated according to three different experimental protocols proposed in literature which include the most realistic scenarios of falls and ADL for the elderly. The first protocol, proposed by us in a previous work, considers only a limited number of indoor events. The second, used by Chen, also introduces outdoor scenarios. The third protocol, proposed by Bianchi, provides for the largest number of indoor and outdoor events.

Results show that the data fusion coming from the barometer, inertial and magnetic sensors, allows to detect scenarios of falls that no wearable system currently proposed in literature is able to assure. Our system, through an accurate altitude estimation, dramatically reduces the number of false negatives, especially in events such as syncope and backward falls ending sitting, which are hardly recognizable by conventional fall detection systems.

As a final note, it would be appropriate to provide an unique experimental protocol including all possible falls and ADL scenarios typical of elderly, so that each fall detection system can be tested on the same set of events.

In the future, in order to improve the performance of the system, it will be implemented a method that automatically calculates the optimum thresholds of the algorithm for each subject. For the calculation of such thresholds, a specific preliminary calibration procedure will be planned and then performed by the individual subject. The final aim will be to deliver this device to the elderly, in order to evaluate the weaknesses of the entire system and thus optimize the algorithm.

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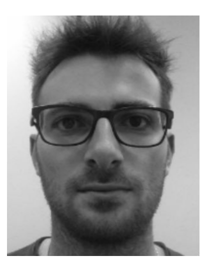

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