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# Device Attitude and Real-Time 3D Visualization: An Interface for Elderly Care

Manuel Abbas<sup>1</sup>, Joaquim Prud'Homme<sup>1</sup>, Fabien Lemoine<sup>1</sup>, Dominique Somme<sup>2</sup>, and Régine Le Bouquin Jeannès<sup>1</sup>

<sup>1</sup> Univ Rennes, Inserm, LTSI, UMR 1099, F-35000 Rennes, France

<sup>2</sup> CHU de Rennes Service de Gériatrie, F-35000 Rennes, France

{manuel.abbas, regine.le-bouquin-jeannes, fabien.lemoine}@univ-rennes1.fr – joaquim.prud-homm@inserm.fr – dominique.somme@chu-rennes.fr

**Abstract** – This paper proposes an innovative graphical user interface to visualize the attitude of a sensing device in a three-dimensional space, serving a wide-range of medical applications. Based on inertial measurement units (IMU) or on Magnetic, Angular Rate and Gravity sensors (MARG), the proposed tool estimates Euler angles using a predefined attitude filter to display the orientation of the device relative to the Earth frame in real-time. The device is schematized by linking six polygonal regions, and is subject to sequential rotations by updating the graph each 350 ms. Two public datasets were used to demonstrate the value of this contribution in fall risk assessment and body posture monitoring for elderly care.

**Keywords:** graphical user interface, device attitude, sequential rotations, Euler angles, elderly care.

## I. INTRODUCTION

In the past decades, minimized electronic sensors have been known for their low prices, and their widespread use in the healthcare domain [1]. The integration of these sensors in wearable devices or smartphones has been shown to be reliable for many monitoring systems and e-health applications [2]. In the literature, Kwon *et al.* have inspected the accelerometer of an iPhone for heart rate measurement [3]. Najafi *et al.* have evaluated the characteristics of some postural transitions, namely stand-to-sit and sit-to-stand, and their correlation with falling risk in elderly, using a miniaturized gyroscope [4]. Milici *et al.* have proposed a magnetometer-based solution for sleep quality monitoring [5]. Some other studies have used a combination of sensors to classify activities of daily living (ADLs) [6]. Now, sensor fusion techniques have been developed to estimate the attitude of sensing devices [7]. In other words, the orientation of the device relative to the Earth frame is measured by merging acquired data from a tri-axial accelerometer and a tri-axial gyroscope, or from these two sensors and a tri-axial magnetometer. These approaches are useful for human motion tracking [8], which is the base of several medical solutions. Two types of accelerometers exist. The first one concerns capacitive accelerometers, also known as Micro-Electro-Mechanical Systems (MEMS). These accelerometers depend on a change in electrical capacitance to

measure acceleration. The second type refers to piezoelectric accelerometer, which is made of a quartz crystal. A force acting on the piezoelectric element is produced when the accelerometer is moving. A charge output, generated from these vibrations, is proportional to the applied force and is used to measure acceleration. The first type has the advantage of measuring the static acceleration caused by the gravity. This measurement is important for orientation estimation techniques. This justifies why MEMS sensors are preferred for this task.

Given these aforementioned elements, we propose in this paper an interface we developed to visualize the orientation of a sensing device in real-time. The corresponding device, which consists of inertial sensors, is plotted in a three-dimensional graph. Its attitude is estimated by fusing acquired data, and the graph is updated by rotating the vertices and the faces of the plot correspondingly. Analyzing medical reports and questioning patients are not always sufficient to accurately check their health. Clinicians may need to visualize the orientation of wearable devices to assess the movements of their patients (or a certain event like a fall) and/or to restore them to normal behavior. The proposed tool answers these questions.

The remainder of the paper is organized as follows. Section II discusses the principle of orientation estimation algorithms. Section III describes the proposed interface and its characteristics. Some real world examples are given in section IV, before addressing some limitations and practical considerations in section V. Section VI concludes the paper.

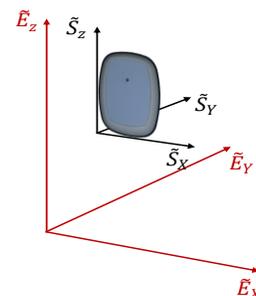


Figure 1. A sensing device, with its corresponding frame ( $\vec{S}$ ) and the Earth frame ( $\vec{E}$ )

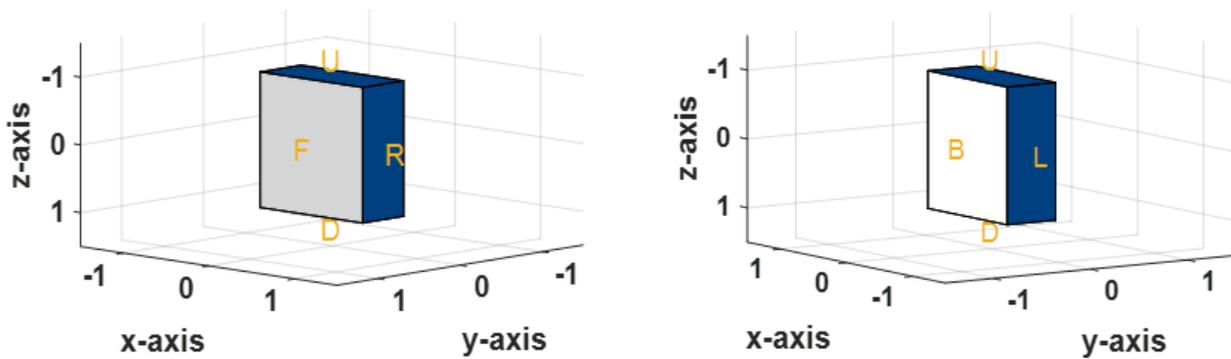


Figure 2. Two different views of the plotted sensing device in a three-dimensional space, and its corresponding labels in yellow

## II. PRINCIPLE OF ATTITUDE ESTIMATION

The orientation estimation of a device with respect to an inertial frame or reference is done using sensor fusion techniques. Reading multimodal data from different sources gives valuable information to understand and symbolize the motion of the sensing device. Inertial measurement units (IMUs), which consist of an accelerometer and a gyroscope, are able to monitor translational and rotational motions. On the other hand, MARG (Magnetic, Angular Rate, Gravity) devices include a third sensor, namely a magnetometer. This type of sensing unit has the advantage of measuring the attitude relative to the Earth magnetic field. The choice of the sensing device depends on the requirements of the developed system. An IMU could be sufficient for some applications. In this paper, both devices (IMU and MARG) are investigated in the next sections.

Fig. 1 illustrates a sensing device (IMU or MARG), with its corresponding coordinate system (sensor frame) in black, and the Earth frame  $\vec{E}$  (in red). The goal is to estimate the orientation of the sensor frame  $\vec{S}$  relative to  $\vec{E}$ . This orientation is represented by Euler angles [9], defined by subsequent rotations of  $\phi$  around  $\vec{E}_x$ ,  $\theta$  around  $\vec{E}_y$ , and  $\psi$  around  $\vec{E}_z$ . Hence, acquired data from inertial sensors are processed to estimate the sequence of Euler angles, using Kalman filters [10], gradient descent step [11], quaternion representation [12]... To our knowledge, the two widely used orientation filters is the one proposed by Mahony *et al.* [13] and by Madgwick *et al.* [14]. The efficiency of these algorithms has been proven at relatively low computational cost. The output of these algorithms are three time-series, having the same sampling rate of the deployed modalities, representing the progression of Euler angles over time. Both algorithms are considered in this paper.

## III. REAL-TIME ORIENTATION DISPLAY VIA GRAPHICAL USER INTERFACE

A graphical user interface (GUI) tool was developed on Matlab to display the orientation of a sensing device based on its acquired data. The sensing device in Fig. 1 is symbolized by plotting three pairs of polygonal regions. Each of these six regions represents one face of this device. The color of the frontal zone is set to grey ( $c_1$ ), and that of the backward zone to white ( $c_2$ ), while the remaining faces are colored in dark blue ( $c_3$ ). The three hexadecimal color codes ('r', 'g', 'b') are as follows:

$$\begin{cases} c_1 \rightarrow (0.8353, 0.8353, 0.8353) \\ c_2 \rightarrow (1, 1, 1) \\ c_3 \rightarrow (0, 0.2510, 0.5020) \end{cases}$$

Moreover, the six regions are labeled using the following letters: 'U' which stands for up, 'D' for down, 'L' for left, 'R' for right, 'F' for front, and 'B' for back. The color of these letters is set to yellow. Fig. 2 illustrates the plotted device in a three-dimensional space. This is the initial position of the device, *i.e.* at the beginning of the algorithm ( $t = 0$ ).

Now, the Euler angles are updated after the acquisition of each data-point from the inertial sensors. The orientation filter reads data from sensors, processes them, and fuses them to estimate the angles. Each 350 ms, the graph is updated by rotating the simulated device and the corresponding labels, according to the output of the filter. This frame rate, *i.e.* the frequency at which consecutive images appear on a display, seems adequate for the human eye. This update is done by pivoting the centers of the device faces (the midpoint between any two opposite vertices) around the axes, using the estimated Euler angles, as indicated in the previous section.

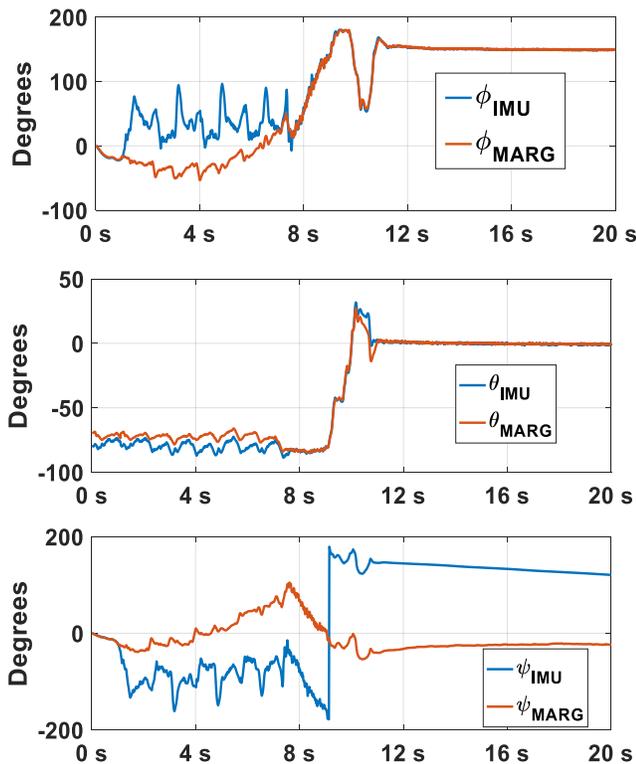


Figure 3. The estimation of Euler angles using (i) IMU and (ii) MARG sensors using Madgwick's algorithm

Two modes are considered in this tool. The first one is the real-time mode, where data are read continuously using a Bluetooth dongle for example. The proposed technique applies Mahony's or Madgwick's algorithm and updates the graph accordingly. The second one is the replay mode, where data have been acquired beforehand. The user can load data and visualize the sequential orientation of the sensing unit. The type of the sensing device (IMU or MARG) and the orientation filter (Mahony *et al.* or Madgwick *et al.*) are chosen before launching the algorithm.

#### IV. REAL WORLD APPLICATIONS USING PUBLIC DATASETS

The proposed tool, *i.e.* orientation estimation and the visualization of the sensing device, serves a wide-range of healthcare applications. In this section, we conduct two comparative studies following two medical applications: IMU vs MARG and Mahony's filter vs Madgwick's filter.

##### A. Fall risk assessment

Falls are one of the main causes of mortality in elderly. While most of the proposed solutions target fall detection, the clinician may need to evaluate this fall by observing the successive movements of the wearable device during this fall.

The initial state of the human body (standing, sitting, lying, walking, etc.) which precedes the fall, the velocity of the impact, and the direction of the fall (forward, backward, lateral) are important factors from a medical point of view. Our tool answers all these questions and provides an added-value for the practitioner. To address the real world situation, we resorted to the *FallAID* public dataset [15]. This dataset contains acquired data from tri-axial accelerometers, tri-axial gyroscopes, and tri-axial magnetometers, including human falls. The subjects wore a necklace device while simulating falls and ADLs. Both algorithms were tested to calculate Euler angles, and they provided almost the same results. For reasons of clarity, only Madgwick's algorithm is considered in this sub-section. The focus is on the comparison between both sensing units, *i.e.* IMU (accelerometer + gyroscope) and MARG (accelerometer + gyroscope + magnetometer). Fig. 3 illustrates the time-series of the estimated Euler angles from both sensing units, representing a fall forward from walking caused by syncope (fainting) without recovery. It is clear from this figure that the subject was walking during the first 8 seconds, where MARG shows that  $\phi \approx 0^\circ$ ,  $\theta \approx -90^\circ$ , and  $\psi \approx 0^\circ$  (the subject was standing). The impact phase was located between the 8<sup>th</sup> and 12<sup>th</sup> seconds (the shock is around the 10<sup>th</sup> second), where a change in angles occurred. The subject was lying on the floor (inactive) for the remaining 8 seconds. A video has been created to display the orientation of the device during this fall, using both estimations (see Appendix).

The variability of the IMU estimation is higher while the subject was walking, compared to the MARG estimation which is smoother. Moreover, concerning the angle  $\psi$ , a certain phenomenon appears in the IMU estimation. A sudden change from  $-180^\circ$  to  $180^\circ$  occurs between the 9<sup>th</sup> and 10<sup>th</sup> seconds (when the body was on the verge of hitting the floor), due to the effect of the angular velocity. From 3D visualization point of view (see video), there is no rotation around this axis. This means that the device kept the same inclination. Now, from a signal point of view, this switch from  $-180^\circ$  to  $180^\circ$  means that a certain rotation occurred around the z-axis. In this case, by using convolutional methods or auto-correlation for example, a certain deviation would be detected, since the signal level changed (see blue signal in Fig. 3). This may lead to biased results when it comes to the analysis/estimation of fall direction and the final body state (after the impact on the ground). Based on the previous observations, MARG sensors may be preferred for postural transitions and recurrent movements (like walking), since they involve higher degrees of freedom, thus having an advantage over IMUs by providing robust orientation estimation.

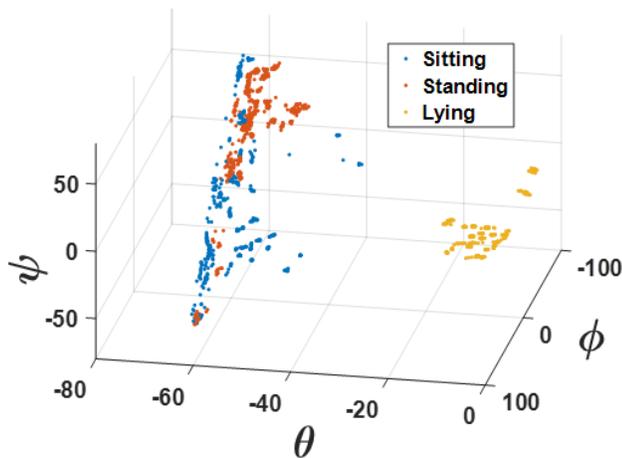


Figure 4. The distribution of body postures following the mean values of Euler angles

### B. Body posture monitoring

Another medical application is the distribution of the body posture over the course of a day. This information is valuable for health monitoring and frailty prevention in elderly care. Hence, we resorted to another public dataset [16], available in the UCI Machine Learning Repository [17]. The subjects have worn the smartphone on the waist and simulated six different activities. This dataset only contains data acquired from an accelerometer and a gyroscope. Hence, the considered sensing unit in this sub-section is IMU. The reliability of this type is sufficient for this application, since the estimation of the body posture is done while the subject is inactive. The targeted classes for this task are (i) Sitting, (ii) Standing, and (iii) Lying. Euler angles were estimated from 2.56-second windows, using both algorithms, *i.e.* Madgwick's and Mahony's algorithms. Three features were calculated, namely the mean values of  $\phi$ ,  $\theta$ , and  $\psi$ . Fig. 4 illustrates the distribution of these posture classes following the three extracted features. It is clear that the third class is well separated from the other two classes. On the other hand, sitting and standing clusters present some intersections. To predict the posture of the human body, these three features feed a set of machine learning (ML) classifiers. These classifiers are the following ones: (a) Neural Network (*NN*) with 2 hidden layers of 8 and 2 neurons respectively, and 'ReLU' as activation function; (b) Support Vector Machine with a radial basis function kernel (*SVM<sub>R</sub>*); (c) Random Forest (*RF*) with 20 estimators of depth equal to 2; (d) Adaboost (*Ada*) with 100 estimators; (e) Naive Bayes (*NB*) with a Gaussian Distribution; (f) Linear Discriminant Analysis (*LDA*). Table I illustrates the different results. *NN* achieved the highest accuracy and it is equal to 89.6%. Both orientation filters provided close results in terms of

performance, except for *NN* and *Ada*. The confusion occurs between sitting and standing. The waist position alone does not seem to be sufficient for this task. Another position and/or additional features are required to increase the achieved accuracy.

TABLE I. THE DIFFERENT ACHIEVED ACCURACIES (%) OF ML CLASSIFIERS

	Machine Learning Classifier					
	<i>NN</i>	<i>SVM<sub>R</sub></i>	<i>RF</i>	<i>Ada</i>	<i>NB</i>	<i>LDA</i>
Madgwick <i>et al.</i>	89.6	87.8	87	88.2	88.7	87.2
Mahony <i>et al.</i>	88	87.2	87.4	84.7	87.9	87.8

As seen in Table I, Madgwick's algorithm had the upper edge when it comes to predicting the body posture. Nevertheless, Mahony's algorithm could be better suited for other applications.

### V. DRAWBACKS AND PRACTICAL CONSIDERATIONS

In this section, we discuss some artifacts and limitations related to an attitude estimation system. We have seen in section IV that MARGs are preferred to IMUs when it comes to postural transitions estimation. Now, electronic devices, ferrous materials, and some other mechanical and electrical infrastructures are sources of magnetic fields. These artificial fields contaminate the Earth's magnetic field measurements and decrease the reliability of sensor fusion techniques in heavily disturbed areas like indoor environments [18]. Hence, the indoor performance of MARGs could be limited.

The use of a gyroscope is important for the attitude estimation. However, its power consumption is very high compared to that of the accelerometer [19], which reduces the battery life and the autonomy of the sensing device.

High sampling rates increase the computational load of attitude estimation systems. The general tendency is to lower it in order to reduce the complexity. However, very low rates may not be able to capture certain movements. Therefore, the accuracy/complexity tradeoff should be considered when developing such approaches. It is worth mentioning that a sampling rate of 50 Hz leads to satisfactory performance [9].

### VI. CONCLUSION AND PERSPECTIVES

This paper discussed the attitude estimation of inertial sensors. Based on widely used orientation filters, a GUI tool was developed to visualize the orientation of a rigid body (a sensing device) in a three-dimensional space. Such tool is important for a wide-range of real world applications in elderly care, as seen in section IV while using public datasets.

In a future work, the orientation of the human body (instead of the device) is going to be considered using wearable sensors. The output of the proposed tool is going to

be exploited in order to constitute a monitoring system by developing a human activity recognition process.

#### APPENDIX

The video can be found on Google drive via the link: <https://drive.google.com/file/d/1KqL0oahTCC4jkoFwQAX7E5LWkXDNVqIJ/view?usp=sharing>

Its goal is to represent the developed tool and to display the effect of MARG estimation (on the left) and IMU estimation (on the right) on the visualization process, using Madgwick's algorithm.

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