Estimation of Angles from Upper and Lower Limbs for Recognition of Human Gestures using Wireless Inertial Sensors

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Abstract

Human motion analysis is defined as any procedure involving any means for obtaining a quantitative or qualitative measure of it. Quantitative analysis involves the measurement of biomechanical variables, such as pressure distribution, temporal gait parameters, among others, whereas qualitative analysis has been defined as the systematic observation and introspective judgment of the quality of human movement for the purpose of providing the most appropriate intervention to improve performance. In this research we are interested in the former analysis. Continuous monitoring of human motion in daily environment provides valuable and complementary information to that obtained in laboratory tests. Also, the human motion analysis helps the specialist and/or researcher in the field to obtain a quantitative assessment of motion parameters of the patients. Calculating variables about human motion using wearable inertial sensors is possible by applying computational techniques for information fusion, but it poses considerable challenges such as data processing of multiple sensor readings from human soft tissue. Therefore, in this PhD research proposal we propose to use angles between segments of upper and lower opposite limbs, as the unit of measure to characterize human movements, because they are less sensitive to the particularities of persons, such as height, weight, gender and age. Our approach can be synthesized as follows. First, angles of segments and joints of human limbs will be estimated. Second, postures from sets of angles will be identified. Third, human gestures will be classified from series of postures. Finally, identified gestures will be validated in applications of serious games in daily living environments.

Keywords

Human motion analysis, inertial and magnetic sensors, estimation of angles, human gesture classification, daily living environments.

Contents

1 Introduction

1.1 Research Problem

"Human motion analysis is defined as any procedure involving any means for obtaining a quantitative or qualitative measure of it" [1].

Quantitative analysis involves the measurement of biomechanical variables, such as pressure distribution, temporal gait parameters, human posture, among others. Because of the huge amount of data, this analysis requires computer-based processing [2]. In contrast, **qualitative analysis** has been defined as the "systematic observation and introspective judgment of the quality of human movement for the purpose of providing the most appropriate intervention to improve performance" [3]. In this research we are interested in the quantitative analysis of human motion.

Calculating biomechanical **variables** from wearable inertial sensors is possible by using computational techniques for information fusion. From the calculated **variables**, it is possible to determine positions of the limbs, and even recognize certain human gestures.

This research proposes to use **angles** between segments of upper and lower opposite limbs, as the unit of measure to characterize human movements, because they are less sensitive to the particularities of persons [4], such as height, weight, gender and age, in contrast to other measures such as relative position or optical flow of limbs. Also, this research proposes the calculation of these angles using only wearable sensors, that can be easily worn and carried by people in daily scenarios.

The techniques to be developed in this research involve significant computational challenges:

- **The lack of accurate global reference.** In contrast to methods relying on fixed sensors, when using wearable sensors we do not have an accurate and invariant reference. That means that we have to incorporate in our methods a calibration phase in which an initial reference is established and then, constantly updated.

- **The need of local estimations as a direct consequence of previous challenge.** Not having a unique global reference means that all the calculations have to be estimated locally. That means that we have to develop techniques inexpensive enough for the microprocessors embedded in wearable sensors.

- **The need of a prompt response.** Since these technologies are used in applications of human-computer interaction in daily scenarios, an important requirement is the time response. That means that is necessary to develop a system capable of producing an appropriate output in real time [5].

- **The need of a more refined analysis.** Several techniques for determining human activity based on wireless devices have been proposed. However, these techniques score a reasonable good performance when determining which activity makes a person, but not the way as such activity is realized. The latter is relevant for rehabilitation interfaces and exergames, for instance, and for determining how well or badly an activity is done [6].

- **The importance to consider anatomical constraints.** In most of works the motion angles are estimated with some restrictions or considering less degrees of freedom allowed to a segment or joint. More accurate estimations, such as orientation of the complex shoulder joint, are needed for a more refined analysis of human motion than current estimations [7].

1.2 Motivation

The **human motion analysis** helps the specialist and/or researcher in the field to obtain a quantitative assessment of motion parameters of the patients. Measuring body movements accurately is crucial to identify abnormal neuromuscular control, biomechanical disorders and injury prevention[1].

Specialized systems, such as Vicon [8] or Optotrak [9], have a high accuracy when operating in controlled environments, e.g. several fixed cameras calibrated and correlated in a specific place following a specific capturing configuration. These systems can provide a large amount of redundant data. Ambulatory systems, such as those using a Kinect [10] to capture human motion, are set in relatively uncontrolled environments and have a restricted field of view. These systems have a restricted margin of maneuverability and are intended for indoor use mainly. In contrast, wearable sensors have the advantage of being portable and suitable for outdoor environments. These systems are arranged with respect to an anatomical reference of the human body to measure specific biomechanical variables or motion patterns.

Continuous monitoring of **human motion** in daily environment provides valuable and complementary information to that obtained in laboratory tests. However, it has been extremely difficult to go beyond the laboratory and obtain accurate measurements of human physical activity in daily life environments [11].

Develop and implement **ambulatory and wearable systems** is important to reach a larger population and more complex scenarios than current systems for motion analysis.

The ultimate incentive of this research is to generate knowledge to enhance human-computer interaction, namely for applications oriented to the promotion of active aging, such as rehabilitation applications, serious games or exergames, and strengthening the social network of elderly, that can be used in daily care centers, retirement houses, and homes, for instance.

Our approach can be synthesized as follows. First, angles of segments and joints of human limbs will be estimated. Second, postures from sets of angles will be identified. Third, human gestures will be classified from series of postures. Finally, identified gestures will be validated in rehabilitation applications, such as serious games[2], and in daily living scenarios.

As preliminary results, an algorithm to estimate angles from wireless inertial and magnetic sensors was tested for pronation/supination and flexion/extension human movements of 10 test subjects. Two sensing devices were evaluated using an optical system as reference instrument in an experimental setting designed for this experiment. According to the obtained results we conclude that it is feasible to implement methods for representing accurately human movements from wearable sensors.

[1] http://www.inr.gob.mx/i17.htm, accessed: Dec 1, 2014

[2] Serious games are games that are have been designed with a primary focus other than entertainment [12] and in principle they could be used to construct novel forms of cognitive assessment [13] and for physical function rehabilitation purposes [14]

2 Background

2.1 Relevant concepts

In this section important concepts for the research are presented.

Angle

"An 'angle with vertex A' is a point A together with two distinct non-opposite rays $\overrightarrow{AB}$ and $\overrightarrow{AC}$ (called the sides of the angle) emanating from A" [15]; we use the notation $\sphericalangle A$ for this angle.

Sensing device

The term sensing device describes any encapsulated unit that may contain one or more of the following sensors: accelerometer, gyroscope or magnetometer; as well as additional components such as batteries, communication modules, micro-processors and so on, arranged to jointly operate.

IMU

An inertial measurement unit, or IMU, "is an electronic device that measures linear acceleration, angular velocity and direction of magnetic field, using a combination of sensors: accelerometer, gyroscope and magnetometer. The measurement of Roll, Pitch and Yaw entails the use of the three different sensors (3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer) to measure a relative orientation" [16], these components are geometrically positioned to provide X, Y and Z coordinate-based measurements, respectively, see Figure 1.

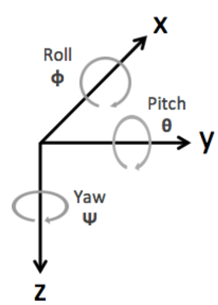


Figure 1. X, Y and Z coordinate system

An accelerometer sensor measures linear acceleration that is quantified in meters per second squared (m/s^2), or in g unit ($1g = 9.81m/s^2$). A gyroscope sensor measures angular velocity that is quantified in degrees per second (dps). A magnetometer sensor measures the strength of a magnetic field that is quantified in Teslas (T).

Segment

A segment "is one of the constituent parts into which a human body is divided or marked off by or as if by natural boundaries" [17]. The human segments studied in this research are: forearm, arm, upper back, lower back, thigh and shank.

Joint

A joint "is the point of contact between segments of a human body whether movable or rigidly fixed together with the surrounding and supporting parts (as membranes, tendons, or ligaments)" [17]. The human joints studied in this research are: elbow, shoulder, hip and knee.

Posture

A posture is a representation of human limbs angles and describes the orientation of the joints in which the wearable inertial system is setting. To describe a posture given a time frame a pose vector is used: $P_{tx} = \{\sphericalangle E, \sphericalangle S, \sphericalangle K, \sphericalangle H\}$, and represents elbow, shoulder, knee and hip angle, respectively.

Gesture

A gesture "is a movement of part of the body to express an idea or meaning" [Oxford English Dictionary, 2014]. We use the term gesture to represent an action consisting of a succession of movements of the upper and lower limbs, that can be defined as: $G = (P_t)_{t=1}^{t_n} = \{P_{t_1}, P_{t_2}, P_{t_3}, ..., P_{t_n}\}$, where P_{tx} is a posture in a time frame. In this study the gestures can be divided into the following categories: simple actions, training exercises and sports activities.

Real-time

"A real-time system demands that the signal processing time, t_p, must be less than the sampling period, T, in order to complete the processing task before the new sample comes in. That is: $t_p + t_o < T$ where t_o is the overhead of I/O operations" [18]. In our approach a sampling rate of 50 Hz is considered.

2.2 Human anatomy concepts

Human anatomy is the setting (structure) in which the events (functions) of life occur. The three main approaches for studying anatomy are regional, systemic, and clinical (or applied), reflecting the body's organization and the priorities and purposes for studying it. **Regional anatomy** or topographical anatomy considers the organization of the human body as major parts or segments (see Figure 2): a main body, consisting of the head, neck, and trunk (subdivided into thorax, abdomen, back, and pelvis/perineum), and paired upper limbs and lower limbs [19].

2.2.1 Anatomical planes

Anatomical descriptions are based on four imaginary planes (median, sagittal, frontal, and transverse) that intersect the body in the anatomical position (see Figure 3):

- The median plane (median sagittal plane), the vertical plane passing longitudinally through the body, divides the body into right and left halves. The plane defines the midline of the head, neck, and trunk where it intersects the surface of the body.
- Sagittal planes are vertical planes passing through the body parallel to the median plane.
- Frontal planes are vertical planes passing through the body at right angles to the median plane, dividing the body into anterior (front) and posterior (back) parts.
- Transverse planes are horizontal planes passing through the body at right angles to the median and frontal planes, dividing the body into superior (upper) and inferior (lower) parts.

2.2.2 Movements of the limbs

Most movements are defined with reference to the anatomical position, with movements occurring within and around axes aligned with respect to specific anatomical planes (See Figure 4). Terms of movement may also be considered in pairs of opposite movements:

- Flexion and extension movements generally occur in sagittal planes around a transverse axis (See Figures 4 a & b).

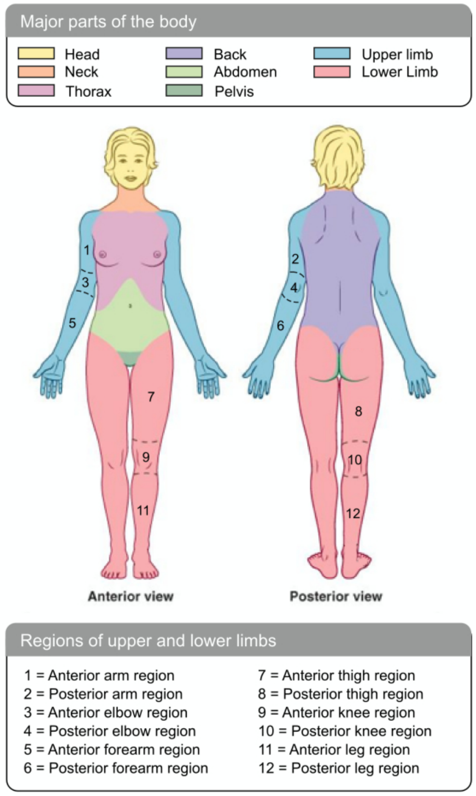


Figure 2. Major parts of the body and regions (segments) of the upper and lower limbs [19]

- Abduction and adduction movements generally occur in a frontal plane around an anteroposterior axis (See Figure 4 c).
- Rotation involves turning or revolving a part of the body around its longitudinal axis (See Figure 4 c).

2.3 Related work

Wearable inertial (*i.e.* accelerometers or gyroscopes) and magnetic (*i.e.* magnetometer) sensors have been used in some clinical applications. Figure 5 depicts a taxonomy introduced in this work based on the application of researches in the field of human motion analysis. The first class corresponds to works focused on measuring movements of a specific segment of the human body, such as the limbs. The outcome of these systems can be a common unit of measurement such as angles, for instance. The second class groups works whose outcome is based on an interpretation or high-level classification of human movements, such as "running" or "walking".

In the first class of our taxonomy works focused on measurements based on the human regional anatomy or topographical anatomy [19] are considered. Common examples are upper, lower or multiple limbs, as well as other regions such as the head, neck and trunk.

Studies included in the second category are too diverse and comprise the estimation of spatio-temporal gait parameters and assessment of gait abnormalities [20], the recognition of meaningful human expressions

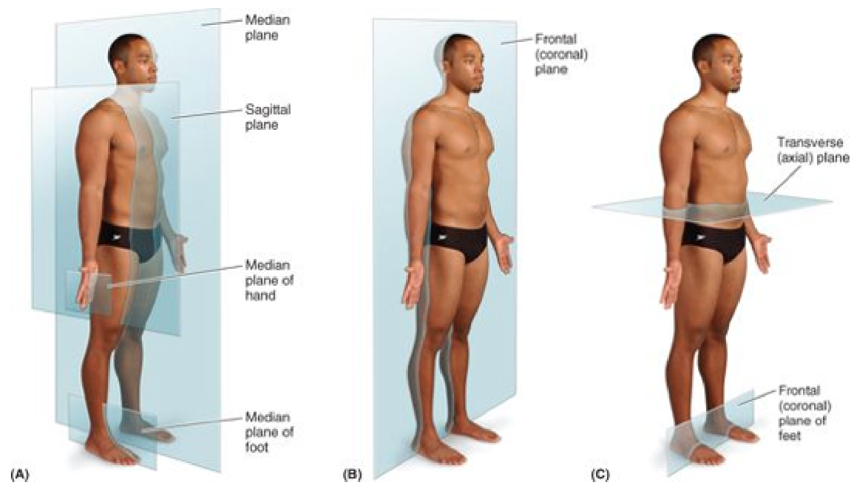


Figure 3. The main planes of the body [19]

involving hands, arms, face or body [21], fall detection and classification of activities of daily living [22].

There are four relevant characteristics to assess in the studies of human motion analysis using wearable sensors: (1) the sensor used for measurement, (2) the measuring motion unit, (3) the sensor fusion algorithms, and (4) the evaluation system. These characteristics are detailed below.

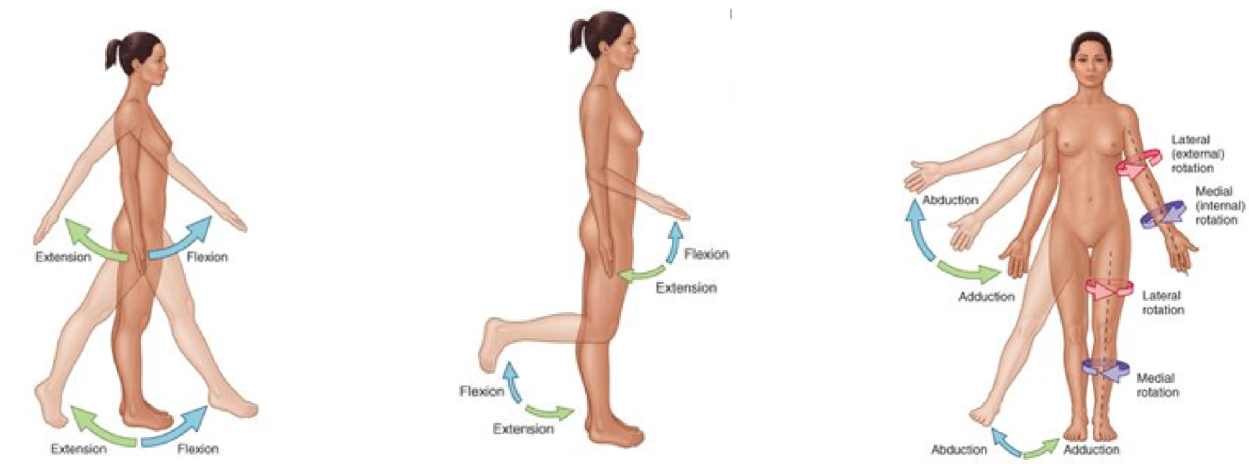
The **sensors** may be (1) inertial as accelerometers and gyroscopes, and (2) magnetic as magnetometers, or (3) a combination of the previous sensors. The **measuring motion unit** can be divided into two dimensions: (1) position or orientation measure, and (2) segment or joint on which the sensors are positioned. Common **classes of algorithms for inertial sensor data fusion** are: (1) integration, (2) vector observation, (3) Kalman filtering, and (4) complementary filtering. Finally, for the **evaluation of the performance** of the studies five approaches are identified: (1) optical motion systems such as Vicon [8] or Optotrack [9], (2) commercial inertial sensors such as MTw sensor from Xsens [23], (3) magnetic position systems such as Liberty from Polhemus [24], (4) goniometers such as PS-2137 from PASCO [25], and (5) expert human evaluation.

A search of literature was conducted on eight Internet databases and includes medical, *i.e. PubMed*; technical, *i.e.* IEEE Xplore; and all-science, *i.e.* Scoops, literature. A list of the topics and classification of the most relevant papers is provided in Table 1.

Table 1. Selected studies according to the measured movement

Measured movement (Anatomical reference)	**Includes**	**Studies selected** (31 papers)
Upper limb	Shoulder, arm, elbow, forearm or hands	14
Lower limb	Thigh, knee, leg or foot	10
Multiple limbs	Upper or lower limbs in the same study	2
Other body regions	Head, trunk, back or hip	5

Moreover, the distribution of the relevant studies per year is shown in Table 2, in which a particular increase in recent years is observed. All these works use "strapdown" systems, in which the sensors are fixed to certain parts of the human body [26].



(a) Flexion and extension of upper limb at shoulder joint and lower limb at hip joint

(b) Flexion and extension of forearm at elbow joint and of leg at knee joint

(c) Abduction and adduction of right limbs and rotation of left limbs at shoulder and hip joints, respectively

Figure 4. Movements of the limbs and segments of the limbs [19]

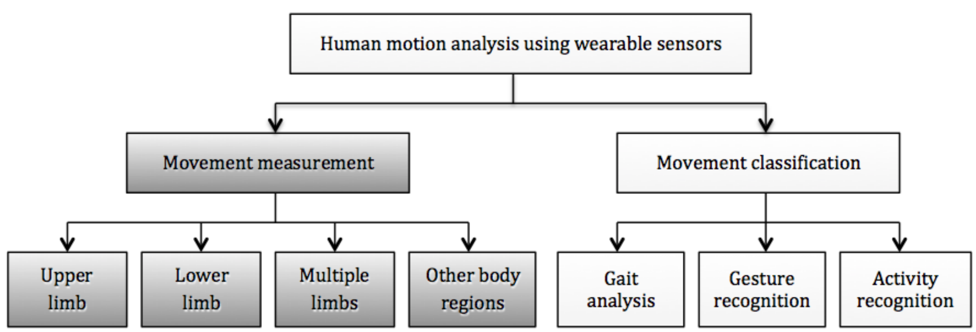


Figure 5. Taxonomy of Human Motion Analysis using wearable sensors

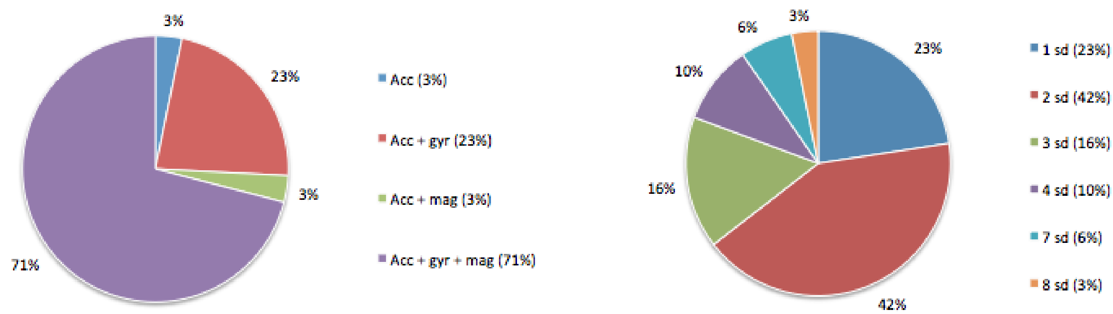
The relevant articles that were analyzed are distributed as follows: 45% focuses on measuring upper limb movements only, 39% focuses on measuring lower limb movements only; 6% measure movements of both, upper and lower limbs simultaneously; and 10% measure movements of other anatomical references, such as head or trunk.

2.3.1 Sensors

There are two levels of analysis of sensors used in these works, the first one concerns the type of sensor used to estimate human motion: accelerometer, gyroscope, magnetometer or a combination of them. The second level concerns the composition of modules used for acquiring motion parameters in a sensing device. The reader should remind that, the term sensing device describes any encapsulated unit that may contain one or more of the previously cited sensors, as well as additional components such as batteries, communication modules, micro-processors and so on, arranged to jointly operate, see Figure 6.

Table 2. Selected studies according to publication year

Year	No. of papers	Author
2014	4	[27, 28, 29, 30]
2013	5	[31, 7, 32, 33, 34]
2012	9	[35, 36, 37, 38, 39, 40, 41, 42, 43]
2011	3	[44, 45, 46]
2010	3	[47, 48, 49]
2009	3	[50, 51, 52]
2008	2	[53, 54]
2007	2	[55, 56]



(a) Type and combination of sensors, Acc: accelerometer, gyr: gyroscope, mag: magnetometer

(b) Number of sensing devices (sd)

Figure 6. Distribution of studies by sensor used: 6(a) type and combination of sensors and 6(b) number of sensing devices

2.3.2 Measuring motion unit

The measuring motion unit can be divided into two dimensions: position or orientation measure, and segment or joint whose position or orientation is measured. The distribution of studies concerning the combination of the two dimensions is shown in Figure 7. Most studies focus on calculating the orientation or position of certain joints of the human body. As stated in the results reported in these studies, the estimation of position and orientation of the hand scored an average root mean square (RMS) of 1.25 cm [46] and 2.82^{o} [44], respectively. The most studied upper joints are the shoulder, elbow and wrist, and the estimation position and orientation of these joints scored an average RMS of 4 mm, 5 mm and 7 mm [54], and 3^{o} [29], 3.5^{o} [48] and 4.1^{o} [29], respectively. The results reported in the estimation of orientation of the thigh, shank and foot scored an average RMS of 1.23^{o}, 1.3^{o} [33] and 2.99^{o} [42], respectively. The most studied lower joints are the hip, knee and ankle, and the estimation of position and orientation of these joints scored an average RMS of 2.1^{o}, 1.7^{o} [53] and 3^{o} [36], respectively.

No studies were reported about estimation of position or orientation of both upper limbs (right upper limb and left upper limb) at the same time, as it was the case for some studies concerning simultaneous estimation of motion for both lower limbs [30, 42, 28, 53, 41]. There are only two works that estimate position or orientation of both, upper and lower limbs simultaneously [49, 55], scoring an average RMS for orientation estimation of 2.6^{o} for the upper limb and of 3.2^{o} for the lower limb [55]. For other anatomical

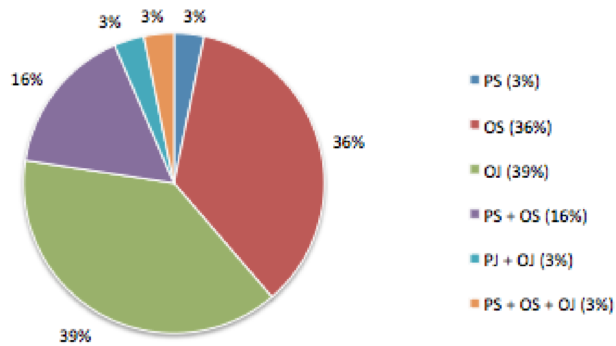


Figure 7. Distribution of studies according to measured motion unit. PS: position of a segment, OS: orientation of a segment, PJ: position of a joint, OJ: orientation of a joint

references, an average RMS of 2.5^o [32], 2.1^o [45] and 4.5^o [56] were reported for head, back and trunk, respectively.

2.3.3 Sensor fusion algorithms

The algorithms used to estimate orientation or positions are divided into five classes: Integration, vector observation, complementary filtering, Kalman filtering, and other algorithms. The distribution of studies according to the algorithms implemented is shown in Figure 8. Below we summarize these algorithms.

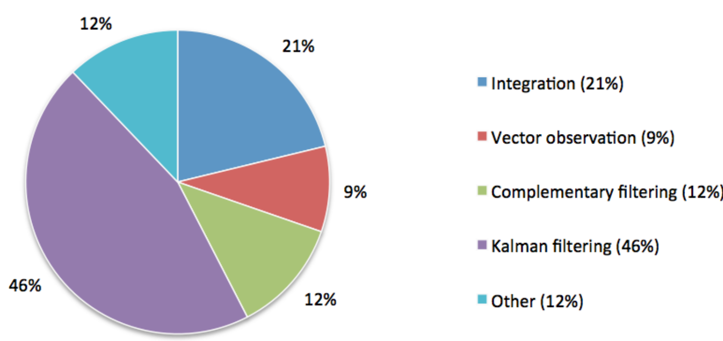


Figure 8. Distribution of studies according to the algorithms used to estimate position or orientations of segments or limbs

Rate gyroscope integration provides an estimate of the relative rotation from an initial known rotation. As the angular velocity measured by the rate gyroscopes is directly integrated this method provides smooth estimates even during rapid movements. Nevertheless, the integration process has two significant disadvantages. Firstly, any bias in the angular rate vector will result in an increasing cumulative error in the estimated orientation. Secondly, the initial orientation of the device must be known. [28]

Vector observation provides an estimate of the orientation relative to a fixed world coordinate frame. By measuring the position of two, or more vectors in the local coordinate frame of a device and comparing these with the known position of the vectors in the fixed coordinate frame, the rotation between the two frames can be calculated. For wireless inertial orientation trackers the reference vectors used are the direction of acceleration due to gravity, defining the $z - axis$ of the world coordinate frame, and the direction of the Earth's magnetic field vector projected into the horizontal plane, defining de world $x - axis$. As there are no correction steps, this approach is only accurate for tracking slow moving objects [37]. Most of these studies are based on TRIAD [57], QUEST [58], FOAM [59] and O2OQ [60] algorithms.

Complementary filters can be used to combine two different measurements of a common signal with different noise properties to produce a single output. An example consists in combining measurements of both, a signal with low and a second signal with high frequency noises. The rate gyroscope integration method suffers from low frequency drift, while the vector observation method suffers from high frequency movement errors. In [61] a complementary filter formula, see (1), is defined:

$$\hat{q}_t = \begin{cases} q'_t + \frac{1}{k}(q''_t - q'_t) & |\|a\| - 1| < a_T \\ q'_t & |\|a\| - 1| \geq a_T \end{cases} \tag{1}$$

where $\hat{q}_t$ is the estimated orientation of the complementary filter; q' and q'' are the rate gyroscope integration and vector observation estimates respectively; k is a filter coefficient that controls blending of the two estimates; a is a measured acceleration vector; and a_T is a threshold for optionally compensate the vector observations during linear accelerations.

The Kalman filter uses knowledge of the expected dynamics of a system to predict future system states given the current state and a set of control inputs [62]. A linear system is a process that can be described by the following two formulas, the state equation (2) and the output equation (3):

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{2}$$

$$y_k = Cx_k + z_k \tag{3}$$

where x is called the state of the system; k is the time index; A, B, and C are matrices: A is a state transition matrix relating the previous state to the next state, B is a matrix relating control inputs to system states, and C is an observation matrix relating system state to observed measurements; u is a known input to the system; y is the measured output; and w and z are the noise. The variable w is called the process noise, and z is called the measurement noise.

There are various proposals based on the Kalman filter used for fusing data from inertial sensors, the filters basically differ in the state vector size and preprocessing steps [63]. In [50] a two step Kalman filter is proposed that considers a measurement update (correction step) and time update (prediction step) using the optimal two-observation quaternion estimation method, O2OQ, for preprocessing.

The other algorithms used to estimate the orientation of segments or joints that are not grouped in the other classes are: Heading fusion algorithm [29], Auxiliary similarity information algorithm [53], Sequential Monte Carlo method [33] also called particle filter, and a physical sensor difference-based algorithm [40].

2.3.4 System used for the evaluation

In studies that estimate human motion using inertial and magnetic sensors, an external system was required to compare the results obtained from the experiments. The evaluation systems can be divided into five categories: optical systems, magnetic systems, inertial sensors, goniometers, or evaluation by human expert. The distribution of studies according to the system used for the evaluation is shown in Figure 9.

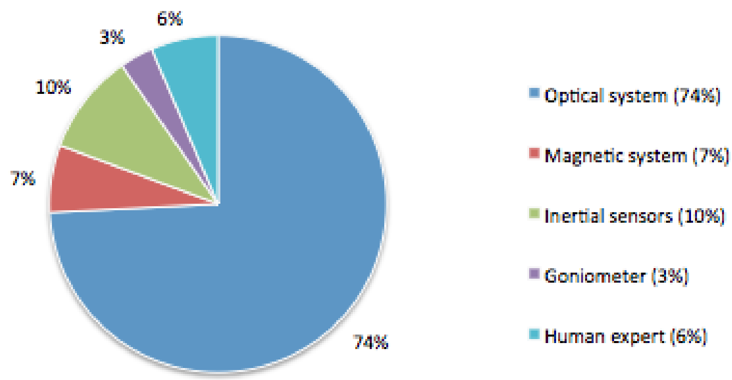


Figure 9. Distribution of studies according to the system used for comparison

In most of the revised studies optical motion systems were used as reference to evaluate the performance of each study. The optical systems that are more commonly used for comparison were [8] and [9] systems.

Regarding the configuration of the experiments, the mean age of the test subjects is 26.25 years ($\pm$ 5.17), indicating a clear trend to test the systems and methods only with young people. Other population groups such as people with mobility problems have not been considered in tests so far.

2.4 Critical analysis

Human motion analysis is effectively a niche opportunity that poses challenging issues for multidisciplinary research. An open issue for engineers is to investigate proper configurations and arrangements of sensors capable of operating in daily environments, as well as methods for self-calibration and self-correction, two areas in which we have identified a lack of literature and research. In the field of computer science, there is a constant need for algorithms able to estimate the position and orientation of upper and lower limbs in real-time simultaneously using local devices mainly.

Finally, it is necessary to investigate methods and technologies for dealing with complex joints involving several degrees of freedom (DOF), such as the shoulder and hip. Characterizing the movement of these parts of the body is necessary for recognizing a broader range of human gestures and for enhancing high-level classification of human motion.

3 Objectives

The **human motion analysis** helps the specialist and/or researcher in the field to obtain a quantitative assessment of motion parameters of the patients. Measuring body movements accurately is necessary for applications of human-computer interaction such as rehabilitation interfaces or serious games [64].

This research proposes to use **angles** between segments of upper and lower opposite limbs, as the unit of measure to characterize human movements because they are less sensitive to changes in anatomy [4], using inertial/magnetic sensors.

3.1 Research questions

This research intends to answer the research questions introduced below.

- How to estimate an angle of a non-static segment of the upper and lower limbs of the human body with respect to an anatomical plane using local information obtained from a sensing device, such as an inertial measurement unit?
- How to estimate an angle of a non-static joint of the upper and lower limbs of the human body, using local information obtained from two sensing devices located on contiguous segments to the joint?
- How to combine at least four joint angles, from upper and lower limbs, merging information from a wearable inertial and magnetic system comprising several sensing devices in order to determine a posture at a given time?
- How to classify human gestures from a set of postures in a period of time for daily living environments?

3.2 General and specific objectives

The **general objective** of this research is:

Development of algorithms for real-time estimation of angles at upper and lower limbs, using a wearable inertial system for characterization of human motion in daily environments.

The **specific objectives** are:

- Implement an algorithm to estimate an angle of upper or lower limb segments, using information obtained from a sensing device aligned with respect to an anatomical plane
- Develop an algorithm to estimate an angle of upper or lower limb joint, using information obtained from two sensing devices placed on contiguous segments of the joint.
- Develop an algorithm to estimate postures combining at least four angles of upper and lower limbs merging information from an wearable inertial system.
- Propose a method to classify human gestures from sequences of postures of upper and lower human limbs for daily living environments.

3.3 Contributions

The main contributions of this research are summarized below:

- An algorithm to estimate joint angles of the upper and lower limbs using inertial/magnetic sensors.
- An algorithm for real-time estimation of postures from a wearable inertial/magnetic system using the previous calculated angles.
- A method to classify human gestures based on the estimated sequences of postures for daily living environments.
- Datasets of controlled experiments conducted in this study.

4 Methodology

In this section, the methods and techniques for achieving our goals are summarized.

1. Characterization and evaluation of inertial sensors in human soft tissue. Sensing devices with different technical features such as: sensitivity, sampling rate, filters, noise, among others, will be evaluated. Further synchronization schemes, sensing axes configuration and calibration are evaluated in pilot tests placing sensing devices in human soft tissue. Based on observations, the device that fulfills requirements from those available in the Robotics Laboratory of INAOE such as accuracy, weight, and its ability to be programmed and modified, will be taken (Figure 10).

(a) LPMS-B IMU

(b) ArduIMU v3

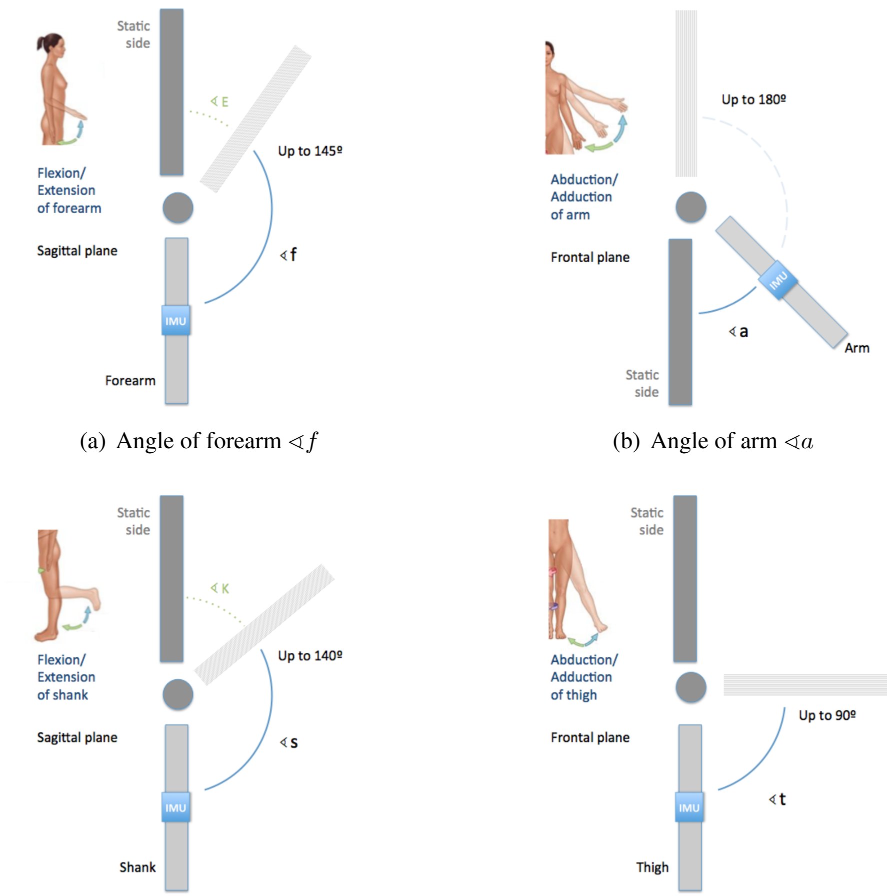
Figure 10. Sensing devices considered in this research

2. Analysis of representation forms for data. In order to calculate information in real-time, different techniques and representation units, like Euler angles or quaternions, will be analyzed. It is necessary to consider an initial configuration with six sensing devices placed on the body, and each device with nine signals, *i.e.* three for an accelerometer, three for a gyroscope, and three for a magnetometer (see Section 2 for a description of these signals). It is worth to mention that, known methods for calculating these estimations, such as rotation matrices for each signal are not the best choice for performing real time operations in wearable systems because they are highly time-consuming alternatives. Thus, a simplified representation of data, such as quaternions, will help to improve the performance of the algorithms that will be proposed.

3. Implement and evaluate an algorithm to estimate angles of segments. Two angles to the upper limb, and two angles of the lower limb are estimated from readings obtained from Inertial/Magnetic Measurement Unit (IMU). Each IMU is placed in one of four different anatomical references: forearm, arm, shank and thigh, in order to estimate movements related with flexion/extension (forearm and shank) and abduction/adduction (arm and thigh). Each anatomical reference represents a ray or side of the angle, and the other side of the angle is represented by the rest of the body. We assume that the body is static, an assumption that will not hold in the next experiment. The angles estimated of abduction/adduction are related directly to angles of shoulder and hip joints, while the angles estimated for flexion/extension are the complementary angles of internal angles of elbow and knee joints. The four angles of segments to estimate are shown in Figure 11, assuming that the body, with the exception of the segment in motion, is static.

Experiment 1: Evaluation of an estimated segment angle

Aim: Test an algorithm to estimate angles of forearm and arm at upper limb, and angles of shank and thigh at lower limb, using information obtained from an IMU, as unique sensing device aligned with respect to an anatomical plane.



(a) Angle of forearm $\lhd f$ (b) Angle of arm $\lhd a$

(c) Angle of shank $\lhd s$ (d) Angle of thigh $\lhd t$

Figure 11. Angles of segments to estimate in Experiment 1

H1: It is possible to calculate angles of segments of the body limbs from the combined signals of an accelerometer, a magnetometer and a gyroscope, with an RMSE of 10%.

Experimental design:

- Experimental unit: segment of human body
- Factor: position of segment to measure
- Treatment: configuration of initial and final position of the segment

Variables:

- Independent: AccX, AccY, AccZ (3D linear acceleration), GyrX, GyrY, GyrZ (3D angular velocity), MagX, MagY, MagZ (direction of magnetic field in 3D)
- Dependent: an angle $\lhd forearm$, $\lhd arm$, $\lhd shank$, $\lhd thigh$
- Controlled: position of sensors and segments with respect to anatomical planes

Potential sources of bias:

- Information bias: internal and external rotation, adduction, abduction, flexion or extension movements that are not being evaluated. Possible solution: constraint of the segment to measure

Evaluation:

- The experiment will be evaluated according to these measures: error and correlation coefficient between the proposal and an optical system used as reference.

4. Development of an algorithm to estimate angles of joints. Two angles to the upper limb, and two angles of the lower limb are estimated from Inertial/Magnetic Measurement Units (IMUs). Two IMUs as sensing devices are placed on contiguous anatomical references: forearm and arm for elbow angle ($\triangleleft E$), arm and upper back for shoulder angle ($\triangleleft S$), shank and thigh for knee angle ($\triangleleft K$), and thigh and low back for hip angle ($\triangleleft H$). Each anatomical reference represents a side of the angle, we assume that both references are dynamics, according to the anatomical constraints of the segments and joints. The angles to be estimated from shoulder and hip correspond to abduction/adduction movements, while the angles from elbow and knee correspond to flexion/extension movements. The four angles of joints to estimate are shown in Figure 12, assuming that the body, with the exception of both segments in motion, is static.

Experiment 2: Evaluation of an estimated joint angle
Aim: Test an algorithm to estimate angles of elbow and shoulder at upper limb, and angles of knee and hip at lower limb, using information obtained from two IMUs as sensing devices.
H2: It is possible to calculate angles of joints of the body limbs from the combined signals of accelerometer, magnetometer and gyroscope, of two IMU's with an RMSE of 10%.
Experimental design:

- Experimental unit: joint of human body
- Factor: position of the contiguous segments to measure
- Treatment: configuration of initial and final position of the two segments

Variables:

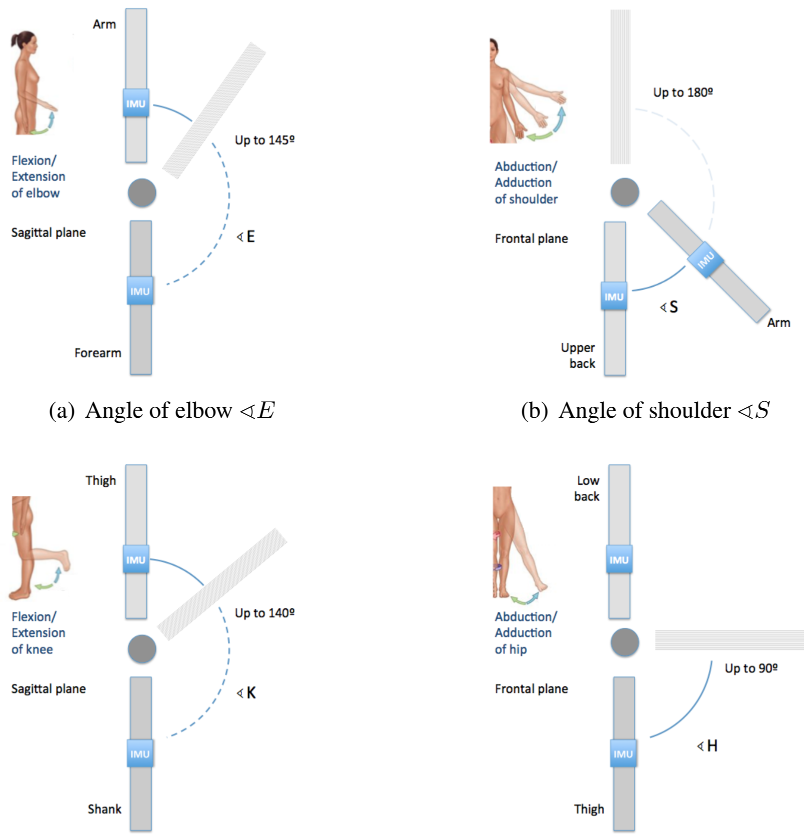
- Independent: AccX, AccY, AccZ, GyrX, GyrY, GyrZ, MagX, MagY, MagZ from two IMUs
- Dependent: an angle $\triangleleft elbow$, $\triangleleft shoulder$, $\triangleleft knee$, $\triangleleft hip$
- Controlled: position of sensors and segments

Potential sources of bias:

- Information bias: internal and external rotation, adduction, abduction, flexion or extension movements that are not being evaluated. Possible solution: constraint of the segments and joint to measure

Evaluation:

- The experiment will be evaluated according to these measures: error and correlation coefficient between the proposal and an optical system used as reference.



(a) Angle of elbow $\sphericalangle E$ (b) Angle of shoulder $\sphericalangle S$

(c) Angle of knee $\sphericalangle K$ (d) Angle of hip $\sphericalangle H$

Figure 12. Angles of segments to estimate in Experiment 2

5. Development of algorithm to estimate postures of upper and lower limbs. The postures are estimated combining the four joint angles obtained previously involving anatomical constraints with respect to an upper and the opposite lower limb at the same time. Remind that, a posture is a representation of the orientation of the joints in which the Wearable Inertial/Magnetic System is setting in a time unit $P_{tx} = \{\sphericalangle E_{tx}, \sphericalangle S_{tx}, \sphericalangle K_{tx}, \sphericalangle H_{tx}\}$, and represents elbow, shoulder, knee and hip angles, respectively. The Wearable Inertial/Magnetic System comprises six Inertial/Magnetic Measurement Units (IMUs as sensing devices) placed on six anatomical references: forearm, arm and upper back for upper limb joint angles ($\sphericalangle Elbow, \sphericalangle Shoulder$) and shank, thigh and low back for lower limb joint angles ($\sphericalangle Knee, \sphericalangle Hip$). In Figure 13 the distribution of IMUs on the named anatomical references and a posture from the joint angles estimated are shown.

Experiment 3: Estimation of a posture of upper and lower limbs

Aim: Test an algorithm to combine angles of elbow and shoulder at upper limb, and angles of knee and hip at lower limb, using information obtained from a Wearable Inertial/Magnetic System comprising six sensing devices in order to estimate a posture in a time frame.

H3: It is possible to estimate a posture from four joint angles of human opposite limbs combining information of six Inertial/Magnetic Measurement Units (IMUs) with a sampling rate less than one frame per second.

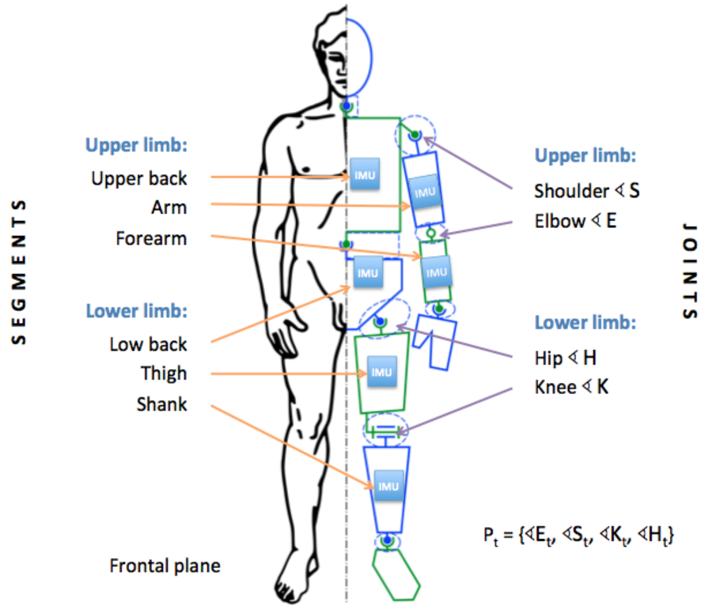


Figure 13. Postures from a Wearable Inertial/Magnetic System

Experimental design:

- Experimental unit: joints of human body
- Factor: position of the six segments to measure
- Treatment: configuration of initial and final position of the six segments

Variables:

- Independent: four angles: $\sphericalangle elbow, \sphericalangle shoulder, \sphericalangle knee, \sphericalangle hip$
- Dependent: a posture in a time frame P_{tx}
- Controlled: position of sensors and segments

Potential sources of bias:

- Information bias: internal and external rotation, adduction, abduction, flexion or extension movements that are not being evaluated. Possible solution: constraint of the segments and joints to measure

Evaluation:

- The experiment will be evaluated according to these measures: error and correlation coefficient between the proposal and an specialized optical system, such as Vicon system, used as reference.

6. Method to classify human gestures using postures for daily living environments. With the estimated postures, a classification model from various human gestures, applying classification techniques such as Hidden Markov Models (HMM), will be created. Remind that, a gesture is an action performed

by a succession of movements or postures of the upper and lower limbs, and can be represent as: $G = (P_t)_{t=1}^{t_n} = \{P_{t_1}, P_{t_2}, P_{t_3}, ..., P_{t_n}\}$, where P is a posture in a time frame. The configuration of the wearable inertial system for this stage is to place sensors on opposite limbs, *i.e.*, measuring the movement of the right upper limb and the movement of the left lower limb simultaneously. In the first validation, the movements of upper limbs and the movements of lower limbs will be classified separately, due the anatomical characteristics of the limb movements. The movements or gestures of upper limbs to classify are related with Functional Range of Motion of the shoulder and elbow [65], and are listed bellow:

(a) Place the hand behind the neck
(b) Reach behind the back
(c) Touch the opposite shoulder
(d) Raise the arm up

The movements or gestures of lower limbs to classify are related to deambulation and are important for the human daily activities [66], as listed bellow:

(a) Walking
(b) Running
(c) Ascending stairs
(d) Descending stairs
(e) Sitting
(f) Standing

For a second validation (external validation) an application on real domain will be prepared. For that, the proposed method and algorithms might be applied in a human-computer interaction domain, like rehabilitation, serious games or interaction on virtual-environments, and might be evaluated using usability metrics for Human Computer Interaction (HCI) and by clinical tests of experts of motion analysis of the National Institute of Rehabilitation.

During 2015 two internships in foreign institutions in which the developed algorithms will be applied have been programmed. These applications include the calculation of angles for human motion of people with mobility problems (in the framework of a joint project with colleagues from Boğaziçi University in Istanbul, Turkey) as well as for the calculation of human gait parameters (in the framework of a joint project with colleagues from *Universidad de Castilla-La Mancha* in Ciudad Real, Spain). These internships shall enrich our research and will not compromise the achievement of our goals.

Experiment 4: Classification of human gestures for upper and lower limbs
Aim: Test an algorithm to classify human gestures from sequences of postures in comparison to related work.
H4: It is possible to classify human gestures using sequences of postures, with joint angles of an upper limb in conjunction with joint angles of the opposite lower limb, with an accuracy of 90%.
Experimental design:

- Experimental unit: person with no report of mobility problems considering some age groups
- Factor: position of the six segments to measure
- Treatment: configuration of positions and velocity of the six segments

Variables:

- Independent: series of postures of two opposite limbs $\{P_{t_1}, P_{t_2}, P_{t_3}, ..., P_{t_n}\}$
- Dependent: human gesture $G = (P_t)_{t=1}^{t_n}$
- Controlled: position of sensors and segments

Potential sources of bias:

- Information bias: internal and external rotation, adduction, abduction, flexion or extension of joints that are not being evaluated. Possible solution: constraint of the segments and joints of upper and lower limbs

Validation:

- The experiment will be validated according to these criteria: *Internal validation*, accuracy and F-measure of the method, with respect to the results reported in the state of the art.

5 Preliminary results

In this section, the preliminary results achieved so far are presented.

5.1 Description

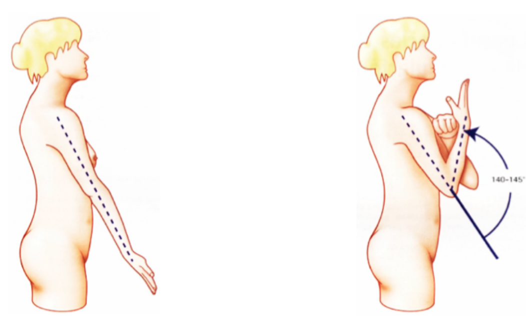
With the aim of characterizing sensing devices of the Robotics Lab and to measure the performance of an algorithm for calculating angles in human tissue, an experiment was designed to measure pronation/supination and flexion/extension of the elbow of 10 test subjects using two different sensing devices placed on their right forearms.

Anatomically the elbow consists of a single joint with only one joint cavity. Physiologically, however, it has two distinct functions: **pronation-supination** (axial rotation), involving the radio-ulnar joint; and **flexion-extension**, involving two joints: humero-ulnar and humero-radial joints [19]. These movements, that are related to the function of feeding of persons [67], are described below.

5.1.1 Flexion/extension

Extension is the movement of the forearm posteriorly. Since the position of reference corresponds to *complete extension*, see Figure 14(a), the range of extension of the elbow is *zero* by definition, except in subjects whose ligaments are flexible and allow *hyperextension* of 5^{o} up to 10^{o}. By contrast, *relative extension* is always possible from any position of flexion [67].

Flexion is the movement of the forearm anteriorly with approximation of the forearm to the anterior aspect of the arm. *Active flexion* has a range of 145^{o}, see Figure 14(b). *Passive flexion* has a range of 160^{o}, and occurs when approaching the wrist to the shoulder [67].



(a) Complete extension (b) Flexion of 145^{o}

Figure 14. Flexion and extension of the elbow [67]

5.1.2 Pronation/supination

Pronation and supination movements can only be analyzed with the elbow flexed 90^{o} and close to the body [67].

The **middle position**, or zero position, is situated on a vertical plane parallel to the sagittal plane, attained when the palm faces medially and the thumb points superiorly, is neither in pronation nor supination, see Figure 15(a). It serves as a reference position from which the range of pronation and supination is measured.

The **supination** is performed when the palm is directed upward with thumb out and is situated in the horizontal plane. The range of motion is 90°, see Figure 15(b).

The **pronation** is performed when the palm is directed downward with thumb inwards and barely reaches the horizontal plane. The range of motion is 85°, see Figure 15(c).

(a) Middle position (b) Supination of 90° (c) Pronation of 85°

Figure 15. Pronation and supination of forearm [67]

5.1.3 Algorithm

An algorithm [68] implemented in the Robotics Lab of INAOE was applied in this study. This algorithm is divided into three main stages: (1) calibration, (2) estimation, and (3) correction. The algorithm is shown in Figure 16 and its main stages are described below.

1. **Calibration.** For calibrating inertial sensors they must be exposed to various situations and then measure the actual error. The calibration of the accelerometer is done moving the sensor in all possible orientations. For each axis the maximum and minimum values from the obtained readings are identified, then the error or offset is calculated by subtracting the mean to the known value of gravity, that is $1g$. For the calibration of the gyroscope an average of readings while the sensor is static is first calculated, the offset. For the calibration of the magnetometer the sensor is turned in all possible orientations and then an average error or offset is calculated for each axis. The second step requires the calculation of a rotating matrix to multiply the actual readings of the sensor, distributed in the shape of an ellipsis, and transforming the distribution into a sphere. Finally, the offsets are subtracted from the raw readings from the three sensors. The stage of calibration is made once (step 1 of the algorithm) and must be recalculated each time the experimental conditions have changed.

2. **Estimation.** In this stage, a first calculation of angles is performed. Since this calculation is inaccurate it is updated in a next stage. The initial readings from sensors are obtained (step 2). From the readings from the accelerometer and magnetometer, a rotation matrix known as the Direction Cosine Matrix (DCM) is calculated (step 3). Then the rotation matrix is updated using the readings from the gyroscope (step 4). The readings of the gyroscope are integrated taking into account a measurement error (Me). Initially Me is equal to 0 and it is updated in the next stage. Finally, the rotation matrix is normalized to preserve its orthogonality (step 5).

3. **Correction.** In this stage, estimations are corrected by applying known error models of the sensors. The drift error is corrected by using the readings of both, the accelerometer and the magnetometer, taking into account known errors of these sensors (step 6). This value was obtained from the data

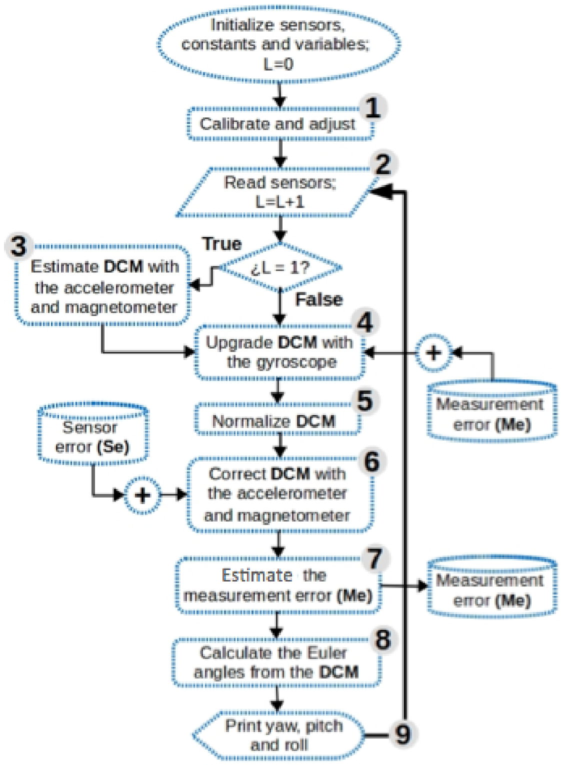


Figure 16. Flow diagram used to calculate orientation, and then angles of pronation/supination and flexion/extension movements

sheet of the sensors. With these values, the measurement error Me is updated (step 7). Then Euler angles are calculated from the rotation matrix (steps 8 and 9).

The stages of estimation and correction are alternated from the second iteration from step 2. The measurement error calculated in step 7 becomes the known error in the next iteration.

5.2 Evaluation

5.2.1 Measurement instruments

Two different sensing devices were used, our sensing device (OSD) and a commercial sensing device (CSD). A video-camera based system to calculate ground truth values was also used. Both sensing devices as well as the video-camera based system operate with a sampling rate of 50 Hz. In all the experiments described in this proposal both sensing devices were worn simultaneously by the subjects, and meanwhile the experiments were recorded by the video-camera based system. More specifications of these instruments are detailed below.

- **OSD**. Our sensing device comprises an ArduIMU v3 (3D Robotics, USA) with three different MEMS sensors (3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer), on-board Atmega328 microprocessor running at 16MHz, bluetooth RN-42 communication module for distances to 20m, and a lithium battery of 3.7V at 1000mAh. The approximate weight of our sensing device is 35gm.

- **CSD**. The commercial sensing device is a LP-Research Motion Sensor Bluetooth version (LPMS-B), a miniature wireless inertial measurement unit (IMU). This device includes three different MEMS sensors: 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. Its communication distance scope is 18m, it has a lithium battery of 3.7V at 800mAh, and it weights 34gm.
- **Video-camera based system**. The video system consists of both, video-camera and tracker software. The video-camera is a Nikon D5200 with 24.1MP CMOS sensor and Full HD (1900×1080p) video recording. The tracker software is a free video analysis and modeling tool built on the Open Source Physics (OSP) Java framework, able to track a visual mark and calculate its orientation with respect to a given axis.

5.2.2 Experimental settings

To perform pronation/supination and flexion/extension tests, an experimental platform was designed and built. It consists of a translucent rectangular frame of 80×80cm and a weight of 3kg, with a rotatory circular plate in the middle with visual marks and limit stops (see Figure 17(a)). These stops can be manually adjusted and set on arcs of 30, 60 and 120 degrees. Additionally, the rotatory plate has two handles for frontal (pronation/supination test) and lateral (flexion/extension test) movements, as illustrated in Figures 17(b) and 17(c), respectively.

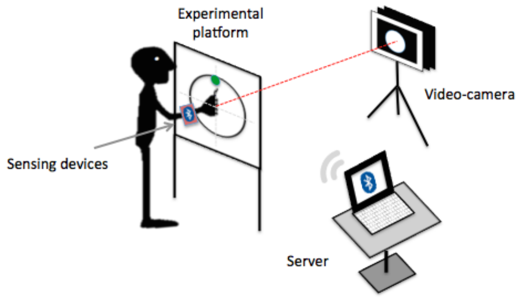
(a) Experimental platform (b) Pronation/Supination test (c) Flexion/Extension test

Figure 17. Details of the experimental platform

A sketch of the general setup involving the measurement instruments and the experimental platform used in our research is given in Figure 18 where a general scheme and a picture of the real environment are shown for a pronation/supination test. It is important to notice that all estimations are made locally by the sensing devices, and the server is only in charge of data acquisition for further comparison.

5.2.3 Subjects and conditions

Ten asymptomatic subjects participated in the tests, 6 men and 4 women, with a mean age of 27.8 (±4.94) years, and a height of 1.67 (±0.09) m. All subjects gave their informed consent to participate in these experiments.



(a) General scheme

(b) Real environment

Figure 18. Setup of experiments

Both sensing devices were placed on the forearms of test subjects using an adjustable elastic band with axes manually aligned previously using a mechanical goniometer. To neutralize the movement of the shoulder a belt attached to the body at the level of the breast was used. Since both devices are wireless there is no need of additional cables that might obstruct the movement of the limbs.

Each subject performed four sets of movements (treatments) for both pronation/supination and flexion/extension motion. For the first three sets subjects were asked to repeat systematic movements with a number of stops within arcs or 30, 60 and 120 degrees. For the fourth set, subjects were asked to perform freely movements within an arc of up to 175 degrees for pronation/supination and up to 145 degrees for flexion/extension movements without any limit stop for the rotatory circular plate. These movements were performed by the subjects in random order.

5.3 Analysis of results

Eighty sets were processed in total (half for the experiments of pronation/supination and half for the experiments of flexion/extension), all comprising the angles calculated by three sources: (1) our sensing device, (2) the commercial sensing device, and (3) the video-camera based system or gold standard.

The root-mean-square error (RMSE) between the estimated values of the sensing devices and the ground-truth values, as well as the Pearson correlation coefficient (PCC) for the same values were calculated, see Formulas (4) and (5).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{4}$$

$$\text{PCC} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

where x_i is a value calculated by our sensing device or the commercial sensing device, and y_i is the value calculated by the video system for each frame, $\bar{x}$ and $\bar{y}$ are the mean values, and n is the total number of frames.

Tables 3 and 4 summarize the results per treatment (arcs of 30, 60 and 120 degrees, and free movements). Two remarks can be highlighted from these tables. First, there is a very good agreement between the estimations made separately by independent devices with respect to the ground- truth values, as can be seen in the high correlation between the compared values (columns PCC). Second, the performance of both sensing devices is quite similar, according to the mean error calculated for treatment (columns ^{o}RMSE). On average, the commercial sensing device is around half degree more accurate than our sensing device for small arcs (30^{o}), whereas the second device is up to two degrees more accurate that the former for bigger arcs (60^{o}, 120^{o} and free movements) for pronation/supination movements, on the one hand. On the other hand, the commercial sensing device is up to 0.76 degrees more accurate than our sensing device for all treatments of flexion/extension movements.

Table 3. Pronation/supination test

Treatment	Commercial sensing device ^{o}RMSE mean (σ)	Commercial sensing device PCC	Our sensing device ^{o}RMSE mean (σ)	Our sensing device PCC
30^{o}	2.91 (1.62)	0.98	3.41 (1.93)	0.98
60^{o}	5.09 (1.24)	0.98	4.76 (1.17)	0.98
120^{o}	11.11 (3.26)	0.99	9.01 (3.08)	0.99
Free	10.57 (2.73)	0.98	10.10 (2.61)	0.98

Table 4. Flexo-extension test

Treatment	Commercial sensing device ^{o}RMSE mean (σ)	Commercial sensing device PCC	Our sensing device ^{o}RMSE mean (σ)	Our sensing device PCC
30^{o}	3.84 (0.90)	0.98	4.26 (0.94)	0.98
60^{o}	5.25 (1.35)	0.99	5.85 (1.04)	0.99
120^{o}	6.81 (2.17)	1.00	7.57 (1.67)	0.99
Free	6.04 (2.07)	0.99	6.68 (2.30)	0.99

The detailed distribution of these results is presented in the form of boxplots depicted in Figures 19 and 20. The statistical distribution of data sets is consistent with the results summarized in Tables 3 and 4. In general it can be noticed that the performance of both sensing devices (SD) decrease with respect to the extension of a movement, that is directly related to the duration of a test: the longer the movements that are tracked the greater the error.

5.3.1 Discussion

Our sensing device that was designed and programmed from the scratch achieved a performance comparable with a commercial sensing device, according to a video-camera based system using a standard software for optical tracking. We focused on the measurement of pronation/supination and flexion/extension movement of limbs since the proper measurement of these movements is considered crucial for designing reliable technologies.

From this study it was found that it is feasible to implement methods for estimating angles representing human movements of upper limbs using wireless devices. The following algorithms to develop shall incorporate better filters for calculating Euler angles, also quaternions will be considered for representing the orientation of segments. The next step is to merge the angles obtained in individual segments to estimate joint angles. These joint angles will be used to determine positions and then to classify human gestures.

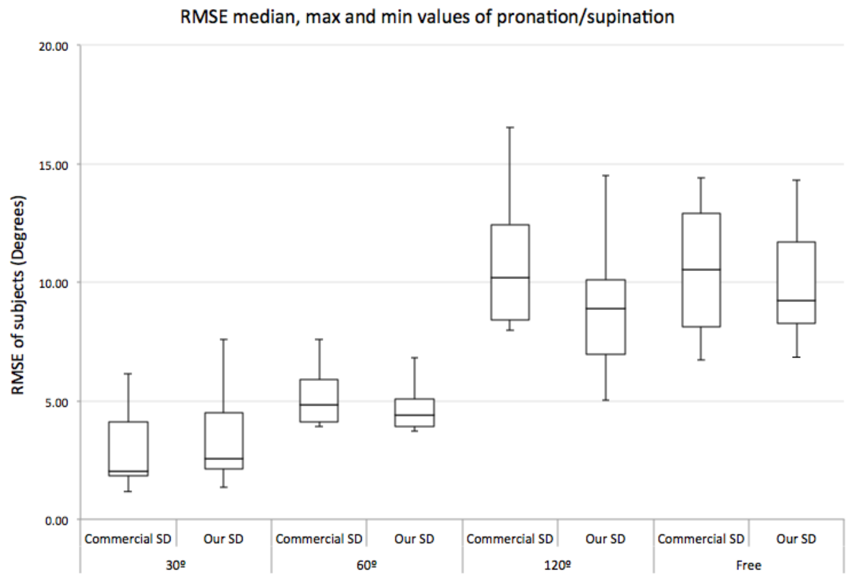


Figure 19. Boxplot of Pronation/Supination

6 Plan of work

In this chapter a plan of work to accomplish this research is detailed. First, the activities of the first year are summarized, and prospective activities to develop in the next years are listed. Then, a schedule of activities is shown according to the objectives introduced in Chapter 3.

6.1 Activities of the work plan

In Chapter 4 the main steps of this PhD research were presented. The temporality of these activities is described below, starting with the activities and goals that have been met so far.

6.1.1 Activities that are finished

Initial activities (January - October 2014)

- Attending to INAOE PhD Seminar
- Review and analysis of the state of the art
- Writing and submission of a survey entitled "Wearable Inertial Sensors for Human Motion Analysis: A review" to the International Journal of Medical Informatics

Objective 1, part 1: Estimation of angles of segments (June 2014 - December 2014)

- Characterization and evaluation of inertial sensors
- Experiment 1: Estimation of an angle of a segment respect to an anatomical plane. Forearm segment respect to the frontal plane (flexion/extension) and forearm with respect to the sagittal plane (pronation/supination)

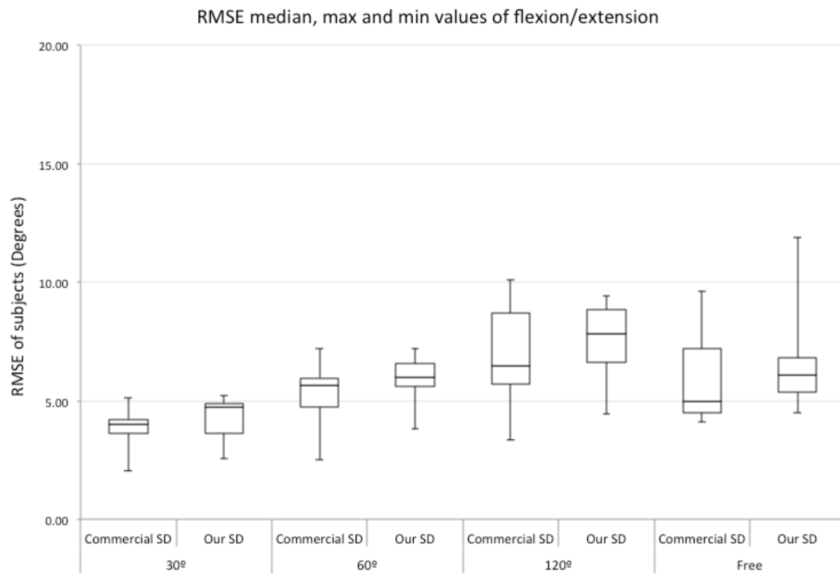


Figure 20. Boxplot of Flexion/Extension

- Analysis of the results
- Writing and submission of a conference article about preliminary results

6.1.2 Activities in progress

Objective 1, part 2: Estimation of angles of segments (January 2015 - May 2015)

- Analysis of data representation
- Development of an algorithm to estimate angles of segments based on complementary filter or Kalman filter.
- Experiment 1: Estimation of an angle of a segment with respect to an anatomical plane. Arm and thigh respect to the sagittal plane, and shank respect to the frontal plane.
- Analysis of the results

Objective 2: Estimation of angles of joints (January 2015 - December 2015)

- Development of an algorithm to estimate angles of joints
- Experiment 2: Estimation of an angle of a joint.
- Analysis of the results
- Writing and submission of a conference article
- Internship at Boğaziçi University (March - May 2015)
- Internship at *Universidad de Castilla-La Mancha* (June - July 2015)

6.1.3 Future work

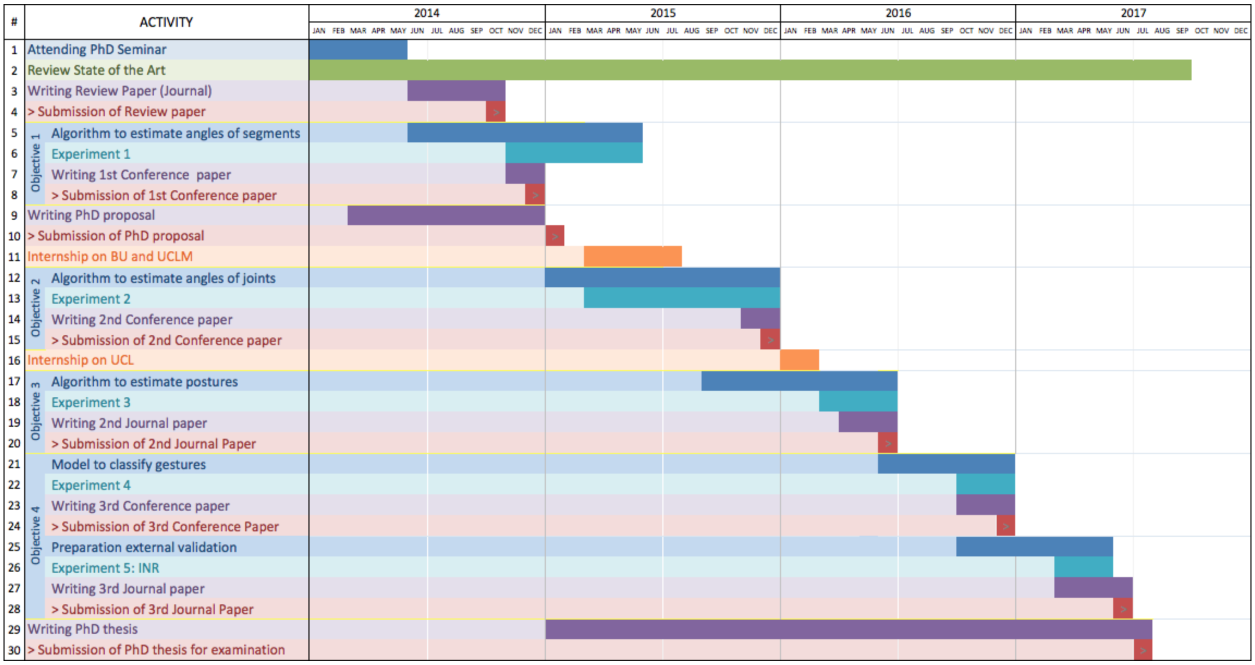
Objective 3: Estimation of postures (September 2015 - June 2016)

- Development of an algorithm to estimate postures
- Experiment 3: Estimation of a posture
- Analysis of the results
- Writing and submission of journal article

Objective 4: Classification of gestures (June 2016 - May 2017)

- Development of algorithm to classify human gestures
- Experiment 4: Classification of human gestures
- Analysis of the results
- Writing and submission of conference and journal articles

6.2 Schedule


#
ACTIVITY
2014
2015
2016
2017
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
Objective 1
Objective 2
Objective 3
Objective 4
1 Attending PhD Seminar
2 Review State of the Art
3 Writing Review Paper (Journal)
4 > Submission of Review paper
5 Algorithm to estimate angles of segments
6 Experiment 1
7 Writing 1st Conference paper
8 > Submission of 1st Conference paper
9 Writing PhD proposal
10 > Submission of PhD proposal
11 Internship on BU and UCLM
12 Algorithm to estimate angles of joints
13 Experiment 2
14 Writing 2nd Conference paper
15 > Submission of 2nd Conference paper
16 Internship on UCL
17 Algorithm to estimate postures
18 Experiment 3
19 Writing 2nd Journal paper
20 > Submission of 2nd Journal Paper
21 Model to classify gestures
22 Experiment 4
23 Writing 3rd Conference paper
24 > Submission of 3rd Conference Paper
25 Preparation external validation
26 Experiment 5: INR
27 Writing 3rd Journal paper
28 > Submission of 3rd Journal Paper
29 Writing PhD thesis
30 > Submission of PhD thesis for examination

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