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Attitude Estimation for Posture Detection in eHealth Services

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Abstract—We investigate the influence of two attitude estimation methods for human posture detection. In the context of ADL (*i.e.* Activities of Daily Living) we analyze inertial sensors to reveal uncomfortable situations. Quantifying postures such as standing up, walking, lying down or sitting may feature people autonomy and well being. We report comparisons between two main attitude estimation strategies. Our experimental protocol uses a precise ground truth obtained from two annotators. The dataset involves 9 participants and provides 50 various data sequences. We discuss the obtained promising results, analyze advantages and limits when using attitude estimation in this context.

Keywords—Inertial Measurement Unit; Attitude Estimation; Posture Detection; eHealth; Actigraphy.

I. INTRODUCTION

Nowadays, eHealth services based on inertial sensors increasingly rely on methods for detecting human postures and actions. Human action recognition based on inertial sensors has been an active area of research due to its success in robotics [13], human computer interaction [6], guidance [7], *etc.* Actions may be viewed as sequences of static and dynamic postures during the time. Nevertheless, human posture detection remains challenging, in particular for eHealth applications [2]. Indeed, posture analysis in Activities of Daily Living (ADL) is crucial because it may reveal a disease, a loss of autonomy, difficult working conditions, *etc.* In this case, device attitude estimation (*i.e.* device orientation with respect to Earth's local frame [18]) is fundamental.

Modern IMUs (Inertial Measurement Units) embed accelerometer, gyroscope, and magnetometer sensors which enable methods for attitude estimation. These methods investigate various domains such as: aerospace [8], unmanned aerial vehicles [4], indoor positioning [15], *etc.* Moreover, the particular context of smartphones carried by people in their everyday lives brings new challenges for detecting their postures. If people let their phone on a pocket, upside-down or in their backpack, attitude estimation is relevant to transform input data in a reference orthonormal coordinate system such as a torso relative one. In a torso linked referential, postures as *standing up* or *lying down* are indeed easier to detect. External accelerations, gyroscope variations

and magnetic perturbations need to be controlled when attitude estimation is realized to prevent additional issues.

Our contributions are the investigation of a posture detection system precision in the context of everyday life scenarios. We consider classical postures (such as *lying down*, *sitting*, *standing up*, *walking*, *etc.*) with various human behaviors in an indoor environment. We then analyze, compare and evaluate two state-of-the-art methods for attitude estimation. One originality is an indirect evaluation of attitude estimation methods with posture detection error quantification in regards to a human-made ground truth. The optimal automatic system should be as smart as human perception of postures.

The paper is organized as follows: the next section briefly reviews the state of the art of posture detection systems and models. In section 3, we review two classical attitude estimation methods. In section 4, we describe our experimental protocol and results are presented. Finally, Section 5 summarizes our contributions and concludes the paper.

II. HUMAN POSTURE DETECTION

Human posture detection based on IMU data may be described as challenging sequential pattern recognition. The main objective is to determine as precise as possible starting and ending timestamp of a labeled posture. Classically, as in [3], postures are defined as a hierarchical representation from a root posture as *standing up* to more precise situations as *standing with right arm up* or *lying down with curled up legs on right side* (see Fig. 1). Generally, automatic posture detection systems use 3 main strategies based on: heuristics, statistical inference or machine learning.

In the first strategy, heuristics from IMU data are built to detect postures. For instances, in [20], the authors develop a sleep posture estimator using 3-axis accelerometer data in order to prevent Obstructive Sleep Apnea Syndrome (OSAS). Likewise, when a device is worn on the torso such as a necklace, and if the z accelerometer axis is collinear to the gravity force, some rules may be provided. For example, the detection of the *standing up* position is when z accelerometer data are around g and x accelerometer are around 0. In the same way, the detection of the *lying down* position is when z accelerometer data are around 0 and x

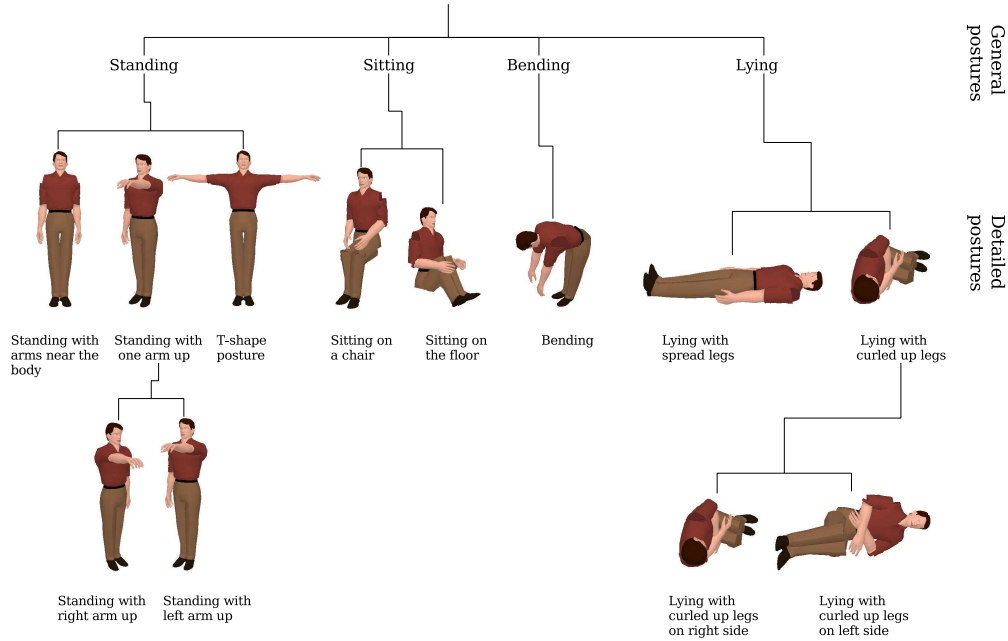


Figure 1: Hierarchical representation of human postures (extracted from [3]).

accelerometer are around g . Of course, threshold parameters should be fixed in advance, which is a real drawback for uncontrolled real life situations.

The second strategy suggests modeling the temporal structure of postures, with Hidden Markov Models (HMM). For instance, hand gestures in [14], which may be viewed as body postures, are modeled class by class from finite samples and the detection process consists of maximizing the likelihood of each class model outputs from input data.

The third method is to learn specialized classifiers (*e.g.* Support Vector Machine (SVM), Neural Networks (NN), *etc.*), which detect specific human posture from IMU data. In [12], Nelson *et al.* study how to maintain a healthy living for patients with Mild Cognitive Impairment (MCI). Their system based on IMU data models people activities with SVM based on their posture feature vectors.

In this study, we investigate the coupling between a posture detection method and two attitude estimators. Consequently, we build a posture detection algorithms based on the first strategy with heuristics in order to evaluate the attitude estimator added values. Fig. 2 shows our design. First, classical signal processing methods are applied to filter and denoise raw IMU data (*i.e.* a Butterworth filter with a Cutoff frequency of 0.01). Then, an attitude estimator is computed (see Section III) in order to calibrate data in a torso based referential. Following the next steps, rules are combined to classify IMU data to 5 human postures: *walking*, *bending*, *lying down*, *standing up* and *sitting*. From accelerometer data, dynamic versus static phase is obtained

by thresholding data variation on a sliding window. For dynamic phases, we label temporal segments as *walking* and *bending* in regard to a step detector. Here, successive peaks on accelerometer energies with a frequency between 0.6 Hz and 2.5 Hz define a walking step. For static phases, we test first a *lying* and in second a *standing* pattern detectors based on samples revealing these situations. Finally, if no label is assigned after the *lying* and *standing* detectors, then the remain segments are classified as *sitting* postures. The schema relies then on a device attitude estimator, which may strongly influence the automatic posture detection accuracy.

III. DEVICE ATTITUDE ESTIMATION

A. Background

Attitude estimation using IMU data is an important task in order to give an accurate posture detection for ADL monitoring. The 3-dimensional attitude of a rigid body is determined as the axes orientation of the body frame $B(X_B, Y_B, Z_B)$ with respect to a local Earth-fixed frame $N(X_N, Y_N, Z_N)$. It can be generally represented in 3 principal forms: Euler angles, quaternion, or Direction Cosine Matrix (DCM). The quaternion representation offers a linear formulation of the attitude dynamics in contrary to the other representations. In this paper, the unit norm quaternion is used to represent the attitude. It is defined as:

$$q = [q_0 \quad \vec{q}^T]^T = [q_0 \quad q_1 \quad q_2 \quad q_3]^T \in \mathbb{R}^4, \quad (1)$$

where q_0 and \vec{q} are the scalar and the vector parts of the quaternion, respectively.

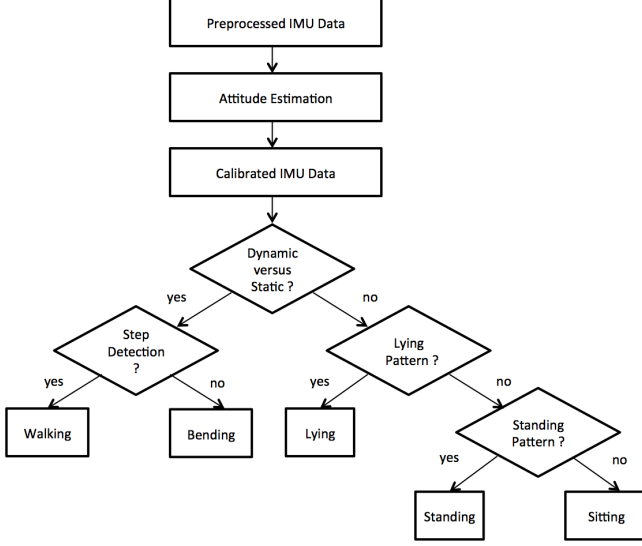


Figure 2: Posture Detection Automate with classic heuristics.

For IMU sensors, we consider a triad of sensors consisting of a gyroscope measuring the angular velocity, an accelerometer measuring the sum of the gravity and the device external acceleration and a magnetometer measuring the magnetic field. The classical kinematic equation to describe the variation of the attitude in term of quaternion is defined as follows [16]:

$$\dot{q} = \frac{1}{2}q \otimes \bar{\omega}, \quad (2)$$

where $\bar{\omega} = [0 \ \omega^T]^T$ is the quaternion representation of the angular velocity $\omega = [\omega_x \ \omega_y \ \omega_z]^T$ expressed in B .

The literature proposes different methods for attitude estimation [5], [9]–[11], [17]. In the following, we report the two different methods used in this study, exploiting firstly complementary filters [9] and secondly Kalman filters [10].

B. Complementary Filters (CF)

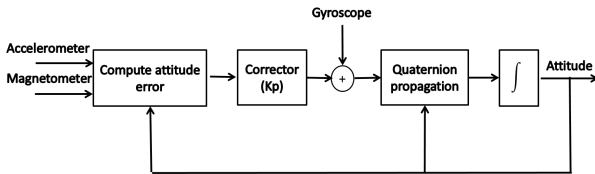


Figure 3: CF block diagram algorithm [9].

In the study of Mahony *et al.* [9], attitude estimation is performed from low cost IMU sensors. The input data is then very noisy with sampling period variations. In order to resolve these issues, the authors write the filtering problem as deterministic observers, linked on the Special Orthogonal group $SO(3)$, driven by reconstructed attitude and angular velocity measurements. This method leads to determine two

non-linear observers on $SO(3)$, termed the direct CF and passive CF.

As described in the Fig. 3, the main idea is to calculate the error by cross-multiplying measured and estimated vectors. Then a correction step is used to correct the measured angular velocity. Again the quaternion propagation is integrated to obtain an estimate of the orientation.

The direct CF proposes non-linear observers using quaternion representations. The passive CF is derived from the reconstructed attitude based on the gyroscope measurements, avoiding coupling the constructed attitude error with the predictive velocity update. Additionally, the authors propose a formulation of the passive CF into an explicit CF from gravitational and magnetic field measurements that do not require online algebraic attitude reconstruction, which is a weakness for embedded systems. In this method, the attitude detector accuracy depends mainly on the K_p gain parameter. Their experimental results appear very challenging on a robot and an unmanned aerial vehicle.

C. Quaternion Adaptive Kalman Filters (q-AKF)

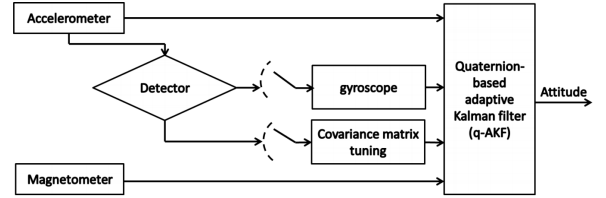


Figure 4: q-AKF block diagram extracted from [10].

Likewise, Makni *et al.* [10] consider the challenge of rigid object attitude estimation under external acceleration using IMU data. Their study focuses on attitude estimation during dynamic phases. Consequently, for compensating the external accelerations, a quaternion-based Adaptive Kalman filter (q-AKF) is designed (see Fig. 4).

First, a detector decides if the object is in a static or dynamic phase. Then, the external acceleration covariance matrix is estimated to feature the filter gain. The second challenge tackled in this study is the energy consumption issue when using a gyroscope. For preserving IMU battery life, the authors design a switching policy in order to exploit gyroscope data only when it is useful. The efficiency of the two contributions shows challenging results and the attitude detector accuracy depends mainly on the P parameter, the initial value of the covariance matrix corresponding to the estimation error.

IV. EXPERIMENTS

A. Dataset

1) *Proposed scenario:* The objective of the scenario in [1] is to collect inertial data of many participants in a real-life scenario (cf. Fig. 5). As activities of daily living are



Figure 5: One sample posture sequence to be performed.

composed of 4 main postures (e.g. *standing up*, *sitting*, *lying down*, *walking*), the participants were asked to follow a particular protocol for about 12 minutes. Each participant performs a specific posture sequence in a particular order as follows: (*standing up* - *walking* - *standing up* - *sitting*). This sequence is repeated 6 times and may be preceded by a *lying down* posture or followed by a (*standing up* - *walking* - *standing up* - *lying down*) sequence. Each data sequence represents then human behaviors similar to an everyday life, but condensed in 12 minutes.



Figure 6: SK6 device.

2) *Protocols*: 9 participants (5 males and 4 females) were recruited to participate in the experiment [1]. The study was limited to French native participants in order to have homogeneous behavioral patterns and a standard annotation protocol. Ages are ranged from 22 to 55 years old with an average of 38. Participants had different functions: interns, developers, PhD students, researchers, ergonomists and project managers.

A device, named SK6 [19], as shown in Fig. 6, was fixed on the participant and collect inertial data. 3D accelerometer, 3D gyroscope, 3D magnetometer data are sampled every 100 ms, as shown in Fig. 7. The mean duration of each sequence is about 7643 samples (i.e. 13 minutes and 14 seconds long).

3) *Data Annotation*: One independent annotator segments manually each posture on the posture sequences in regards to the scenario, shown in Fig. 5. A second annotator validates the provided labels. This process was used for all inertial features in order to establish our ground truth (GT). The 4 main postures (i.e. *lying down*, *sitting*, *standing up*, *walking*) are labeled and also a *bending* label is added to mark the transition postures between *lying down* and *sitting* or *standing up* situations. These particular transition postures are indeed more fuzzy situations. This experiment design was thought to handle a list of classical postures known to largely contribute on activities of daily living. Finally, each sequence presents then around 35 annotated segments.

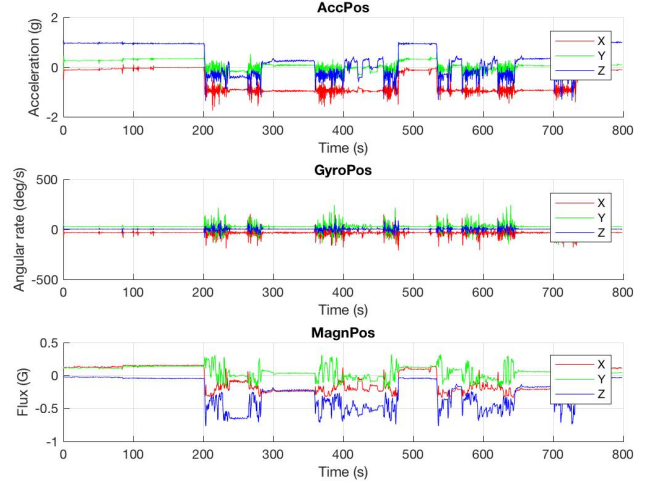


Figure 7: Accelerometer, gyroscope and magnetometer data for one participant during one IMU data acquisition.

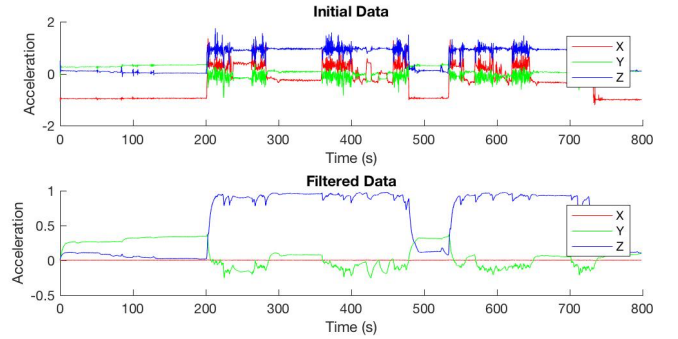


Figure 8: Raw and filtered accelerometer data for one participant.

B. Results

Fig. 8 presents raw data of one session and the filtered data, obtained before the attitude estimation phase, used for posture detection. We observe that the low-pass filter on the *z*-axis data provides a smoother signal, denoising then some interferences. The posture detector is then facilitated when automatically labeling *walking* or *standing up* signal segments. Likewise, signal processing on *y*-axis reveals clearly situations when participants are lying down (i.e. in the beginning of the scenario and around 500 seconds). The two resulting postures, namely *sitting* and *bending* are then deduced from the 3 previous ones, as described in Fig. 2.

Each labeled segments build finally a specific APD (Automatic Posture Detector-based) posturogram that is compared to the specific GT (Ground Truth) posturogram for each participant. Fig. 9 shows two posturograms for one participant and the superposition of the two previous ones.

It is then notable that on this user session, the automatic posture detector performs well, underlying the ground truth.

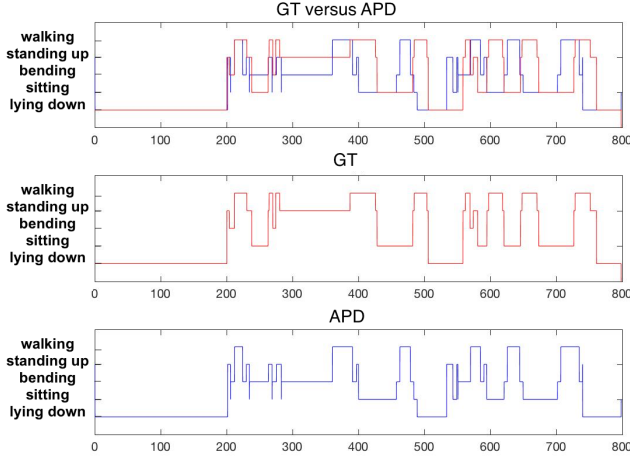


Figure 9: Posturogram alignments between the Ground Truth (GT) and the Automatic Posture Detection (APD).

Some errors appear when distinguishing *standing up* and *bending* postures. These two postures are quite similar in real life, and these errors are due to some standing detector imprecisions. Sometimes, some errors show light delays when detecting postures. These time variations may be caused by some issues to determine precisely starting times of a new posture. Again, *bending* postures are less marked situations and consequently more difficult to detect because they often result from transfer phases between two marked situations (*i.e.* between *standing up* and *sitting* postures or between *standing up* and *walking* postures).

Posture detection evaluation is then performed by computing a DTW (*i.e.* Dynamic Time Warping) based metric. In order to compare the precision of the APD posturogram in regards to the ground truth, this metric measures similarity between the two temporal sequences. Table I presents our evaluation with 3 configurations: firstly, with no attitude estimation before our posture detector, secondly with Complementary Filter (CF) attitude estimator (see III-B), and thirdly with q-AKF attitude estimator (see III-C). An average posture detection error is computed from a 5-cross validation process. 5 validation datasets are used to optimize CF and q-AKF methods while 5 test datasets are used to evaluate blindly the precision of the full posture detection process (*i.e.* including attitude estimation performances). One repetition contains 25 sequences from random participants.

In Table I, we observe that the minimal average error is performed by the q-AKF attitude estimator and our posture detector with a score of 0.192646 ± 0.023791 . This means that around 80.74% of the posture sequences were correctly classified. This score is better than using CF attitude estimator (0.197152 ± 0.021079) or no attitude estimator (0.216408 ± 0.0009055). It reveals that using an attitude estimator is relevant for posture detection and that CF attitude estimation is less adequate in this context. Particularly,

our protocol gives significance for dynamic phases, which may correspond better to q-AKF attitude estimation design. The main remaining confusions concern *standing up* and *sitting* postures and *standing up* and *bending* postures. On the contrary, the *walking* and *lying down* postures are mainly correctly classified by our specific detectors.

Table I: Average posture detection errors.

Methods		Validation	Test
No attitude estimation	Mean	0.210572	0.216408
	Standard Deviation	0.005730	0.009055
(CF) [9]	Mean	0.197685	0.197152
	Standard Deviation	0.023632	0.021079
(q-AKF) [10]	Mean	0.190133	0.192646
	Standard Deviation	0.025875	0.023791

As a complement, Fig. 10a presents the influence of the parameter K_p , representing the gain in the CF formulation, on posture detection accuracy. The average minimal error over the 5 validation datasets is 0.197685 ± 0.023632 obtained for $K_p = 0.8$. Likewise, Fig. 10b shows the posture detection accuracy when the parameter P varies over the 5 validation datasets and the mean minimal reached error is 0.190133 ± 0.025875 obtained for $P = 4 \times 10^{-5}$. P is the initial values of the covariance matrix used in the q-AKF attitude estimator.

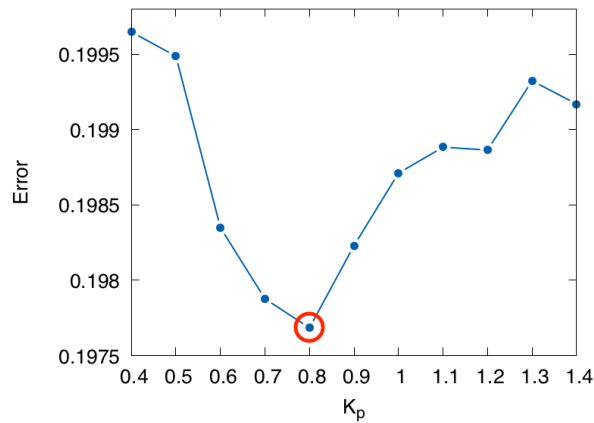
V. CONCLUSIONS AND PERSPECTIVES

We investigate the influence of two attitude estimation methods for posture detection in the particular context of everyday indoor situations. We propose an experiment based on 9 participants for evaluating the precision of posture detection. Our experiments shed light on the relative impacts of the attitude estimation computation on inertial data based posture detection. The best overall result obtains 0.192646 of errors, which is very promising to feature human behavior when performing activities of daily living.

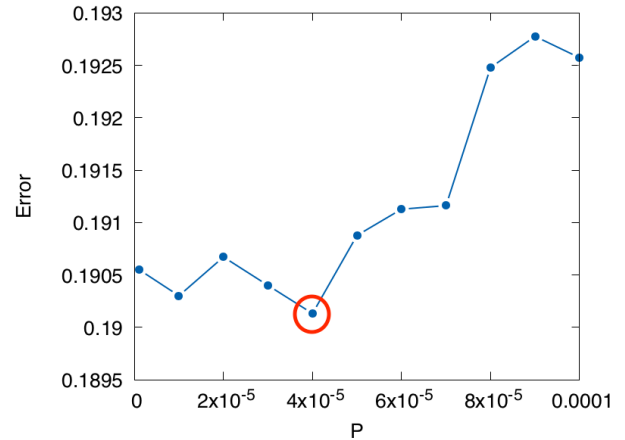
Some challenges remain opened with large scaled datasets and environment perturbations as biases or acceleration noises due to means of transports in outdoor situations, for instance.

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(a) Minimal error for K_p values using (CF).



(b) Minimal error for P values using (q-AKF).

Figure 10: Optimal parameters on the validation dataset.

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