A NOVEL FEATURE EXTRACTION TECHNIQUE FOR HUMAN ACTIVITY RECOGNITION

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ABSTRACT

This work presents a novel feature extraction technique for human activity recognition using inertial and magnetic sensors. The proposed method estimates the orientation of the person with respect to the earth frame by using quaternion representation. This estimation is performed automatically without any extra information about where the sensor is placed on the body of the person. Furthermore, the method is also robust to displacements of the sensor with respect to the body. This novel feature extraction technique is used to feed a classification algorithm showing excellent results that outperform those obtained by an existing state-of-the-art feature extraction technique.

Index Terms— Activity Classification, Ambulatory Monitoring, Features Extraction, Inertial Sensors, Magnetic Sensors, Orientation Estimation, Quaternions.

1. INTRODUCTION

The task of Human Activity Recognition (HAR) using wearable sensors has recently become a popular topic of research in context-aware monitoring applications, such as home-based rehabilitation, or ambulatory monitoring of elderly or patients with brain disorders [1]. The low cost, small size, and low energy consumption of the devices allow pervasive data acquisition without disturbing daily activities.

The most popular approach for HAR using sensors uses inertial based sensory systems (see [2] for a review). A basic Inertial Measurement Unit (IMU) consists on a 3-axis accelerometer and a 3-axis gyroscope enabling the measuring of acceleration and angular velocity, respectively. A Magnetic, Angular Rate, and Gravity (MARG) sensor is an extended IMU that also integrates a 3-axis magnetometer.

In this work, we focus on the feature extraction of the signals acquired by a MARG sensor, since it is the one that provides more information for indoor scenarios (i.e., without GPS signal). A MARG sensor provides the measurements referenced to the sensor frame. However, these raw signals are sensitive to the placement of the sensor on the body of the person, in terms of position and orientation. Most of the classification algorithms for HAR proposed in the literature are fed with raw or mildly processed signals [2, 3]. Few of them try to extract the orientation of the sensor or the person in order to feed the classification algorithms [4]. In this paper, we propose to use as inputs of the classification algorithms the orientation of the person w.r.t. the earth frame, and the acceleration in the person frame. To that end, a novel scheme of feature extraction for HAR algorithms is presented, including an efficient algorithm based on quaternion representation that computes the orientation of the person from the measurements of the MARG sensor.

This paper is organized as follows: In Section 2, we propose the algorithm for feature extraction based on estimating the orientation of the person. In Section 3, the classification results obtained with the proposed algorithm are presented. Finally, in Section 4, conclusions and future work are discussed.

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2. PROPOSED ORIENTATION ESTIMATION ALGORITHM

2.1. Quaternions and Notation

Throughout this paper we use quaternions to represent three-dimensional orientations and rotations. Quaternions retain several advantages compared to Euler rotation matrices: they do not suffer from problematic singularities such as gimbal lock [5], and they are more compact, computationally efficient, and numerically stable.

Quaternions constitute a four-dimensional space over the real numbers. They are composed by the real axis and three imaginary orthogonal axes. Here we list some relevant quaternion properties, where the $\otimes$ operator denotes the Hamilton product, and the $\hat{}$ accent denotes a normalised vector:

1. A rotation through an angle of α around a unit vector $\hat{\mathbf{u}}$ is represented by the unit quaternion

$$\hat{\mathbf{q}} = \cos\left(\frac{\alpha}{2}\right) + \sin\left(\frac{\alpha}{2}\right)\Big(u_x\mathbf{i} + u_y\mathbf{j} + u_z\mathbf{k}\Big). \quad (1)$$

2. Two rotation quaternions $\hat{\mathbf{q}}_1$ and $\hat{\mathbf{q}}_2$ can be combined into one equivalent quaternion, $\hat{\mathbf{q}} = \hat{\mathbf{q}}_2 \otimes \hat{\mathbf{q}}_1$ that rep-

resents a rotation given by $\hat{\mathbf{q}}_1$ followed by a rotation given by $\hat{\mathbf{q}}_2$.[1]

3. For any unit quaternion $\hat{\mathbf{q}}$, its inverse is equal to its conjugate $\hat{\mathbf{q}}^{-1} = \hat{\mathbf{q}}^*$.

4. If a quaternion $\hat{\mathbf{q}}$ represents a rotation, and $\mathbf{v}$ is a three-dimensional vector, the rotated vector $\mathbf{v}'$ can be computed as $\mathbf{p}' = \hat{\mathbf{q}} \otimes \mathbf{p} \otimes \hat{\mathbf{q}}^*$, where $\mathbf{p} = p_x\mathbf{i} + p_y\mathbf{j} + p_z\mathbf{k}$ and $\mathbf{p}' = p'_x\mathbf{i} + p'_y\mathbf{j} + p'_z\mathbf{k}$.

2.2. Coordinate Systems

Three different three-dimensional frames are described in order to compute the orientation of the person w.r.t. the earth. First, the sensor frame (S) is defined along the orthogonal axes of the physical device, $\{{}^S\mathbf{x}, {}^S\mathbf{y}, {}^S\mathbf{z}\}$. The recorded signals are referred to this frame. Secondly, the earth frame is defined by the orthonormal set of vectors $\{{}^E\mathbf{x}, {}^E\mathbf{y}, {}^E\mathbf{z}\}$={North, West, Up}. Finally, we define the person frame, defined by an orthonormal set of vectors whose directions when the person is standing are aligned as $\{{}^P\mathbf{x}, {}^P\mathbf{y}, {}^P\mathbf{z}\}$={Forward, Left, Up}.

We use a notation system of leading superscripts and subscripts to describe relative frame orientations and vector representations adopted from [6]. A leading subscript denotes the frame being described, and a leading superscript denotes the frame this is with reference to. For example, ${}^A_B\hat{\mathbf{q}}$ describes the orientation of frame B relative to frame A while ${}^A\mathbf{v}$ represents a vector described in frame A.

2.3. Feature Extraction Algorithm

The proposed feature extraction scheme processes the magnetic, angular rate, and accelerometer signals provided by the MARG sensors in order to excerpt

1. the orientation of the person w.r.t. the earth frame, and
2. the acceleration in the person frame, ${}^P\mathbf{a}$.

In contrast to other feature extraction schemes [4, 7], we consider that angular rate measurements provided by gyroscopes are not valuable signals any longer for the classification algorithms, since their information is incorporated to the orientation of the person.

Therefore, the main goal consists in computing ${}^P_E\hat{\mathbf{q}}$, i.e., the orientation of the earth frame (E) relative to the person frame (P). The proposed algorithm makes use of quaternion property 2., decomposing the estimation of ${}^P_E\hat{\mathbf{q}}$ as a concatenation of the estimation of the orientation of ${}^E\mathbf{z}$ w.r.t. to ${}^P\mathbf{z}$, ${}^P_E\hat{\mathbf{q}}_\mathbf{z}$, followed by the estimation of the orientation of the plane ${}^Exy$ w.r.t. the plane ${}^Pxy$, ${}^P_E\hat{\mathbf{q}}_\mathbf{xy}$, i.e.,

$$ {}^P_E\hat{\mathbf{q}} = {}^P_E\hat{\mathbf{q}}_\mathbf{xy} \otimes {}^P_E\hat{\mathbf{q}}_\mathbf{z}, \tag{2} $$

where ${}^P_E\hat{\mathbf{q}}_\mathbf{z}$ is also decomposed as

$$ {}^P_E\hat{\mathbf{q}}_\mathbf{z} = {}^S_E\hat{\mathbf{q}} \otimes {}^P_S\hat{\mathbf{q}}_\mathbf{z}. \tag{3} $$

The orientation of the earth frame relative to the sensor frame, ${}^S_E\hat{\mathbf{q}}$, is computed by means of the gradient descent algorithm proposed in [6]. This algorithm has shown an accurate performance close to a Kalman-based algorithm [8], while remaining computationally very efficient. The algorithm updates the current orientation via integration of the provided angular rate, and corrects the gyroscope drift with accelerometer and magnetometer measurements. This correction is driven by a parameter, β, that represents the correction rate of the gyroscope drift (see [6] for more details). The authors prove that, if the sampling rate is large enough, the algorithm performs accurately just computing one gradient descent iteration per sample, which implies a very low computational cost. The convergence of the algorithm can be tuned by increasing the parameter β (see Section 3 for more details).

The second term of equation (3), ${}^P_S\hat{\mathbf{q}}_\mathbf{z}$, corresponds to the orientation of the ${}^S\mathbf{z}$ axis w.r.t. the ${}^P\mathbf{z}$ axis. Note that, if the sensor is strongly attached to the body of the person, this orientation should remain constant. Nevertheless, considering that the sensor is fixed to the clothes (for instance bounded by a belt at the waist), ${}^P_S\hat{\mathbf{q}}_\mathbf{z}$ may suffer from small variations. Although knowing ${}^S_E\hat{\mathbf{q}}$ during the standing position would be enough to find this orientation, with unlabelled data it is not possible to determine a priori when the person is standing. Nonetheless, walking sequences are easier to detect automatically, and while walking, the person is in average also upright; i.e., the ${}^P\mathbf{z}$ axis is aligned to the ${}^E\mathbf{z}$ axis in average. For this purpose, we have used a walking detection algorithm similar to that proposed in [4]. Therefore, ${}^S_P\hat{\mathbf{q}}_\mathbf{z}$ can be computed by averaging ${}^S_E\hat{\mathbf{q}}$ during the walking period. Due to quaternion property 3., we obtain the second term of equation (3) as ${}^P_S\hat{\mathbf{q}}_\mathbf{z} = {}^S_P\hat{\mathbf{q}}^*_\mathbf{z}$. Note that although there exist several ways to average a quaternion [9], we use an unweighted mean of ${}^S_E\hat{\mathbf{q}}$ during the walking period since it provides good results while being computationally efficient. In this way, ${}^P_S\hat{\mathbf{q}}_\mathbf{z}$ is updated every time a walking period is detected.

Finally, we compute the first term of equation (2), ${}^P_E\hat{\mathbf{q}}_\mathbf{xy}$, by estimating the direction of the velocity in ${}^Exy$ plane when the person is walking. For that purpose, we integrate the acceleration in the earth frame to get the velocity [10], we remove the velocity drift [11], and we compute the angle γ of the projection of the velocity vector onto the ${}^Exy$ plane w.r.t. ${}^E\mathbf{x}$. Let ϕ be the angle between ${}^E\mathbf{x}$ and the projection of the vector ${}^P_E\hat{\mathbf{q}}_\mathbf{z} \otimes \mathbf{i}$ onto the ${}^Exy$ plane. Then, defining $\theta = \gamma - \phi$, and according to quaternion properties 3. and 4., ${}^P_E\hat{\mathbf{q}}_\mathbf{xy} = \cos(\theta/2) + \mathrm{sen}(\theta/2)\mathbf{k}$.

Algorithm 1 summarises the process to compute ${}^P_E\hat{\mathbf{q}}[n]$, the orientation of the earth frame w.r.t. the person frame. The calculation is performed for the N available samples of magnetic field, angular rate, and acceleration measurements ac-

[1] Note that quaternion multiplication is not commutative

quired by the MARG sensor. Note that β, the key parameter of the sensor orientation algorithm [6] must be selected at the beginning, and it plays a key role in the performance of the classification algorithm, as it can be seen in Section 3.

Algorithm 1 Pseudocode of person orientation algorithm

Select β
for $n = 1 : N$ **do**
  Compute ${}^S_E\hat{\mathbf{q}}[n]$ with the algorithm of [6] and β
  Detect whether the person is *walking*
  if *walking* **then**
    Update ${}^P_S\hat{\mathbf{q}}_{\mathbf{z}}[n]$
    Update ${}^P_E\hat{\mathbf{q}}_{\mathbf{xy}}[n]$
  else
    ${}^P_S\hat{\mathbf{q}}_{\mathbf{z}}[n] = {}^P_S\hat{\mathbf{q}}_{\mathbf{z}}[n-1]$
    ${}^P_E\hat{\mathbf{q}}_{\mathbf{xy}}[n] = {}^P_E\hat{\mathbf{q}}_{\mathbf{xy}}[n-1]$
  end if
  ${}^P_E\hat{\mathbf{q}}[n] = {}^P_E\hat{\mathbf{q}}_{\mathbf{xy}}[n] \otimes {}^S_E\hat{\mathbf{q}}[n] \otimes {}^P_S\hat{\mathbf{q}}_{\mathbf{z}}[n]$
end for

3. EXPERIMENTS

3.1. Experimental Setting

The evaluation of the proposed method is performed using real data acquired by APDM OPAL miniature sensors [12]. These sensors provide three-axis acceleration, three-axis gyroscope, and three-axis magnetometer data. 18 data sequences have been collected, each one from a different person. A single sensor has been placed at the waist of each subject, and they have been asked to perform some of activities in no particular order. These sequences are combinations of five different activities: running, walking, standing, sitting, and lying. This data acquisition procedure has provided us with 6 hours and 21 minutes of real data samples acquired at a sampling rate of 128 Hz.

In order to randomize the testing process, we have built 25 sets of sequences. For each set, we have randomly selected 12 sequences for training from the database, and the 6 ones left have been used for testing. The 25 sets have been used to test all feature extraction algorithms, in order to maintain the consistency. The data have been processed both with the Acceleration Quaternion method (AQ) presented in this paper (using different values of β) and with the Acceleration Angular Rate method (AAR) proposed in [4]. The AAR method makes use of angular rate and acceleration signals, transforming them to a virtual sensor orientation.

For sake of simplicity and a fair comparison in terms of computational complexity, we have not made use of ${}^P_E\hat{\mathbf{q}}_{\mathbf{xy}}$ in equation (2). Thus, we have provided the classification algorithm with the orientation of the ${}^P\mathbf{z}$ w.r.t. the earth.[2] We have visually checked that the processed acceleration and quaternion signals are consistent with the dynamics of the activities performed.

3.2. Training description

Although the proposed feature extraction technique is not restricted to any classification algorithm, in this paper, we evaluate its performance by applying it to an state-of-the-art hierarchical dynamic model (HDM) based on hidden Markov models (HMM). We train a different HMM for each activity independently using the Baum Welch algorithm, following the scheme of [7].

Each HMM is modelled using five states per activity, i.e., having a global model with 25 identifiable states, and a Gaussian Mixture Model (GMM) observation probability distribution with three components. We use the Forward-Backward algorithm to obtain the Maximum a Posteriori estimate of the test sequences.

3.3. Results

We compare the performance of the proposed AQ algorithm (with three different values of β) with the AAR algorithm. Table 1 shows the probability of error of both methods broken down by activity. The proposed AQ algorithm exhibits a lower error rate for all tested β, largely outperforming the AAR algorithm in some activities, and remaining very close in the others. Note that decreasing from 0.16 to 0.11 in probability of error is a remarkable reduction, since the bottleneck must presumably lie on the classification algorithm.

Activity	AAR	AQ $\beta = 1$	AQ $\beta = 3$	AQ $\beta = 5$
Running	0.38	0.18	0.19	0.20
Walking	0.02	0.05	0.02	0.05
Standing	0.03	0.06	0.05	0.05
Sitting	0.15	0.12	0.06	0.07
Lying	0.21	0.23	0.23	0.23
Mean	**0.16**	0.13	**0.11**	0.12

Table 1. Probability of error comparison of the AAR method and the proposed AQ mehod.

In Table 2, the feature extraction algorithms have also been compared in terms of the F-measure [13]. For all different values of β, the classification with the proposed algorithm outperforms that obtained with the AAR method. Again, the AQ method with $\beta = 3$ obtains the better results.

Finally, Figure 1 shows the F-measure range of accumulating the 6 test sequences of the 25 different sets, i.e., 150 different test sequences in total. For each method, the horizontal red line inside every box shows the median value, the

[2] We believe that most of the useful information residing in the orientation of the subject must rely on the inclination of its z-axis w.r.t. the earth. Nevertheless, further investigations will be performed.

Activity	AAR	AQ $\beta = 1$	AQ $\beta = 3$	AQ $\beta = 5$
Running	0.75	0.88	0.87	0.86
Walking	0.92	0.95	0.95	0.94
Standing	0.98	0.96	0.97	0.97
Sitting	0.81	0.76	0.81	0.79
Lying	0.82	0.84	0.86	0.85
Mean	**0.86**	0.88	**0.89**	0.88

Table 2. F-measure of the AAR method and the proposed AQ mehod.

upper and lower edges of the blue boxes are the 25th and 75th percentiles respectively, and the vertical black dashed lines extend to the extreme cases. It can be seen that most of the test sequences for all three values of β fall around a F-measure of 0.9 whereas for the AAR method they are around 0.85. The worst sequence with the proposed AQ method with $\beta = 3$ obtains a F-measure = 0.8 while the worst one with AAR remains at 0.75.

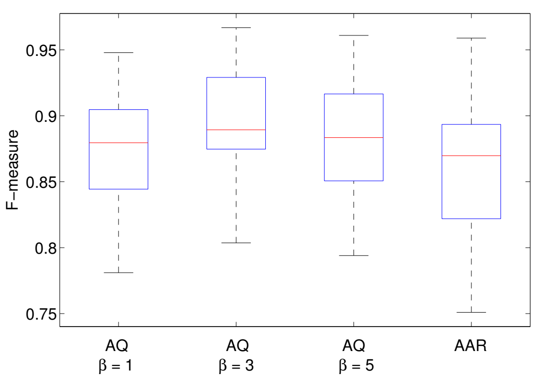

Fig. 1. F-measure results for all test sequences using the AAR method and the proposed AQ method.

4. DISCUSSION AND CONCLUSIONS

We have presented a novel feature extraction technique for human activity recognition based on quaternion representation. The proposed algorithm computes the acceleration referred to the person frame, and the orientation of the person frame with respect to the earth frame. Numerical results show a substantial improvement in the results of the classification algorithm when the feature extraction is performed with the proposed method. The computational cost of the proposed algorithm is linear with the length of the sequence and extremely low for each sample, requiring only few quaternion multiplications and additions. Moreover, the simplicity of the algorithm would also allow, with a slight adjustment, an online estimation of the person orientation.

5. REFERENCES

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