Detection of quasi-static instants from handheld MEMS devices

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Abstract— **In this paper, an algorithm for detecting quasi-static (QS) instants from handheld MEMS devices is presented. An adaptive approach is adopted for considering the different characteristics of several common motion modes for mobile phone users: walking with hand swinging, texting, phoning, and carrying the device in a bag. For this purpose, a decision tree classifier with probability of detection greater than 90% for each examined motion mode has been designed and implemented. Finally, the use of QS instants for performing step detection from handheld devices is analyzed.**

Keywords—**Pedestrian Navigation; Pedestrian Dead Reckoning; MEMS; Step**

I. Introduction

The extraordinary diffusion of smart-phones and other kind of personal digital assistants (PDAs) is pushing cell-phone manufacturers to add more and more functionalities to these portable devices, including pedestrian navigation applications.

In particular MEMS (Micro-Electrical-Mechanical Systems) technology is playing a key role in the design of the new generation of handheld devices. In fact, thanks to their reduced size, low power consumption and high sensitivity, MEMS sensors can be easily embedded in smartphones providing innovative capabilities. MEMS gyroscopes and accelerometers are the primary sensors for tracking the motion and position of a pedestrian driving his car, walking downtown or indoor.

However, the main drawback of low grade MEMS sensors is that, since their signal is affected by various noises and drifts [1], they cannot constitute a self contained system. In order to bound the above error sources, frequent GPS updates can be used. Unfortunately GPS cannot guarantee sufficient accuracy, availability, and continuity of the navigation service where satellite signals are blocked or degraded by multipath, such as indoor or in urban canyons. These environments represent the main challenge for pedestrian applications because, contrary to vehicles, pedestrians spend much of their time in the indoors or in light indoor environments [2].

In this context, different approaches have to be investigated. Contrary to strap-down navigation, pedestrian dead reckoning (PDR) offers an interesting strategy because it exploits the kinematic of the human gait instead of double integrating the inertial data [3]. Given a starting known position, PDR algorithm propagates the user`s position by estimating the heading and the user's travelled distance. Traditionally, PDR algorithms compute the travelled distance by first detecting the user's steps and second determining their length. This technique has been used for navigation application in many research works [3], [4]. Already published techniques are very effective when the sensor is fixed on the user's body, especially when it is located on the user's foot. In this case the stance phases of the foot, i.e. when the foot is flat on the ground, can be identified. Periodic zero velocity updates (ZUPTs) [4] are then performed to bound the position error accumulation.

However, body fixed locations are not realistic for many applications since generic users usually carry their mobile devices in their hands, pant pockets, or handbag. For the above cases, which are the heart of this paper, the situation is completely different from the foot case because periods of zero velocity cannot be identified while the subject is moving.

Even if for handheld devices, there is no real period that can be considered as completely static, quasi-static (QS) instants, i.e. where the sensor is not significantly moving, still represent moments of great interest for PDR algorithms. During these periods, it is not likely to detect a constant acceleration [5], but it is still possible to identify instants during which the sensor's attitude and position variations are not significant. When QS periods occur, the kinematic linear acceleration can be considered negligible with respect to the gravity acceleration. Therefore, at these instants, accelerometers can also act as an inclinometer enabling the estimation of the orientation angles between the sensor frame and the navigation frame. In addition, these QS instants reflect specific moments of the human walking gait and can subsequently assist PDR algorithms from handheld devices. Consequently, in this paper, algorithms for identifying QS instants from handheld MEMS devices and deriving human walking gait analysis are presented.

Many detectors [6] have been proposed for identifying stance phases for foot mounted sensors. Indeed, when the sensor is fixed on the foot, it has been shown that the combination of two traditional detectors, i.e. the acceleration energy detector and the angular rate energy detector, improves the robustness of zero-velocity identification. In fact, by combining measurements from gyroscopes and accelerometers, the probability of false detection is minimized. However, to the authors' knowledge, no specific development has been made for handheld MEMS sensors.

Considering the fact that a generic mobile device can be subjected to various types of motions and that the pattern of the sensor signals is less predictable than in the foot case, the type of motion encountered by the inertial sensors is first identified. Four motion modes, typical for mobile phone users, are considered. The knowledge of the motion mode is further exploited for adapting the QS detection parameters and increasing their robustness.

The paper is organized as follows: in Section II, the signal model is introduced. Thereafter, in Section III.A, the general problem of QS detection is presented, in Section III.B, the proposed algorithm for motion mode recognition is explained and, in Section III.C, the algorithm for detecting QS instants is contextualized for different motion modes. In Section IV, results that relate QS instants to the gait cycle are reported. Finally, in Section V, some conclusions are drawn.

II. SIGNAL MODEL

The detection of QS instants is performed by using the measurements from 6 degree of freedom inertial measurement unit (IMU). It comprises a tri-axis accelerometer and tri-axis gyroscope that respectively provide the acceleration and the angular velocity of the rigid body in the inertial frame. The IMU's output can be modeled as the sum of the response to the experienced inertial force and a noise term, given by

$$s[n] = \begin{bmatrix} a[n] \\ \omega[n] \end{bmatrix} + \begin{bmatrix} \eta_a[n] \\ \eta_\omega[n] \end{bmatrix}. \qquad (1)$$

- n represents the temporal index.
- $a[n]$ is the acceleration vector and $\eta_a[n]$ is the associated noise vector.
- $\omega[n]$ is the angular rate vector and $\eta_\omega[n]$ is the associated noise vector.

The inertial sensors being of low grade, stochastic error modeling is usually performed for removing sensor's errors in the measurements. However, the proposed algorithms extract information from moving windows whose mean is usually subtracted. Therefore, they are immune to stochastic IMU errors.

III. QUASI-STATIC DETECTION ALGORITHM

A. Quasi-static detector

The identification of QS instants is a classical binary hypothesis testing problem where two possible hypotheses can be defined:

- QS state (hypothesis H_0): the sensor is nearly static and the signals detected by the IMU are essentially constituted of noise.
- Dynamic state (hypothesis H_1): the sensor is moving and the IMU measures the response to the inertial forces as described in (1).

Because under H_0 the sensor is almost stationary, the accelerometer output is mainly due to the gravity. At the same time, the angular rate sensed by the gyroscope is expected to be almost equal to zero. H_0 is formulated by

$$\frac{1}{N}\sum_{n=1}^{N}\left\|a[n]\right\| \approx g \qquad (2)$$

and

$$\frac{1}{N}\sum_{n=1}^{N}\left\|\omega[n]\right\| \approx 0, \qquad (3)$$

where N is the length of the moving analysis window.

As shown in Fig. 1, expressions (2) and (3) can be verified using two energy detectors in parallel combining the information from the accelerometer and the gyroscope. The energy detectors are also commonly used for detecting stance phases with foot mounted sensors. They are selected for their low implementation complexity and their ability to perform detection without any a priori knowledge about the signal of interest.

For foot mounted sensors, it has been shown in [6] that combining these two detectors gives better performance than using a single one. However, for handheld IMUs, the situation is quite different. In fact, the hand experiences many vibrations which may happen even if the IMU is globally not moving.

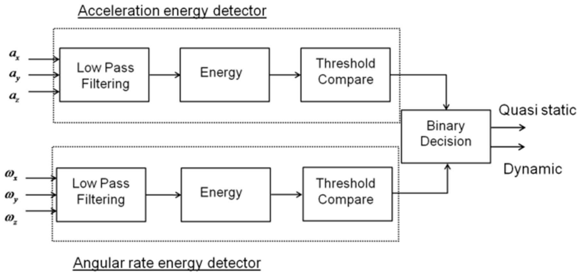

Figure 1. Detector of quasi-static instants - general scheme.

The acceleration energy detector (upper branch of Fig. 1) considers only the accelerometer output and performs decisions according to the following statistic:

$$T_a(s_a) = \frac{1}{N}\left\|\sum_{n=1}^{N} s_a[n]\right\|^2 \le \lambda_a. \qquad (4)$$

In (4), $s_a[n]$ corresponds to the accelerometer component of (1) after being low-pass filtered by a 10th order Butterworth filter. The low-pass filtering process has the purpose of de-noising the signal, considering that the energy of the accelerations for human motion is below 15 Hz [7]. After above pre-processing phase, the QS detector is applied for verifying if the statistic T_a is below the empirically determined threshold λ_a within the sensing window of length *N*. Both parameters *N* and λ_a are changing depending on the IMU's motion state.

The angular rate energy detector (lower branch of the scheme in Fig. 1) bases its decision solely on the gyroscope measurements. The corresponding decision rule is given by

$$T_\omega(s_\omega) = \frac{1}{N}\left\|\sum_{n=1}^{N} s_\omega[n]\right\|^2 \le \lambda_\omega, \qquad (5)$$

where $\tilde{s}_\omega[n]$ is the gyroscope component of equation (1) after being low pass filtered and λ_ω is an adaptive threshold for assessing the level of experienced rotations during the period of *N* samples.

Critical parameters for designing any energy detectors are the size of the analysis window and the values of the threshold. For this research, their selection is strictly related to the power level of the motion modes performed by the subject holding the device in hand. In general, a sensor placed in the hand of a walking user experiences different acceleration and angular rate energies for the different motion modes. For example, a sensor in the swinging hand is exposed to higher accelerations and angular velocities than a sensor in texting or phoning mode, which affects the QS detection algorithm. Due to the dissimilar energy levels experienced in different motion modes, especially for the angular rate, different decision thresholds have to be fixed.

Consequently, improved performances can be achieved using a priori knowledge about the motion of the pedestrian and its hand. Information about the IMU's motion state is used for feeding the adaptiveness of the QS detection filters. A dedicated classifier for identifying selected common motion modes has been designed and implemented. The following section briefly describes the motion mode detector for handheld device in the context of pedestrian navigation.

B. Motion Mode recognition

When the IMU is handheld, it is of great interest to define more precisely the expected carrying mode due to the variety of motions that the hand can perform. Four different modes have been identified as typical for mobile phone users and are considered for better characterizing the hand motion.

1) Hand swinging: the user holds the mobile device in his/her swinging hand while walking.

2) Hand texting: the user does not significantly move the mobile device. For example the walking user is texting or reading a message on the phone.

3) Hand phoning: the user is using the mobile device to make or receive a call while walking.

4) Bag carrying: the user is carrying the mobile device in his/her bag.

Because with handheld devices it often happens that motions are not correlated with the actual true user's displacement, it is important to identify these events and remove them from any navigation process. Consequently a fifth category has been added.

5) Irregular motion: this class includes the motions that the user performs while he is standing but that are not related to a real user's displacement. For example the subject is searching the phone in his bag without walking.

In order to identify the named activities the following features are extracted dividing the norm of the accelerometer and gyroscope signals in windows of length N equals to 128 samples:

- the gyroscope energy,
- the accelerometer energy,
- the gyroscope variance, the accelerometer variance and
- the dominant frequencies of the gyroscope and accelerometer used to assess the signal periodicities.

As shown in Fig. 2, a decision tree classifier using the above features has been designed. Performances of the proposed classifier are assessed with experimental data collected with two males and two females undergoing the different motion modes. Using the proposed decision tree, each motion mode could be recognized with accuracy greater than 90%, i.e. percentage of correctly identified samples.

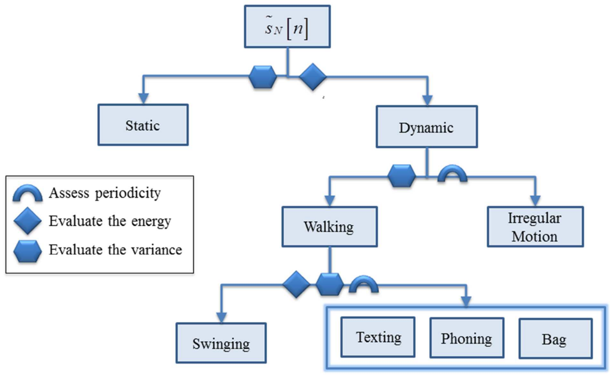

Figure 2. Decision tree classifier for the recognition of the user's state.

C. Detection of Quasi-Static instants for different motion modes

After identifying the motion's state, QS instants are identified using properly tuned energy detectors.

In Fig. 3 the results of the QS detection are illustrated for the hand swinging case. For assessing the algorithm, synchronized accelerometer outputs recorded with two IMUs, one located on the foot, the other one in the hand are shown. QS instants, detected using both the angular rates and accelerations data, are plotted in red in Fig. 3. It is noted that the acceleration signals are unbiased because the mean over N samples has been removed.

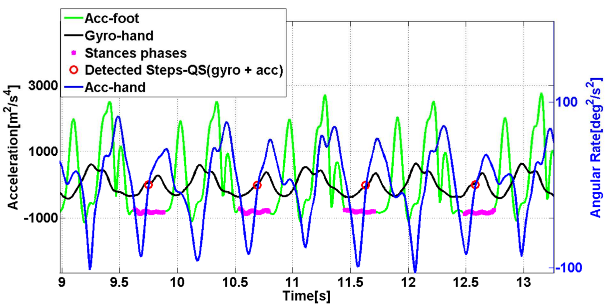

Figure 3. Norm of the accelerometer signal for the sensors placed on the foot (green) and in the hand (blue) and norm of the handheld gyroscope (black) in the swinging mode. The QS instants, marked with red dots, allow the detection of the stance phases of the foot, marked with magenta dots.

During activities, such as walking while texting a message, phoning or carrying the mobile in the bag, the signal recorded by the gyroscope is mainly due to the noise components and to random motions of the hand. Subsequently, in these cases, since the gyroscope signal does not provide useful information about the motion of the subjects it is down weighed for QS detection.

As shown in Fig. 3, QS instants (red dots) are correlated with the foot stance phases (magenta dots). Therefore it seems that they can be used to identify the steps from handheld devices.

IV. QUASI-STATIC DETECTION AND GAIT ANALYSIS: PRELIMINARY RESULTS

The last goal of this work is to investigate the relationship between QS instants and human gait. By comparing the step events detected from handheld device with the one from the foot mounted IMU, the use of handheld QS instants for analysing human walking gait can be assessed.

The algorithm shows high performance for the texting, phoning and bag cases with a probability of correct detection greater than 95%. Reduced probability of detection is observed in the hand swinging case when gyroscope and accelerometer measurements are combined for QS detection. Detailed analysis has shown that QS instants detected with the accelerometers and QS instants detected with the gyroscope are sometimes not synchronized. In fact a preliminary analysis shows that the hand is introducing higher small motions when the arm is swinging.

For texting and phoning modes, the hand is almost stationary and, subsequently, the motion detected by the sensors is mainly due to the motion of the lower part of the user's body. For this reason, in the above cases QS instants are more likely to be directly related to the stance phases of the foot. In order to better examine the characteristics of the texting mode, a frequency analysis of the related accelerometer signal has been performed. This approach is justified by the periodicity of the accelerometer signal, which is due to the repetition of the fundamental pattern of the gait cycle. The frequency analysis allows capturing these periodicities, since temporal periodicities correspond to peaks in the frequency domain. The first three dominant frequencies of the accelerometer signal, corresponding to the inverse of three main temporal periodicities, are considered over time [7]. Moreover, due to the non stationary nature of accelerometer signals, the Short Time Fourier Transform (STFT) [8], a technique traditionally used for non-stationary signals has been adopted. This signal processing technique divides non-stationary signals in short temporal windows, where the signal can be considered stationary. Then for each window the spectrogram is evaluated by squaring the absolute value of the STFT.

In Fig. 4, the first three dominant frequencies over time for the texting case are reported. The first frequency assumes values close to 1.2 Hz, which corresponds to a temporal periodicity of about 0.8 seconds. This value is within the range of typical step durations (0.8-1.2 seconds) [8]. This observation confirms that the trend of the accelerometer signal pattern for the texting mode is close related to the foot pattern. By comparing the second dominant frequencies for sensors placed simultaneously on the foot and in the hand, the same pattern for the second dominant frequencies can be observed. Even for the swinging case the second dominant frequency shows a pattern very similar to the foot case.

This finding is used to improve the robustness of the QS detection and finally the step detection from handheld device. Besides in the hand swinging case, preliminary funding suggests that QSs instants are likely related to the moments of maximum elevation, backward and forward, of the arm. Further studies are ongoing to confirm these preliminary results.

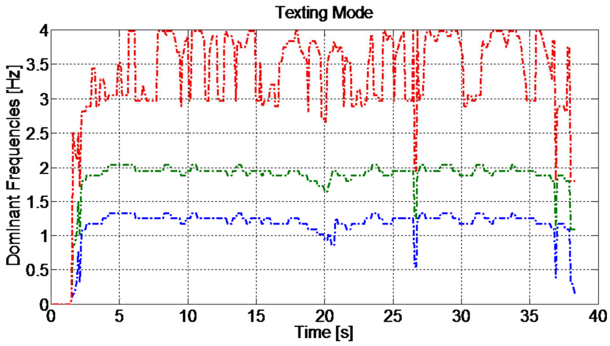

Figure 4. First three dominant frequencies in the texting motion mode.

V. CONCLUSIONS

In this paper an algorithm for detecting QS instants from handheld devices has been proposed. An adaptive approach has been applied to optimize the parameters of the detector according to the different user's motion modes. Indeed a decision tree classifier, whose performances have been assessed with experimental data collected with four test subjects, has been proposed. Finally, the feasibility of using QS instants from handheld device to detect user's step has been investigated and showed promising preliminary results.

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