A Movement Based Personal Health System for the Ambulatory Monitoring of Dementia Progression

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I. Motivation and Goals

Personal Health Systems (PHSs) offer independence and support for older and/or immobilized people and are generally focused to achieve a particular goal. Due to an ageing demographic the arising occurrence of dementia in recent years has resulted in high socio-economic costs. The interest in dementia-oriented PHSs enabling the capture of activities, lifestyle and behavior patterns, along with medical data, to remotely provide clinicians with an image of patient condition and disease progression, is growing steadily. Movement parameters known to be important when accessing dementia include gait variables, physical activity levels, low/high level activity recognition and body posture, indoor/outdoor tracking (in case the patient wanders aimlessly), and sleep quality measures. Several technology-based solutions have been proposed to measure these factors employing, for instance, static cameras, optical devices, RFID, and Assisted-GPS often used in tandem with inertial sensors [1-3]. Generally, such approaches focus on one or two of the mentioned aspects in isolation and in laboratory environments involving extensive and costly infrastructure. Wearable cameras have been also considered for activity recognition and navigation purposes, however the computational burden involved in the data processing is significant. To date, studies solely employing inertial sensor-based dementia-oriented PHSs also focus on limited aspects of the disease consequences, such as whole-body mobility [4], activity recognition and wandering estimation [5], and gait variables measured during a constrained "Up & Go Test" [6]. While some effort has been extended toward combining physical activity measures (walking activity/gait), sleep quality measures, and social activity measures, by adopting inertial sensor, GPS and audio devices there is an inherent increase in the overall infrastructure complexity [7]. The goal of this work is, therefore, to implement a complete pure inertial sensor-based PHS requiring minimal infrastructure for evaluating the status of persons with dementia in a home-environment considering multiple key parameters simultaneously. The clinical aim is to understand the evolution of the disease and to identify possible early interventions. A framework, consisting of several algorithms considering the crucial aspects of dementia disease, has been implemented and tested in a lab-environment. Medical feedback extrapolated from these algorithms is then passed to clinicians and caregivers to study patients' condition and disease progression. The obtained results are promising and demonstrate the appropriateness of the realized system.

II. Methods

The relationship between gait abnormalities and postural instability (regarding low-level activities, such as standing, sitting, and lying) with cognitive decline has already been well-established. Likewise, patients with dementia tend to suffer from a high incidence of apathy, with consequent reduction of physical activity level. Moreover, variations of sleeping features (such as sleeping time reduction, or agitation) are also a symptom of dementia. In order to quantify such characteristics, algorithms encompassed in a framework have been implemented for the following parameters:

1) Detection of human body movements and analysis of activity/inactivity periods has been carried out by adopting the Stance Hypothesis Optimal Detector (SHOD) algorithm [8]. This magnitude-based methodology exhibits good accuracy and low computational complexity. Indeed, it can be proved that, if the inertial sensor (accelerometer and gyroscope) noise standard deviations are correctly set, SHOD performance is always better when compared to other magnitude-based detectors [9].

2) Orientation changes during sleeping time (e.g. the number of turns, the angular range and angular velocity), are a good indication of the sleep quality/anxiety. The orientation of a sensor in this work is fully defined by the magnetic field vector and the acceleration vector (which equals gravity in static position).

3) Gait analysis, which in the current version is limited to information such as cadence (steps/min), number of steps, steps time and walk time, is obtained through the assessment of an automatic accelerometer-based step detection algorithm for lower limbs derived from the peak-detection method based on combined dual-axis signals (PDMCDA) [10]. To improve performance the input accelerometer vector is smoothed with a Savitzky-Golay filter and the PDMCDA final curve is normalized. Moreover, instead of a fixed threshold, an adaptive threshold, estimated from the energy of the processed accelerometer signal, has been adopted to detect the steps.

4) Finally, the objective clinical information regarding the type of activities of the subject, which can be related to the level of motor function over time, is monitored employing a

body posture detector. The related posture transition time is recorded also. The typical low-level daily postures are considered as "static" and are discriminated from "active" activities (i.e. Walking and Transition/Posture Change). This is possible by dividing the processed accelerometer signal, obtained from a fusion of the accelerometer data flows collected from different body segments, into sections marked as "static" or "active". Subsequently, every section is labelled to a correspondent posture/activity through a decision rule method (Fig. 1) whose thresholds have been empirically defined taking into account sources of error, such as body segments tilt and inertial sensors body-relative motion. Data time-stamps are then used in sections labelled as "Transition/Posture Change" to allow the consequent posture transition time calculation.

III. RESULTS

The employed PHS is constituted of three 25 mm Tyndall Wireless Inertial Measurement Units (WIMU) attached to the chest, the thigh, and the shank of the subject. The WIMUs consist of tri-axial accelerometer, gyroscope and magnetometer and transmit the data to a PC-connected base station via the 802.15.4 protocol. The framework algorithms are implemented in Matlab. The validation protocol is as follows:

- (In)Activity discrimination and orientation changes: nine two minute experiments involving in total 99 activity/inactivity periods performed by patients instructed with a random binary generator.
- Step detection: seven test with various simulated walking pattern (including walking backward, forward, laterally, roundly with/without shuffling) for overall 753 performed steps (within 50 and 200 for each test).
- Body posture/transition time: seven test consisting of overall 71 posture/activities (21 standing, 10 sitting, 8 lying sections, 5 walking sequence, and 27 transitions) performed by patients instructed with a random activity generator.

The WIMU on the thigh has been taken into account for discriminating active and inactive periods since the thigh is the body segment involved in most of human movements. The accuracy is measured by comparing SHOD results for each sample with the visually inspected signal and is equal to 94.57%. For the orientation algorithm, data gathered from the WIMU located on the chest have been considered since is the body segment which presents less dynamism (reduced external acceleration) compared to other parts, limiting the periods in which the steady-state assumption is not valid. An appropriate sensors calibration and the removal of soft materials nearby the WIMU have mitigated the typical error sources, introducing an average error lower than 7 degrees. With regard to the step detection algorithm, the accelerometer of the WIMU on the shank is considered. The average accuracy of 95.42% has been achieved and the method proves reliable. Finally, all three WIMUs data are fused for the body posture detection (92.95% of average accuracy) and the transition time calculation. Results are summarized in Table I, but the transition times are not indicated as tend to be overestimated, although consistent, due to a coarse sections data division. Future work will build on good system performance to date and will involve both healthy and dementia patients in a clinical setting. New approaches concerning the transition time calculation and the adoption of gyros for the orientation estimation will be investigated. Stride length/speed estimation will be added to complete the gait analysis and provide robust disorder/abnormality detection. Such parameters, together with the orientation estimation, will also make possible the implementation of a pedestrian dead-reckoning system useful for patient indoor/outdoor tracking. Finally, the possibility to adopt only one WIMU mounted on patient's hip/waist will be studied in order to further reduce the infrastructure and enhance the ease of use for patients and clinicians.

Algorithms	Average Accuracy	
(In)Activity Discrimination	94.57 %	
Orientation	Error < 7 deg.	
Step Detection	95.42 %	
Body Posture Detection	92.95 % (66 / 71)	Standing: 21 / 21
		Sitting: 9 / 10
		Lying: 7 / 8
		Walking: 3 / 5
		Posture Changes: 26 / 27

Table I. Results

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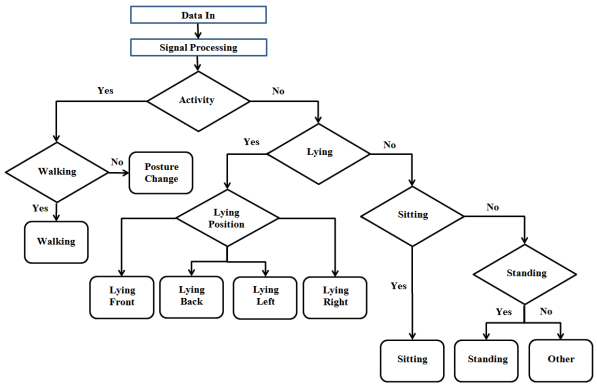

Figure 1. Decision rule flowchart for discriminating body postures