Citation for published version:
Martinez Hernandez, U & Dehghani-Sanij, AA 2019, 'Probabilistic identification of sit-to-stand and stand-to-sit with a wearable sensor', *Pattern Recognition Letters*, vol. 118, pp. 32-41.
https://doi.org/10.1016/j.patrec.2018.03.020

DOI:
10.1016/j.patrec.2018.03.020

Publication date:
2019

Document Version
Peer reviewed version

Link to publication

Pattern Recognition Letters
journal homepage: www.elsevier.com

Probabilistic identification of sit-to-stand and stand-to-sit with a wearable sensor

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ABSTRACT

Identification of human movements is crucial for the design of intelligent devices capable to provide assistance. In this work, a Bayesian formulation, together with a sequential analysis method, is presented for identification of sit-to-stand (SiSt) and stand-to-sit (StSi) activities. This method performs autonomous iterative accumulation of sensor measurements and decision-making processes, while dealing with noise and uncertainty present in sensors. First, the Bayesian formulation is able to identify sit, transition and stand activity states. Second, the transition state, divided into transition phases, is used to identify the state of the human body during SiSt and StSi. These processes employ acceleration signals from an inertial measurement unit attached to the thigh of participants. Validation of our method with experiments in offline, real-time and a simulated environment, shows its capability to identify the human body during SiSt and StSi with an accuracy of 100% and mean response time of 50 ms (5 sensor measurements). In the simulated environment, our approach shows its potential to interact with low-level methods required for robot control. Overall, this work offers a robust framework for intelligent and autonomous systems, capable to recognise the human intent to rise from and sit on a chair, which is essential to provide accurate and fast assistance.

1. Introduction

Standing up and sitting down are essential functions in humans, which are prerequisites to be independent for performing activities of daily living (ADLs) (Aggarwal and Ryoo, 2011; Kralj et al., 1990). The ability to rise from and sit on a chair is degraded as people approach to the old age, becoming a demanding and complex task that needs assistance from other humans (Ganea et al., 2011). Technology plays a key role to deploy intelligent devices capable to recognise human movements and provide reliable assistance (Patel et al., 2012).

Advances in sensor technology have permitted the rapid development of small size and low cost wearable devices, with sophisticated functions for monitoring human movements (López-Nava and Muñoz-Meléndez, 2016). For instance, wearable devices integrated with electromyography (EMG), inertial measurement units (IMU) and barometric pressure sensors, have been able to read physiological and biomechanical data in real-time (Asbeck et al., 2014; Massé et al., 2014). Recently, robotics has started to benefit from wearable devices in applications for search and rescue, assistive robotics, telemanipulation and telepresence (Martinez-Hernandez et al., 2017a; Jiang et al., 2017; Powell et al., 2016). Despite this progress, the design of fast and accurate machine learning methods, needed to exploit the potential of wearable technologies for recognition of human activities, are still under development.

In this work, an approach composed of a Bayesian formulation and a sequential analysis method, is presented for identification of sit-to-stand (SiSt) and stand-to-sit (StSi) activities. This is a temporal and probabilistic approach, which is a generalisation of state-space models such as hidden Markov models and Kalman filter (Russell et al., 1995; Murphy, 2002). The robustness of this type of probabilistic method has been shown in works on multimodal sensing, perception, control and human-robot interaction (Martinez-Hernandez et al., 2017b,c; Ferreira et al., 2013). First, the proposed approach identifies three activity states; sit, transition and stand. Second, the state of the human body is identified during the transition state by the use of three transition phases. This approach allows to have a better understanding of the state of the human body, which is important to build reliable low-level controllers required for the development of intelligent assistive devices.

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Acceleration measurements, from a wearable sensor attached to the thigh of participants, are used for identification of activity states and transition phases. Data collection and the probabilistic approach are integrated in a hierarchical layered architecture, composed of physical, cognitive and control layers. These architectures are important not only for the implementation of recognition and control methods, but also to allow intelligent systems to perceive and learn from the interaction with the environment (De Santis et al., 2008; Brooks, 1986). Identification of SiSt and StSi, using the probabilistic approach and one wearable sensor, are validated with experiments in offline, real-time and a simulated environment. In the offline and real-time modes, sit, transition and stand activity states are identified with high accuracy. Similarly, identification of the human body during the transition state, based on the use of transition phases, achieves high accuracy. The experiments show that only a small number of sensor measurements is needed to make a decision, making our approach both fast and accurate. The potential for robot control is also validated with a low-level controller and a robotic leg built in a simulated environment.

Overall, the results from all experiments demonstrate the high accuracy and fast response that can be achieved by the Bayesian formulation, but also, its capability to interact with low-level methods for robot control. These aspects make our approach suitable for the development of robotic devices that recognise human movements and provide reliable assistance.

This paper is organised as follows: a description of the related work is presented in Section 2. The proposed probabilistic method is detailed in Section 3. The experiments and results are shown in Section 4. Section 5 presents the discussion of our work. Finally, conclusions are provided in Section 6.

2. Related work

Intent recognition is a high-level process needed for the development of systems capable to assist humans. Multiple approaches, based on heuristic methods and machine learning algorithms, have been studied for recognition of SiSt and StSi activities, which are described in the following paragraphs.

Heuristics-based methods, with predefined set of rules and conditions, have been used for recognition of activities of daily living (ADLs). An angle recognition threshold-crossing method was embedded in the robot suit HAL to assist humans (Tsukahara et al., 2010). This rule-based approach provided 55.6% of support during SiSt and 43.7% during SiSt, limiting the capabilities offered by the robot HAL (Suzuki et al., 2007). A wearable motion system and a rule-based method for real-time detection of activities achieved recognition accuracies of 92.2% and 95.6% for SiSt and StSi, respectively (Yang and Hsu, 2009). The single feature threshold-crossing algorithm, implemented in portable activity recognition systems, was highly susceptible to signal noise obtaining accuracies of 70.8% and 90.3% for recognition of sit and stand (Capela et al., 2015; Haché et al., 2011). These heuristic methods showed to be accurate, however, their nature makes them highly susceptible to failure in the presence of even slight changes in sensor measurements not observed during the training phase.

Machine learning offers sophisticated perception and learning algorithms for high-level recognition systems (De Marsico et al., 2016). Fuzzy Logic (FL) techniques have been studied with different sensing modalities for identification of ADLs and control of robot platforms (Kiguchi et al., 2004). Fuzzy clustering methods and vision sensing were capable to detect SiSt and StSi with accuracies of 94.6%, 84.2% and 69.8%, using Gustafson Kessel, Fuzzy C Means and the Gath and Geva algorithms respectively (Banerjee et al., 2010). The need of a vision system and large preprocessing steps, made this work unrealistic for real-time assistance. A combination of Principal Component Analysis (PCA) and Support Vector Machines (SVM) recognised SiSt transitions with an accuracy of 92.94%. This method was limited by the fixed sampling window and large number of sensors, e.g., IMUs, force sensors and potentiometers (Doulah et al., 2016). Visual input was employed to train a SVM multi-class method, together with a binary tree architecture, for activity recognition (Qian et al., 2010). This multi-class approach was able to achieve a recognition accuracy of 94.6% for SiSt. A vision system with 33 reflective markers, placed over the full body, were used to detect SiSt and StSi. This method required 56 ms and 48 ms to recognise SiSt and StSi respectively, however, the proposed set up is not suitable for real applications, apart from the lack of the analysis of accuracy for activity recognition (Bannwart et al., 2017).

Probabilistic approaches provide well-defined models to develop reliable and intelligent systems (Thrun et al., 2005; Martinez-Hernandez et al., 2016a). Bayesian methods, which are a generalisation of state-space models e.g., HMM and Kalman filter, have been successfully used for perception, decision-making and robot control (Bishop, 2006; Martinez-Hernandez et al., 2016b, 2013). Bayesian networks, trained with multiple information sources, e.g., IMUs and EMG signals, were capable to recognise locomotion activities with different terrain conditions (Farrell, 2013; Young et al., 2014; Martinez-Hernandez et al., 2018; Martinez-Hernandez and Dehghani-Sanij, 2018). Recognition of activity and spatial location was investigated with a dynamic Bayesian network (DBN) (Subramanya et al., 2012). This work was based on measurements from a portable global positioning system achieving an accuracy of 95%. An HMM and accelerometer sensors, attached to upper and lower limbs, were employed for the sequential classification of ADLs with a mean accuracy of 99.1% (Mannini and Sabatini, 2010). Six ADLs were recognised with an accuracy of 84% using a Switching HMM and vision input (Duong et al., 2005). A mean accuracy of 96.41% was obtained for multi-user activity recognition, using a coupled HMM, wearable sensors and wireless networks in a smart home (Wang et al., 2011). Human gait phases were detected using a Kalman filter method and wearable ultrasonic sensors (Qi et al., 2016). This wearable system achieved detection errors of 0.02 and 0.04 for stance and swing phases compared to the reference system. Human fall detection has been studied using Kalman filter approaches, with a diversity of wearable sensors, performing an early detection with accuracies ranging from 95% to 99.4% (Anania et al., 2008; He et al., 2017). A combination of an Extended Kalman filter (EKF) and HMMs permitted to classify and track multiple ADLs with an accuracy of 93% using angle data from a wearable sensor (Wu et al., 2007). Features from sitting, standing and walking were characterised and recognised with high accuracy using Gaussian mixture models (GMM) (Varol et al., 2010). The benefits offered by probabilistic approaches have inspired the investigation presented in this work, where a Bayesian formulation with a sequential analysis method is proposed for identification of SiSt and StSi. This work overcomes various limitations found in previous related works and offers the following advantages: high recognition accuracy and fast decision-making process, small number of sensors and the capability to deal with uncertainty present in sensor measurements. A detailed description of the proposed method is presented in the next sections.

3. Methods

3.1. Data collection

Twelve subjects from the School of Mechanical Engineering, at the University of Leeds, participated in this investigation. The subjects were healthy and free from gait abnormalities and neurological pathologies. Subjects' ages ranged between 24 and 34 years old, heights were between 1.74 m and 1.79 m, and weights ranged between 77.6 kg and 85 kg.

A 9-axis inertial measurement unit (IMU), from Shimmer Inc., was attached to the thigh of participants for data collection. Acceleration measurements from the IMU were collected at a sampling frequency of 100 HZ, which has been successfully employed in previous works (Maqbool et al., 2017). The participants were asked to perform 10 repetitions of SiSt and StSi activities, at their self-selected speed. Acceleration measurements were sent to a workstation, through wireless communication, for their subsequent processing and analysis. The data collected were grouped in multiple datasets for training and testing the method proposed in this work. Figure 1 depicts the setup for data collection using a wearable sensor.

The raw and filtered acceleration signals for SiSt and StSi, measured from the wearable sensor attached to the thigh of participants, are shown in Figure 2A and Figure 2B, respectively. These annotated plots show the sit and stand states (activity states), which are two main parts of acceleration signals. Red colour dashed-lines show the signal parts commonly used to identify the intention to move from sit to stand and vice versa. In this work, an in-depth analysis of the acceleration signals is presented for a better understanding of decision-making and control processes. For this purpose, and in addition to the identification of sit and stand states, the recognition of the transition state and three transition phases is included in our work. This approach identifies whether the subject is in sitting, standing or in transition states, but also identifies what is happening during the transition state for a better understanding of the movement of the human body. Figures 2A and 2B show the transition state and phases for SiSt and StSi activities.

The histograms for activity states and transition phases from acceleration signals are shown in Figure 2C and 2D, respectively. These signals are employed, as described in Section 3.2, to build the nonparametric measurement model of the proposed method for detection of SiSt and StSi activities.

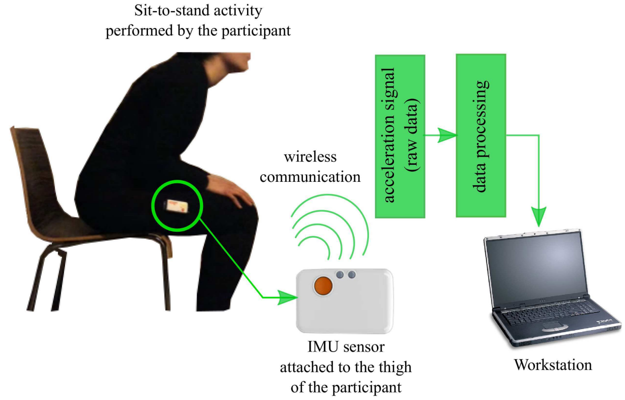

Fig. 1. Data collection from SiSt and StSi activities using one IMU sensor attached to the thigh of participants. Acceleration measurements are sent to a computer, through wireless communication, to form datasets for training and testing the proposed probabilistic method.

3.2. Probabilistic identification method

Identification of SiSt and StSi is performed using an approach composed of a Bayesian formulation and a sequential analysis method. This approach offers a belief network to model probability distributions for temporal reasoning. Bayesian methods are a generalised representation of traditional state-space models such as hidden Markov models (HMM) and Kalman filter, with interesting applications in bioinformatics, speech recognition and robotics (Bishop, 2006; Thrun et al., 2005; Bunke and Caelli, 2001).

Bayesian update: the Bayesian formulation iteratively updates the posterior probability from the product of the prior and likelihood distributions. Measurements from wearable sensors are represented by z. Activity state classes (sit, stand and transition) and transition phase classes (phase 1, phase 2 and phase 3) are represented by $c_n \in C$. Each class c_n is defined by a (u_k, v_l) pair, where u_k with $k = 1, 2, \ldots, K$ and v_l with $l = 1, 2, \ldots, L$ are activity state and transition phase respectively. The Bayesian update is performed as follows:

$$P(c_n|z_t) = \frac{P(z_t|c_n)P(c_n)}{P(z_t|z_{t-1})} \tag{1}$$

where $P(c_n|z_t)$ and $P(z_t|c_n)$ are the posterior probability and likelihood at time t. The prior probability, $P(c_n)$, takes an initial uniform distribution, and then is updated over time with the posterior obtained from the previous time $t-1$. The marginal probabilities $P(z_t|z_{t-1})$ are used to ensure probabilities between 0 and 1. These processes are described in the following paragraphs. Here, the variable u_k with $K = 3$ is the activity state (sit, stand and transition), and the variable v_l with $L = 3$ is the transition phase (phase 1, phase 2, phase 3). The measurements z represent the acceleration signals from the wearable sensor attached to the thigh of the participants.

Prior: a uniform or flat distribution is assumed for the prior probability at time $t = 0$. Then, all activity states and transition classes are equally likely at the beginning of each decision process. This is defined as follows:

$$P(c_n) = P(c_n|z_0) = \frac{1}{N} \tag{2}$$

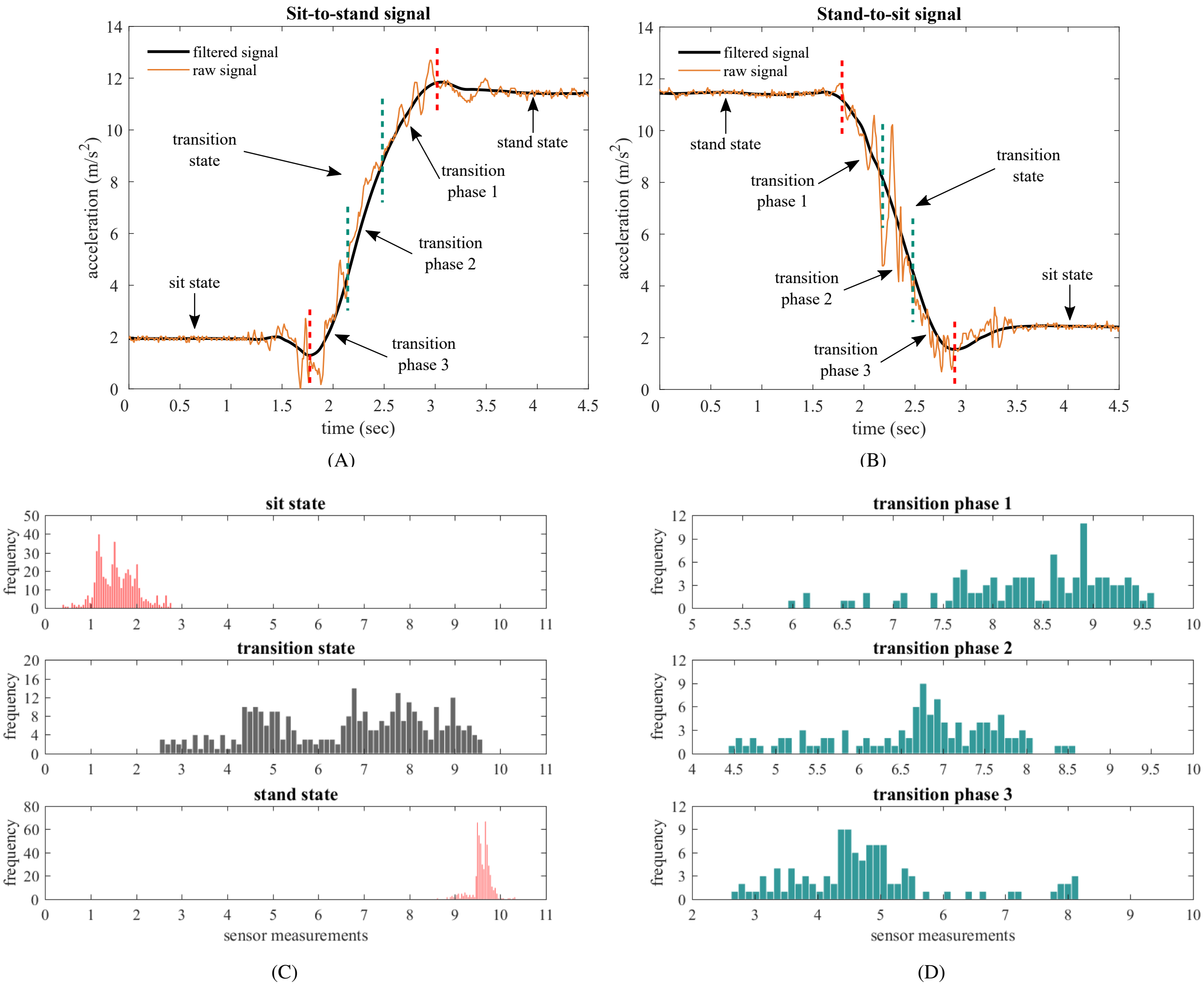

Fig. 2. Acceleration measurements collected from SiSt and StSi activities. (A), (B) Sit, transition and stand activity states for identification during SiSt and StSi. Raw and filtered signals are represented by brown and black colours, respectively. The transition state is divided into 3 phases, which permits to have a better understanding of the human movement during the transition state. (C) Histograms employed for training and testing our proposed method for identification of sit, transition and stand activity states. (D) Histograms for recognition of the human movement during the transition state.

where $P(c_n)$ is the prior, c_n is the class to be estimated, z_0 are the sensor measurements at time $t = 0$ and N is the number of (u_k, v_l) pairs. Thus, in Equation (1), the prior $P(c_n) = P(c_n|z_0) = \frac{1}{N}$ at time $t = 0$. For time $t > 0$ the prior probability is updated with the posterior probability obtained at $t-1$ as follows:

$$P(c_n) = P(c_n|z_{t-1}) \tag{3}$$

where $P(c_n)$ is the prior in Equation (1), c_n is the class to be estimated, and $P(c_n|z_{t-1})$ is the posterior probability obtained from the Bayesian update process at previous time $t-1$.

Measurement model and likelihood estimation: acceleration measurements are obtained, at each time step t, from the inertial measurement unit (IMU) attached to the thigh of the participants. The measurements from this wearable sensor are used to construct the measurement model with a nonparametric approach based on histograms (see Figures 2C and 2D). These histograms are employed to evaluate a sensor measurement z_t at time t, and estimate its likelihood given a perceptual class c_n. This process is performed as follows:

$$P_s(b|c_n) = \frac{h_{s,n}(b)}{\sum_{b=1}^{N_{\text{bins}}} h_{s,n}(b)} \tag{4}$$

where $h_{s,n}(b)$ is the sample count in bin b for sensor s over all training data in class c_n. The histograms are uniformly constructed by binning acceleration measurements into $N_{\text{bins}} = 100$ intervals. The values are normalised by $\sum_{b=1}^{N_{\text{bins}}} h_{s,n}(b)$ to have proper probabilities that sum to 1. The log likelihood of measurement z_t, at time t is obtained as follows:

$$\log P(z_t|c_n) = \log P_s(b|c_n) \tag{5}$$

where $P(z_t|c_n)$ is the log likelihood of the observation z_t given a perceptual class c_n. Normalised values in Equation (1) are ensured with the marginal probabilities conditioned from previous sensor measurements as follows:

$$P(z_t|z_{t-1}) = \sum_{n=1}^{N} P(z_t|c_n)P(c_n|z_{t-1}) \tag{6}$$

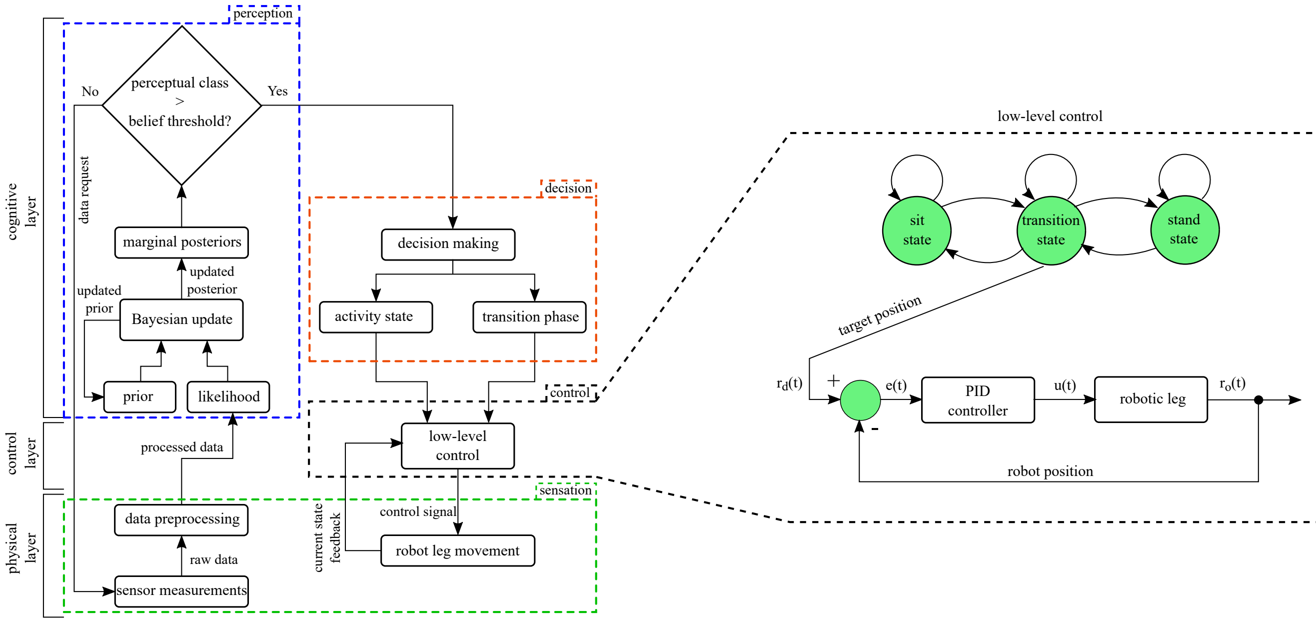

Fig. 3. Hierarchical layered architecture that implements the probabilistic approach for identification of SiSt and StSi activities. (left) The architecture is divided into physical, cognitive and control layers. The physical layer receives the acceleration measurements from the IMU worn by participants. The processes involved in the Bayesian formulation are performed in the cognitive layer. The output from the decision-making process provides the estimated activity state and transition phase, which are used to interact with low-level controllers. (right) Low-level control, using a PID controller, for the control of a robotic leg. In this work, the low-level control is implemented in a simulated environment.

where $P(z_t|z_{t-1})$ are the marginal probabilities. Note that the distribution $P(c_n|z_{t-1})$ is the prior, which as previously described, for iteration time $t = 0$ takes a uniform distribution $P(c_n) = \frac{1}{N}$, and for time $t > 0$ the prior takes the estimated posterior distribution from the previous iteration $t-1$.

Marginal posteriors for activity state and transition phase: posterior probabilities for the perceptual class c_n, that corresponds to a (u_k, v_l) pair, are the joint distributions over the activity states u_k and transition phases v_l for SiSt and StSi activities. The beliefs over individual activity states and transition phases are given by the marginal posteriors as follows:

$$P(u_k|z_t) = \sum_{l=1}^{L} P(u_k, v_l|z_t) \tag{7}$$

$$P(v_l|z_t) = \sum_{k=1}^{K} P(u_k, v_l|z_t) \tag{8}$$

where activity state classes $P(u_k|z_t)$ are obtained by summing the joint distribution $P(u_k, v_l|z_t)$ over all transition phase classes. Similarly, transition phase classes $P(v_l|z_t)$ are obtained by summing $P(u_k, v_l|z_t)$ over all activity state classes.

Stop rule and decision making: the accumulation of evidence or sensor measurements, performed by the Bayesian formulation, stops once a belief threshold $\beta_{\text{threshold}}$ is exceeded. This event triggers the decision making process, to estimate a perceptual class for the current activity state and transition phase using the *maximum a posteriori* (MAP) estimate as follows:

$$\begin{aligned} &\text{if any } P(u_k|z_t) > \beta_{\text{threshold}} \text{ then} \\ &\quad \hat{u}_k = \arg\max_{u_k} P(u_k|z_t) \end{aligned} \tag{9}$$

$$\begin{aligned} &\text{if any } P(v_l|z_t) > \beta_{\text{threshold}} \text{ then} \\ &\quad \hat{v}_l = \arg\max_{v_l} P(v_l|z_t) \end{aligned} \tag{10}$$

$$\hat{c}_n = (\hat{u}_k, \hat{v}_l) \tag{11}$$

where $\hat{c}_n = (\hat{u}_k, \hat{v}_l)$ is the estimated class composed of the estimated activity state $\hat{u}_k$ and transition phase $\hat{v}_l$. The belief threshold $\beta_{\text{threshold}} = [0.0, 0.5, \ldots, 0.99]$ adjusts the confidence of the recognition method to achieve a desired decision-making and recognition accuracy. In addition, the parameter $\beta_{\text{threshold}}$ allows to control the trade-off between accuracy and reaction time or speed for recognition, which are important aspects for the development of intelligent recognition system.

The processes involved in the identification of SiSt activity are shown by the flowchart in Figure 3. The processes are grouped in physical, cognitive and control layers. The physical layer receives sensor measurements to perform data preprocessing. The cognitive layer implements the Bayesian method combining prior knowledge and current sensor measurements. This layer performs the decision-making process to recognise the current activity state and transition phase. The control layer takes the output from the decision-making process to control a robot device. The sensation, perception and decision processes are tested in offline and real-time modes, while the control process is tested with a robotic leg in a simulated environment (see Section 4). Furthermore, Figure 3 shows the communication between high- and low-level controllers, required to develop systems capable to make decisions and perform actions. The *SiSt_recogniser* repository, containing the high-level method for SiSt recognition, is available in GitHub (`https://github.com/urielmtz/SiSt_recogniser`).

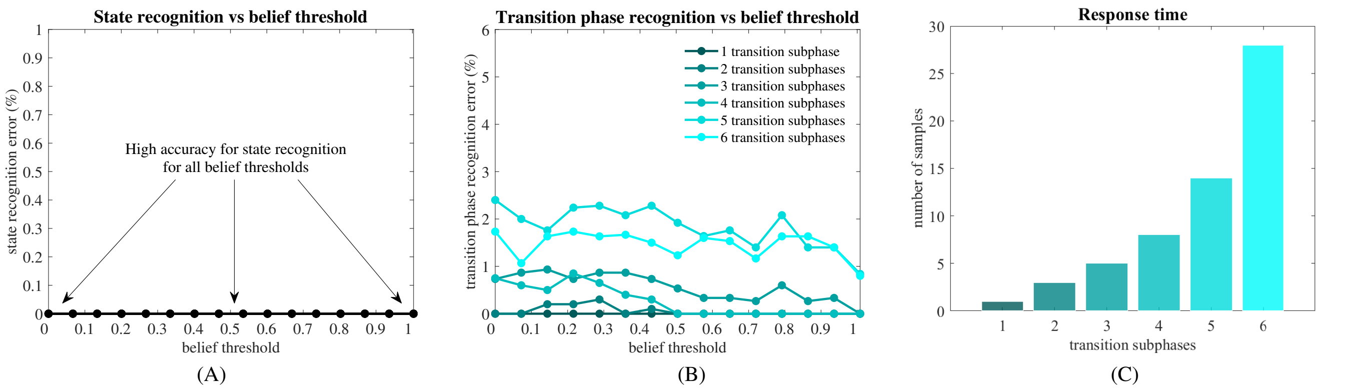

Fig. 4. Identification of SiSt and StSi in offline mode. (A) Mean error of identification of sit, transition and stand activity states against belief threshold. A mean error of 0% (accuracy of 100%) was achieved for all activity states and for all belief thresholds. (B) Mean recognition error of the human movement during transition state using multiple transition phases. Plot B shows the mean recognition error of 0% obtained using 1, 2, 3 and 4 transition phases for different belief threshold values. (C) Mean number of sensor measurements or response time needed to make a decision about activity state and transition phase. The number of samples increases for large number of transition phases used to divide the transition state.

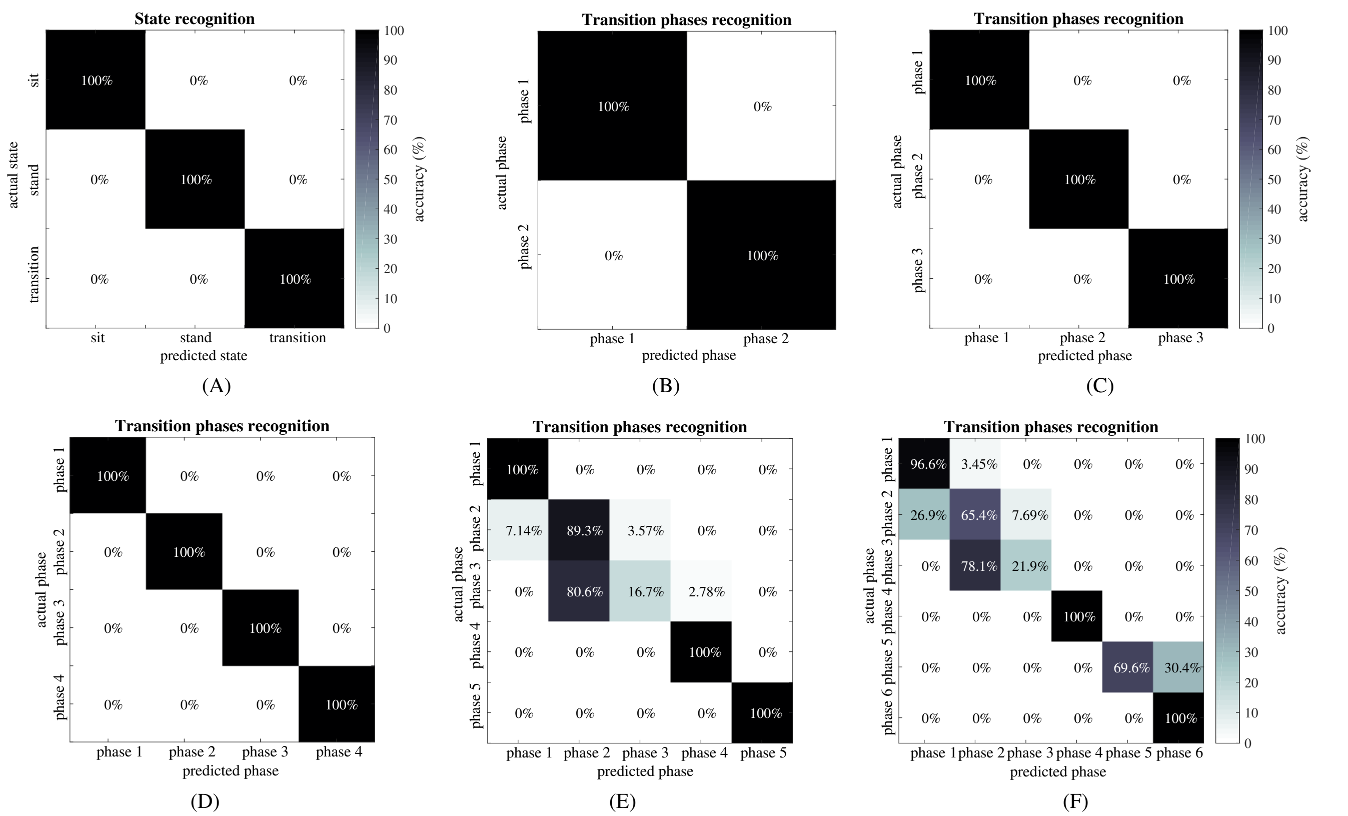

Fig. 5. Identification accuracy of activity states and transition phases, where white and black colours represent low and high accuracy, respectively. (A) Identification of individual sit, transition and stand states, where 100% accuracy was achieved for all activity states. (B-F) Recognition results for individual transition phases during the transition state. This analysis was performed using 2, 3, 4, 5 and 6 transition phases. (B-D) The recognition accuracy of 100% was achieved with 2, 3, and 4 transition phases. Smaller accuracies were observed using (E) 5 and (F) 6 transition phases.

4. Results

Multiple experiments were performed to validate the proposed method for identification of SiSt and StSi activities. For validation, training and testing datasets from a wearable sensor attached to the thigh of participants were employed (see Section 3.1). The experiments were performed randomly selecting sensor samples from the testing datasets composed of measurements from all participants. This process was repeated 10,000 times for the belief threshold $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$, where each value was automatically set, one at a time, to analyse the performance of the proposed method. The experiments performed in the offline and real-time modes, for identification of SiSt and StSi, are described in the following sections.

4.1. *Offline identification of sit-to-stand*

The first experiment was to perform the recognition of SiSt activity in the offline mode. This process permitted to observe the accuracy and speed for recognition of activity states and transition phases. The accuracy results against belief threshold for recognition of sit, transition and stand states are pre-

Table 1. State-of-the-art methods for identification of SiSt and StSi.

Method	# Sensors	Identification accuracy (%)	Identification response time (ms)	Identification in transition state accuracy (%)	Identification in transition state response time (ms)
Rule-based (Yang and Hsu, 2009)	1	92.2 - 95.6	-	-	-
Angle threshold-crossing (Capela et al., 2015)	1	70.8 - 90.3	-	-	-
Fuzzy clustering (Banerjee et al., 2010)	1	94.6	-	-	-
PCA + SVM (Doulah et al., 2016)	14	92.94	43	-	-
SVM multi-class (Qian et al., 2010)	1	94.6	-	-	-
Our probablistic method	1	100	50	100	50

sented in Figure 4A. This plot shows that all activity states were recognised with an accuracy of 100% for all belief thresholds $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. This suggests that the recognition method identifies, with high accuracy, whether the subject is in sit, transition or stand state, using a small number of sensor measurements. Transition phases are important for a better understanding of the state of the human body during the transition state. Then, this state was divided into 1, 2, 3, 4, 5 and 6 phases to observe their recognition accuracies and speeds. Figure 4B shows the results for all transition phases against belief threshold. An accuracy of 100% (recognition error of 0%) was achieved for recognition of 1 to 4 transition phases, while the accuracies for 5 and 6 transition phases were 81.2% and 75.58%. Recognition of 1 transition phase does not provide new information, given that it is the same as the recognition of the transition state. Even though recognition of 4 transition phases achieves an accuracy of 100%, a belief threshold $\beta_{\text{threshold}} = 1$ is required, which reduces the reaction time or speed to make a decision. Then, the optimal number of transition phases is 3, which achieves a recognition accuracy of 100% with a small belief threshold $\beta_{\text{threshold}} = 0.5$. The number of sensor measurements required for recognition with different transition phases is shown in Figure 4C, where the larger the number of transition phases the larger the response time for recognition.

The recognition results of individual activity states and transition phases are shown by the confusion matrices in Figure 5. High and low recognition accuracies are presented using black and white colours respectively. First, 100% accuracy was achieved for recognition of each activity state (Figure 5A). The accuracy results for recognition of individual phases, from 2 to 6 transition phases, are shown in Figures 5B-F. Recognition of 2 to 4 phases achieved an accuracy of 100% for each phase, while these results were affected when 5 and 6 phases were employed during the transition phase. Overall, these results demonstrate that dividing the transition state into 3 phases provides a better trade-off, between accuracy and speed, for recognition of activity states and transition phases during SiSt.

The results obtained from our probabilistic approach for identification of SiSt and StSi are compared to state-of-the-art

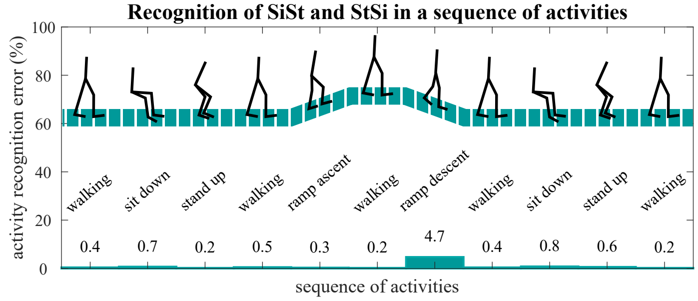

Fig. 6. Recognition of sequential activities. Validation of the proposed method for recognition of SiSt and StSi within the following sequence of activities: walking, sit down, stand up, walking, ramp ascent, walking, ramp descent, walking, sit down, stand up and walking. Recognition of SiSt and StSi achieved a mean accuracy of 99.42%. The lowest 95.30% (4.7% error) and highest 99.80% (0.2% error) accuracies were obtained with the recognition of ramp descent and walking activities, respectively.

methods in Table 1. Most of the methods, including our proposed approach, employed 1 sensor –for instance, motion or vision sensor, except for the method combining PCA and SVM which used 14 sensors (force, pressure and motion). The methods in Table 1 achieved a recognition accuracy between 70.8% and 95.6%, which were overcome by our probabilistic approach with an accuracy of 100%. Interestingly, apart from our work, none of the previous studies showed an analysis and recognition process of the human body during the transition state.

The robustness of the proposed method has been previously validated with the recognition of three locomotion activities; level-ground walking, ramp ascent and descent (Martinez-Hernandez et al., 2018). Here, the probabilistic approach is also validated with the recognition of SiSt and StSi, implemented within the following sequence of activities: walking, sit down, stand up, ramp ascent, walking, ramp descent, walking, sit down, stand up and walking. This sequence of activities and their recognition accuracies are shown in Figure 6. Results from this experiment shows that recognition of SiSt and StSi achieved a mean accuracy of 99.42%. The lowest accuracy of 95.30% (4.7% error) was obtained with the ramp descent activity, while the highest accuracy of 99.80% (0.2% error) was for the recognition of level-ground walking. Overall, the probabilistic method showed to be able to accurately recognise multiple activities using measurements from wearable sensors.

4.2. *Real-time detection of sit-to-stand*

The second experiment was the recognition of SiSt activity in real-time. For this experiment, a wearable sensor attached to the thigh of participants was employed for collection of sensor measurements. The proposed probabilistic method, described in Section 3.2, was prepared according to the results from the analysis performed in the offline mode (see Section 4.1). This means that 3 activity states (sit, transition and stand) and 3 transition phases (phase 1, phase 2 and phase 3) were used for recognition during SiSt activity in real-time mode.

In this experiment, participants were asked to perform the SiSt activity multiple times at their self-selected speed, while performing a natural activity. The results for recognition in real-time are shown in Figure 7. The top row shows the sequence

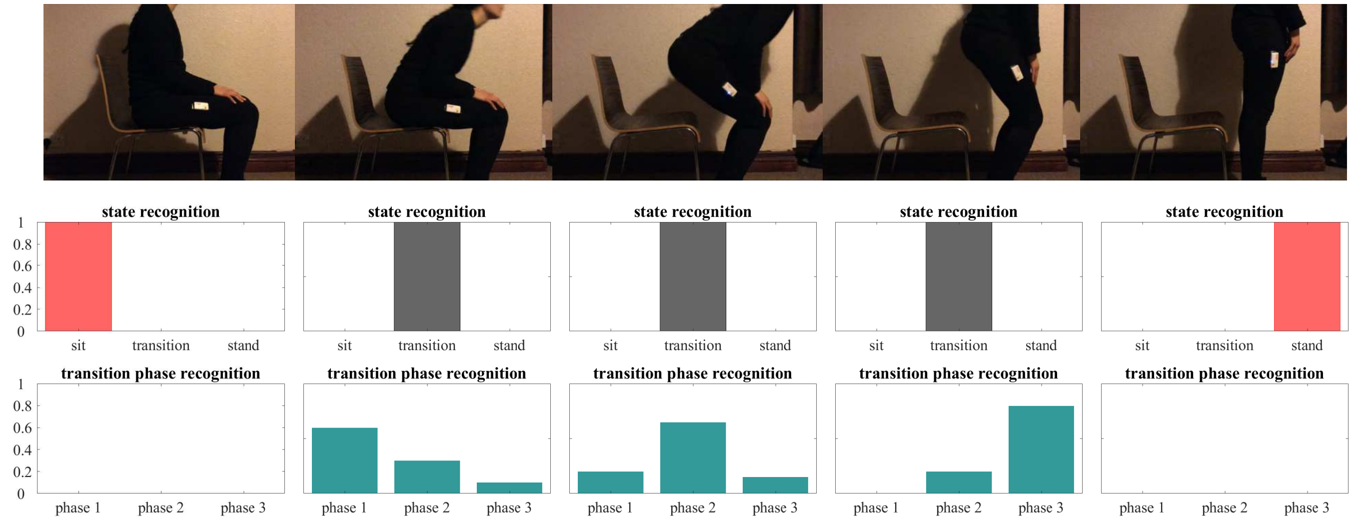

Fig. 7. Identification of SiSt and StSi in real-time mode. (top row) Subject performing SiSt and StSi activities wearing one IMU attached to her/his thigh. (middle row) Bar plots with the identification of sit and stand states (red colour bar) and transition state (gray colour bar). (bottom row) Recognition of the human movement during the transition state (blue colour bars). Note that the recognition of transition phases is active during the transition state only.

of movements performed by a participant during the SiSt activity, where the subject is observed at sit, transition and stand states. The output for recognition of activity states is shown by the bar plots in the middle row. Red colour bars represent the sit and stand phases, while gray colour bars represent the transition state recognised by the probabilistic method. These results demonstrate the high accuracy achieved for recognition of activity states. The bottom row shows, in blue colour bars, the recognition of transition phases during SiSt. These plots show different and gradually updated beliefs during the transition state, where a successful recognition process was achieved for all transition phases. These results in real-time, together with the analysis obtained in offline mode, validate the potential of our proposed approach for recognition of SiSt, but also the capability for a better understanding of the human body movement during the transition state. These aspects are important for a better design and control of robotic devices, in order to provide reliable assistance to humans in SiSt activities.

4.3. Control of a robotic leg in a simulated environment

The third experiment is to show the potential of the recognition method (high-level controller) to communicate with a low-level controller to provide the actual control of a robotic device (see Figure 3). This experiment, which employs the Robot Simulator V-REP from Coppelia Robotics and MATLAB 2016b from MathWorks, was performed using real data from an IMU (see Section 2) to simulate SiSt human movements, recognise the activity and control a robotic leg.

This experiment in a simulated environment is depicted in Figure 8, where measurements from the IMU attached to the thigh of the human are sent to the probabilistic recognition method (high-level controller). The resulting high-level recognition is sent to a low-level controller to control a simulated robotic leg. The low-level controller receives information from the perceived activity state, perceived transition phase and position feedback from the robot. All this information is required for a better control, given that it is important to know the movement performed by the human, but also to know the current state of the robotic device. The control of the robot leg was implemented with a Proportional-Integral-Derivative (PID) controller using the Control System Toolbox and tuning tools from MATLAB, which permitted to automatically tune the proportional, integrative and derivate parameters for control. Figure 3 shows the low-level control loop, integrated in the layered architecture, to control the robotic leg based on the activity state and transition phase recognition from the probabilistic approach.

These multi-layer processes and hierarchical architectures are crucial for wearable robotic devices capable to sense, learn and safely interact with the environment, respond appropriately and provide reliable assistance to humans (Brooks, 1986; Tucker et al., 2015). The results for robot control in the simulated environment are shown in Figure 9, which is segmented into sit, transition and stand states. When the sit state is recog-

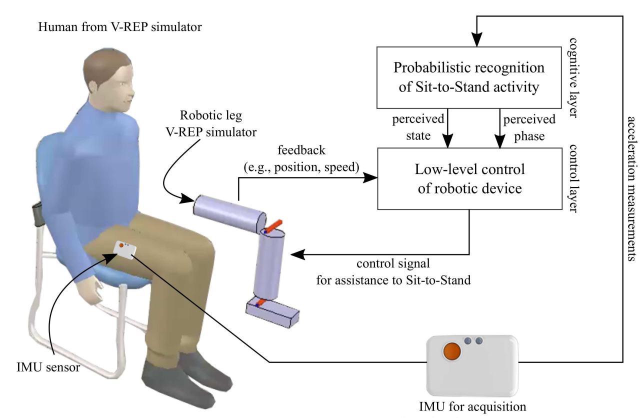

Fig. 8. Control of a robotic leg based on the interaction of our Bayesian formulation (high-level control) with a low-level controller in a simulated environment. This experiment involves a simulated person performing SiSt and StSi activities, using real sensor data previously collected from an IMU. This analysis shows the capability of our approach for robot control.

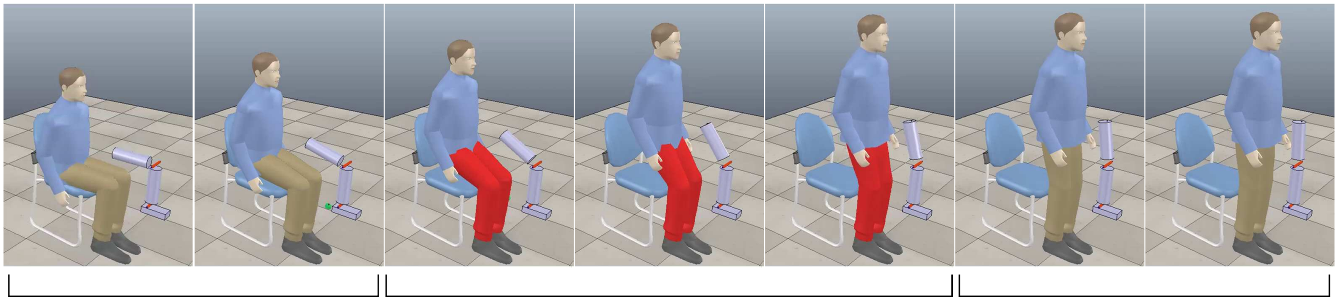

Fig. 9. Simulated robotic leg controlled by a virtual person using real sensor data. The sequence of SiSt and StSi activities performed by the person is divided into *no assistance* (sit and stand states) and *active assistance* (transition state). For visualisation purposes, the trousers of the virtual human change to red colour to show the application of the assistance to stand up. The trousers are in brown colour when there is no need for assistance. The robot leg is controlled or activated to provide assistance when the transition state is identified. The assistance is deactivated when the sit or stand states are identified.

nised by the probabilistic method, this information, together with the position feedback, is sent to the low-level control. In this case, the hierarchical architecture recognises that the human does not need to be assisted, and thus, the robotic leg follows the natural movements of the human while sitting, but an actual assistance is not provided. Similarly, recognition of the stand state makes the robotic leg to follow the natural movements of the human without applying any assistance. Conversely, when the high-level method recognises the start of the transition state, information about the transition state, phase and position feedback is sent to the robotic leg, which in this case is activated to provide assistance to move from sitting to standing position. For visualisation purposes, the trousers of the virtual human in Figure 9 change from brown to red colour to show the active assistance provided by the robotic leg during the transition state. It is important mentioning that both, the probabilistic recognition approach and low-level control method, have the potential to be integrated in small, lightweight and wearable robots, making them capable to not only interact and assist humans, but also to learn and adapt from daily recorded data, and provide remote access to assess the progress of the human. These capabilities and functionalities provided by a wearable robot contribute to the development of cyber-physical systems for healthcare (Schirner et al., 2013; Haque et al., 2014).

All the results from the experiments, in offline, real-time and simulated environment, show that the probabilistic method, composed of a Bayesian approach and sequential analysis method, is capable to recognise, fast and with high accuracy, activity states and transition phases. Furthermore, the results demonstrate that the proposed high-level recognition method can communicate to low-level controllers, integrated in a hierarchical architecture, which offers the potential for the development of intelligent and reliable wearable assistive devices.

5. Discussion

In this work, a Bayesian formulation for identification of SiSt and StSi activities was presented. First, this probabilistic method successfully identified sit, transition and stand activity states. Second, the state of the human body was accurately recognised, during the transition state, using transition phases. Third, experiments in offline, real-time and a simulated environment showed the ability of the proposed formulation to make decisions both fast and accurate.

Probabilistic Bayesian approaches, that take inspiration from human sensing, perception and decision-making (Körding and Wolpert, 2006), offer benefits such as measurement of uncertainty, robustness to sensor noise and natural integration of current and prior information. These benefits are particularly useful for analysis of noisy data from the human body. For example, smooth curves in Figures 2A and 2B are the result of preprocessed data for presentation purposes, however, they are formed by noisy data, difficult to analyse using heuristic or predefined rule-based methods given their high susceptibility to noise, unobserved measurements during the training phase and lack of uncertainty measurement (Yang and Hsu, 2009; Capela et al., 2015; Kiguchi et al., 2004). Here is where probabilistic methods, like the one proposed in this work, play a key role for data analysis and decision-making. These capabilities are supported by the recognition accuracy of 100% and fast decision-making process (50 ms) achieved by our method.

In the analysis of SiSt and StSi identification, the proposed method was able to recognise sit, transition and stand activity states with higher accuracy than state-of-the-art methods (Doulah et al., 2016; Qian et al., 2010; Banerjee et al., 2010). The second experiment provided a thorough analysis for recognition and a better understanding of the state of human body during the transition state. For this process, the transition state was divided into multiple phases, from 2 to 6 phases, analysing their performance in accuracy and response time. The results showed that using 2, 3 or 4 transition phases, during the transition state, the Bayesian formulation was able to successfully recognise the human movement with an accuracy of 100%. With 2 transition phases the recognition process was highly accurate (100%) and fast (30 ms), but the information or knowledge of the state of human body was limited. With 4 transition phases, high accuracy was achieved (100%) but the response time was increased to 80 ms. This analysis suggests that 3 transition phases provide a trade-off between accuracy (100%), speed (50 ms) and the knowledge of the state of the human body during the transition state. All these findings are supported with SiSt and StSi experiments, in offline and real-time modes, performed by participants wearing one IMU. The capability of this work for recognition of level-ground walking, ramp ascent, ramp decent and gait phases with multiple wearable sensors and angular velocity signals has been validated in (Martinez-Hernandez et al., 2018). We consider that the robustness of activity recognition methods, can benefit from the use of barometric pressure sensors, which have shown their potential for discrimination of sitting and standing transitions with an accuracy of 99.5% (Massé et al., 2014).

It is worth mentioning that our method offers a set of advantages over previous works: 1) our Bayesian formulation works with the iterative accumulation of acceleration measurements, and does not rely on angle information, which is highly susceptible to noise or even small changes in the set up, 2) one wearable sensor is sufficient to identify SiSt and StSi, making our method suitable for realistic outdoor applications, 3) normally, probabilistic methods offer robust frameworks to deal with noise present in sensor measurements and 4) our method provides a better understanding of the human body motion during the transition state, which has not been studied in detail in previous works. The use of phases for the study of SiSt was presented by (Schenkman et al., 1990), where the following 4 phases were reported: flexion momentum, momentum transfer, extension and stabilisation. These phases were not composed of segments of the same size, unlike the approach presented in our work. However, we consider that our probabilistic method has the capability to process data segments of different widths or sizes, and then, matching the observations from SiSt obtained by (Schenkman et al., 1990). It is important to note that there is not an exact segmentation of the sensor signal, which is related to various aspects such as sensor capabilities and limitations, sensor noise and duration of the SiSt activity. Here is where probabilistic methods play a key role, dealing with uncertainty and noise from the sensor and environment.

The proposed method for identification is a type of high-level method or high-level control, which normally interacts with low-level controllers to develop robust and intelligent systems. In this study, a hierarchical layered architecture was developed for the implementation and interaction of high- and low-level controllers. A simulated environment, based on the robot simulator V-REP, was used to show the potential of the high-level probabilistic method for controlling a robotic leg while interacting with a low-level controller. Even though this experiment was performed in a simulated environment, real data collected from an IMU were employed for identification of SiSt, StSi and control of the robotic leg. Definitely, controlling a real robot leg requires to consider other aspects at low-level, but in this study the focus was on high-level methods, e.g., identification of human activities. There are various aspects that we plan to investigate in detail in future works: 1) activity identification from participants with a wider range of ages, heights and weights, 2) extend this method for recognition of ADLs performed with upper and lower limbs, 3) design of low-level controllers, connected to the probabilistic recognition method, for control of real robots, 4) implementation of recognition and control methods in a portable and lightweight assistive device and 5) matching of transition phases with those reported in the literature for the analysis of SiSt activity.

Intelligent systems, capable to recognise human motion and provide reliable assistance, involve complex processes at different levels of control. In this work, a high-level method for identification of SiSt and StSi activities was presented. This method has the potential to execute cognitive functions such as perception and decision making, but also to perform fast and accurate decision and actions. All these aspects are essential for the development of safe and intelligent systems to provide reliable assistance to humans in activities of daily living.

6. Conclusion

In this work, a Bayesian formulation, together with a sequential analysis method, was proposed for identification of sit-to-stand (SiSt) and stand-to-sit (StSi). This approach was capable to accumulate acceleration measurements, from a wearable sensor attached to the thigh of participants, and make autonomous decisions. First, the probabilistic method was designed to identify three activity states (sit, transition and stand) from acceleration measurements. Second, the transition state was divided into three transition phases (phase 1, phase 2 and phase 3) to observe the state of the human body during the transition state. Validation of the Bayesian formulation was performed with SiSt and StSi experiments in offline, real-time and a simulated environment using real data from a wearable sensor. The results in the offline mode achieved a recognition accuracy of 100%, with a mean response time of 50 ms, for all activity states and phases. In the real-time mode, all activity states and transition phases were successfully recognised. The potential of the probabilistic approach to interact with low-level controllers, for the control of assistive devices, was successfully demonstrated in a simulated environment. This multi-layer interaction was implemented in a hierarchical architecture, using the Bayesian formulation (high-level method), a PID controller (low-level method) and real data from an IMU sensor. Overall, the results show the capability of our work to make fast and accurate decisions, which are key aspects in the development and control of reliable and intelligent wearable devices to assist humans.

Acknowledgments

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) for the ‘Wearable soft robotics for independent living’ project (EP/M026388/1).

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