Simultaneous Bayesian recognition of locomotion and gait phases with wearable sensors

Uriel Martinez-Hernandez, Imran Mahmood and Abbas A. Dehghani-Sanij

***Abstract*—Recognition of movement is a crucial process to assist humans in activities of daily living such as walking. In this work, a high-level method for simultaneous recognition of locomotion and gait phases using wearable sensors is presented. A Bayesian formulation is employed to iteratively accumulate evidence to reduce uncertainty, and to improve the recognition accuracy. This process uses a sequential analysis method to autonomously make decisions, whenever the recognition system perceives that there is enough evidence accumulated. We use data from three wearable sensors, attached to the thigh, shank and foot of healthy humans. Level-ground walking, ramp ascent and descent activities are used for data collection and recognition. In addition, an approach for segmentation of the gait cycle for recognition of stance and swing phases is presented. Validation results show that the simultaneous Bayesian recognition method is capable to recognise walking activities and gait phases with mean accuracies of 99.87% and 99.20%. This process requires a mean of 25 and 13 sensor samples to make a decision for locomotion mode and gait phases respectively. The recognition process is analysed using different levels of confidence to show that our method is highly accurate, fast and adaptable to specific requirements of accuracy and speed. Overall, the simultaneous Bayesian recognition method demonstrates its benefits for recognition using wearable sensors, which can be employed to provide reliable assistance to humans in their walking activities.**

***Index Terms*—Locomotion mode recognition, gait phase recognition, Bayesian perception, wearable sensors**

I. INTRODUCTION

LOCOMOTION is the capability that not only distinguishes humans from animals, but also it provides humans with independence of mobility to perform activities of daily living (ADLs) [1]. Although human locomotion activities such as walking and running are normally taken as granted, they require complex movements that are commonly affected in people that have reached the old age [2]. Advances in sensor technology have made it possible to develop wearable devices to assist humans in locomotion activities [3], [4], [5], [6]. However, intelligent computational methods for perception of human movements still represent a challenge to achieve robust and reliable control of assistive devices.

In this work, we develop a high-level method for simultaneous recognition of locomotion mode and gait phase (stance and swing phases) for various walking activities. This recognition approach uses a Bayesian formulation that, together with a sequential analysis method, integrates angular velocity measurements from multiple wearable sensors. Our probabilistic method permits to accumulate evidence while dealing with uncertainty for reliable perception and decision-making processes. The accuracy of our method has been demonstrated in previous works, where perception and robot control were investigated using various stimuli [7], [8].

Our high-level recognition method is integrated in a layered architecture composed of physical and cognitive layers, which interact between them and the human wearing the sensors. This interaction in multi-layer architectures is required for the development of reliable perception and intelligent systems [9], [10]. These layers implement our method with three processes; sensation, perception and decision. On the one hand, the physical layer collects and prepares sensor data for cognitive evaluations, e.g., recognition of locomotion mode. On the other hand, accumulation of evidence, perception and decision processes are performed in the cognitive layer.

Angular velocity measurements are obtained from three inertial measurement units (IMU) attached to the thigh, shank and foot of healthy participants. These IMU sensors are synchronised with a workstation for a systematic data collection in real-time from three locomotion activities; level-ground walking, ramp ascent and ramp descent. The data from these walking activities are grouped into datasets for training and testing our method with experiments for recognition of locomotion mode and gait phases. These experiments are implemented to validate the performance of our probabilistic method. First, recognition accuracy and decision time for the three locomotion modes are analysed, where our method demonstrates to be fast and accurate. Second, for recognition of stance and swing phases, the gait cycle is divided into eight periods (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing), achieving fast and accurate recognition results for each period. The results from experiments show that our approach is accurate and fast for simultaneous recognition of locomotion and gait phases, but also it permits to know the state of the human body during the gait cycle.

Overall, our simultaneous Bayesian recognition approach offers a framework for fast and accurate recognition of movements, which can be used to reliably assist humans in ADLs.

This paper is organised as follows: a description of the related work is presented in Section II. Our proposed recognition method is described in Section III. The experiments and results are presented in Section IV. Section V presents the discussion of our work. Finally, conclusions are presented in Section VI.

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II. Related work

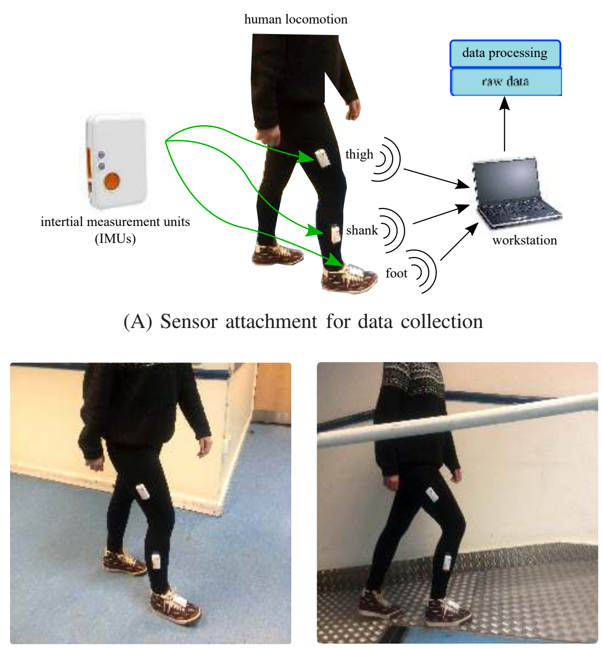
Intent recognition is an important process to reliably assist humans. Multiple approaches, from simple sets of rules to complex learning algorithms, have been studied for recognition of ADLs, which are presented in the following paragraphs.

Finite state machines (FSM) using electromyography (EMG) and myoelectric signals from six muscles were able to recognise level-ground walking, ramp ascent and ramp descent locomotion modes [11]. Transition between states was controlled by a set of fixed rules applied to muscular activity signals. Information from floor reaction force, hip and knee joint angles was evaluated by a FSM to identify movements for sitting, standing and level-ground walking [12], [13]. These hard-coded methods are highly susceptible to fail even for slightly changes in the environment.

Machine learning offers sophisticated algorithms for perception and learning to develop robust and adaptable high-level recognition systems. Entropy distance and image processing techniques were used for recognition of human action and detection of fall events using wearable cameras and inertial sensors [14], [15]. An adaptive algorithm, based on decision trees and four sensors attached to the human body, was implemented for recognition of daily activities such as walking, standing and sitting with an accuracy of 99% [16]. Fusion of a linear discriminant analysis (LDA) method and a two-layered artificial neural network (ANN), was used for identification of locomotion modes with twelve surface EMG signals [17]. LDA and ANN methods have also been used with time-domain and frequency-domain features from nine EMG signals for intent recognition [18], [19]. Other works have implemented ANN combined with heuristic methods for identification of locomotion mode and detection of gait cycle. These works used multiple accelerometer sensors and foot ground contact data from walking, running, stair ascent and descent [20], [21], [22]. Even though all these works achieved a recognition accuracy between 90% and 95%, they required a large number of sensors attached to the human body, which makes the calibration, synchronisation and data collection complicated processes that impact on the computational cost and complexity of implementation.

Real-time recognition of ADLs has been investigated with Fuzzy Logic (FL) methods, where information from joint angles and pressure insole sensors was used for recognition and assistance to the pelvis [23]. FL and combination of ANN and EMG signals, were employed for human intent recognition and prosthesis control achieving an accuracy of 95% [24], [25]. Multiple human activities were recognised using EMG and vision sensors with support vector machines (SVMs). These methods achieved accuracies between 77.3% and 99%, however, they need a large number of sensors that also limits these works to indoor applications [26], [27]. SVM and k-nearest neighbour algorithms, together with 9 accelerometers distributed from the torso to the ankle, achieved an accuracy of 97.6% for recognition of ADLs [28]. The combination of plantar pressure sensors with multi-class SVMs allowed the recognition of normal walking, stair ascent and stair descent activities with accuracies between 91.9% and 95.2% [29]. In general, ANN, SVM and FL provide accurate results, however, they produce black box models which do not provide a measure of confidence, making their implementation in real-time a complicated process. In contrast, probabilistic approaches provide well-defined mathematical models to develop reliable systems for perception and leaning in robotics [30], [31]. Bayesian formulations, have been successfully employed for perception, decision-making and robot control with multiple stimuli [32], [33]. Gaussian mixture models (GMM) allowed to characterised the probabilities of ADLs such as sitting, standing and walking with high accuracy [34]. Dynamic Bayesian networks (DBN), trained with multiple information sources, e.g., IMUs and EMG signals, were capable to identify walking activities on different terrain conditions [35], [36].

Inspired by the benefits offered by probabilistic methods, in this work we present a Bayesian formulation for simultaneous recognition of locomotion modes and gait phases. This recognition method, together with a sequential analysis method that mimics the way in that humans accumulate evidence and make decisions, is capable to make autonomous, fast and accurate decisions. Furthermore, our recognition method allows to adapt the confidence parameter for specific requirements in accuracy and speed. Interestingly, our probabilistic approach permits to achieve high recognition accuracy with a small number of wearable sensors suitable for indoor and outdoor applications. A detailed description of our simultaneous Bayesian recognition method is presented in the next sections.



(A) Sensor attachment for data collection

(B) Level-ground walking (C) Ramp ascent/descent

Fig. 1. Walking activities and wearable sensors for systematic data collection. (A) Diagram that depicts the data collection process using three IMU sensors attached to the thigh, shank and foot of participants. The data received at the workstation is smoothed and prepared in a proper format for their analysis by the recognition system. (B) Level-ground walking on a flat cement surface. (C) Ramp ascent and descent on a metallic ramp with a slope of 8.5 deg. Participants were asked to repeat five times each locomotion mode.

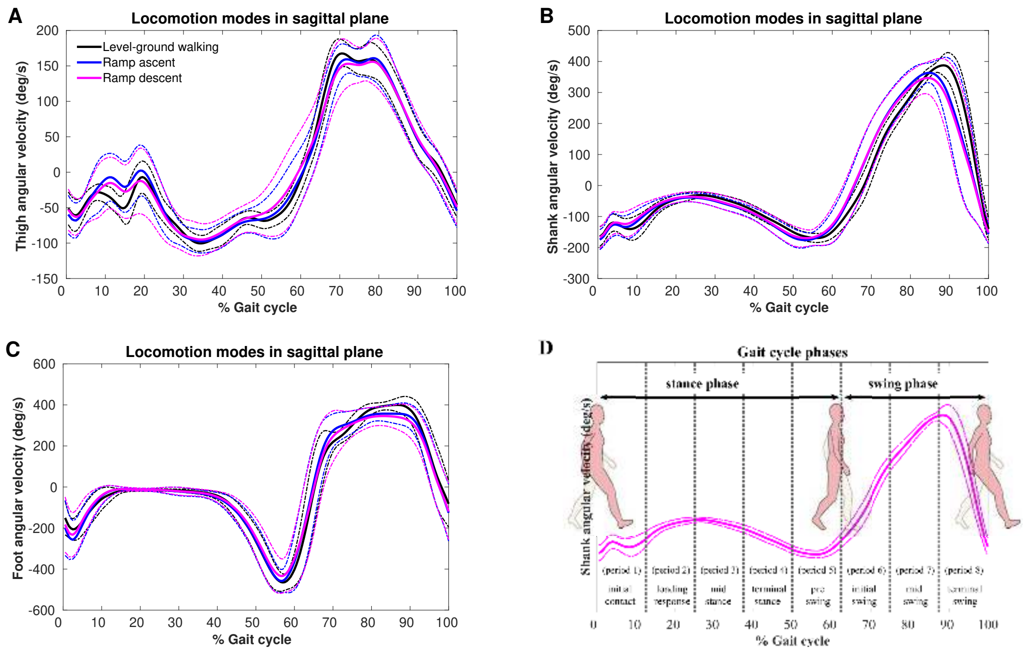


Fig. 2. Data collected from three locomotion modes; level-ground walking, ramp ascent and ramp descent represented by black, blue and magenta colour curves. The data were collected using three inertial measurement units attached to (A) the thigh, (B) shank and (C) foot of healthy participants. Solid lines show the mean angular velocities for each locomotion mode, while dashed-lines represent the standard deviation. Plot (D) shows an example of the gait cycle segmented into eight periods; initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing. These periods are processed by our probabilistic recognition method to know the state of the human body during the gait cycle.

III. Methods

A. Participants and measurements

Eight healthy male subjects were recruited from the School of Mechanical Engineering at the University of Leeds to participate in this investigation. The subjects were free from gait abnormalities, their 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.

Angular velocity signals were collected from three IMUs attached to the thigh, shank and foot of participants using velcro straps. We used six degrees of freedom IMUs, from Shimmer Inc., composed of accelerometer and gyroscope. Signals from all sensors were synchronised and sent to the workstation using the Multi Shimmer Sync software. A foot pressure insole, built with four piezoresistive sensors, was used for detection of the beginning of the gait cycle in the training phase. Figure 1A depicts the data collection process from the wearable IMU sensors, which have shown to be robust and suitable for assistive and rehabilitation robotic devices [37].

Participants were asked to walk at their self-selected speed and complete five repetitions of three locomotions modes; level-ground walking, ramp ascent and ramp descent. For level-ground walking, we used a flat cement surface, while ramp ascent and descent were performed on a metallic ramp with an 8.5 deg slope (see Figures 1B,C). Angular velocity signals were systematically collected, with a sampling rate of 1000 Hz, and prepared in an appropriate format for training and testing with the proposed recognition method.

B. Signal processing and data preparation

Angular velocity signals were filtered by a second-order Butterworth filter with a cut-off frequency of 10 Hz. For detection of the beginning of the gait cycle, we used a threshold-crossing approach with a foot pressure insole, which has been tested in previous works [38]. Figure 2 shows the measurements from the thigh, shank and foot for level-ground walking, ramp ascent and ramp descent, represented by black, blue and magenta colour curves respectively. Solid and dashed lines represent mean angular velocities and standard deviations respectively. The filtered data from the thigh, shank and foot were concatenated to build training and testing datasets for their subsequent analysis. Angular velocities from each gait cycle, shown in Figures 2A,B and C, were used to construct the histograms employed by our method for activity recognition. For recognition of stance and swing phases, each gait cycle was divided into initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing as shown in Figure 2D. An example of the histograms from level-ground walking, employed for recognition of locomotion and gait phases, is shown in Figure 3.

C. Simultaneous Bayesian recognition

Simultaneous recognition of locomotion and gait phases uses a Bayesian formulation together with a sequential analysis method. This probabilistic method iteratively accumulates sensor data, reducing the uncertainty from sensors measurements. The sequential analysis method, together with a belief threshold parameter, allows the recognition system to decide whether there is enough evidence accumulated to make a decision.

Bayesian update: our Bayesian formulation iteratively updates the posterior probability from the product of the prior and likelihood distributions. Here, sensor measurements and perceptual classes are represented by z and $c_n \in C$ respectively. Each perceptual 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 the locomotion and gait periods respectively. The Bayesian update process is as follows:

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

where $P(c_n|z_t)$ and $P(z_t|c_n)$ are the posterior probability and likelihood at time t. The prior probability at time $t-1$ is represented by $P(c_n|z_{t-1})$. The variable u_k with $K = 3$ represents the three locomotion modes employed for estimation in this work (level-ground walking, ramp ascent and ramp descent), while v_l with $L = 8$ are the eight periods for estimation of gait phases (stance and swing phases). The measurements z represent the angular velocity signals from the IMU sensors attached to the lower limbs of human participants.

Prior: for the initial time $t = 0$ we assume uniform prior probabilities for all the locomotion modes and gait phases, which is defined as follows:

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

where c_n is the perceptual class to be estimated, z_0 are the sensor observations at time $t = 0$ and N is the number of pairs (u_k, v_l) to be estimated. For time $t > 0$ the prior probability is updated with the posterior from $t-1$ as follows:

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

Measurement model and likelihood estimation: angular velocity information from S_{sensors} is obtained at each time step. We use three IMU sensors ($S_{\text{sensors}} = 3$) attached to the thigh, shank and foot of participants. In this work, no assumptions are made on the distribution of the data. For that reason, a nonparametric approach, based on the histograms from sensor information (see Figure 3), is used to construct the measurement model for the Bayesian formulation. The histograms are used to evaluate an observation z_t at time t, and estimate the likelihood of a perceptual class c_n. The measurement model is represented as follows:

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

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 were uniformly constructed by binning angular velocity information into $N_{\text{bins}} = 100$ intervals. The values are normalised by $\sum_{b=1}^{N_{\text{bins}}} h(b)$ to have probabilities that sum to 1. The likelihood of the observation z_t, at time t, by evaluating Equation (4) over all the sensors is obtained as follows:

$$\log P(z_t|c_n) = \sum_{s=1}^{S_{\text{sensors}}} \frac{\log P_s(w_s|c_n)}{S_{\text{sensors}}} \quad (5)$$

where w_s is the signal sample from sensor s and $P(z_t|c_n)$ is the likelihood of the observation z_t, given a perceptual class c_n. Normalised values are ensured with the marginal probabilities conditioned from previous sensor observations as follows:

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

Marginal locomotion and gait period posteriors: the posteriors for the perceptual class c_n, that corresponds to a (u_k, v_l) pair, are the joint distributions over the locomotion modes u_k and gait periods v_l joint classes. Then, the beliefs over individual locomotion and gait periods perceptual classes are given by the marginal posteriors as follows:

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

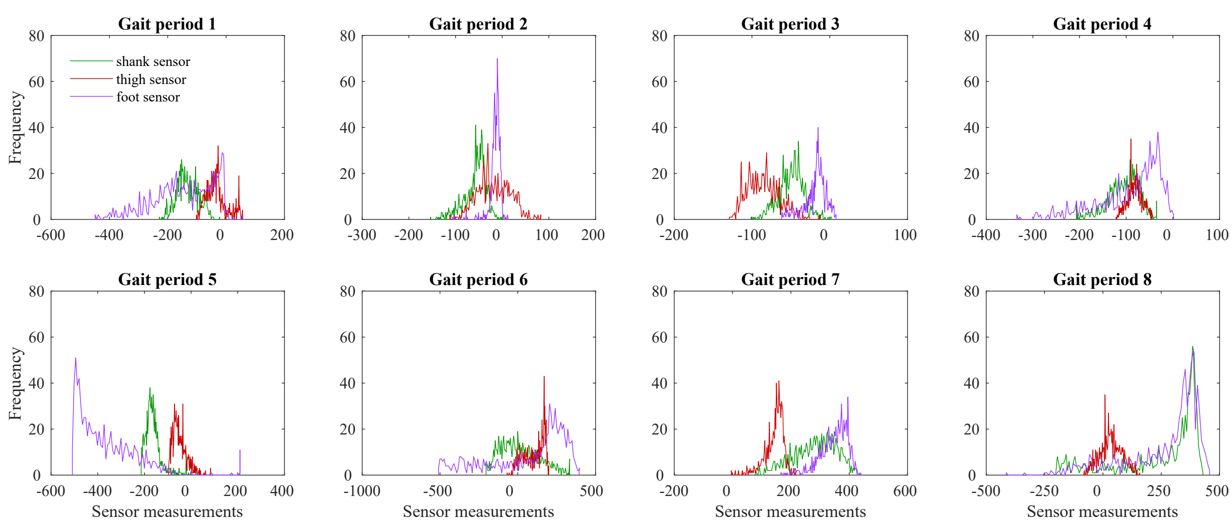


Fig. 3. Histograms from level-ground walking employed by our method for simultaneous Bayesian recognition of locomotion modes and gait phases. This is an example of the histograms from the sensors attached to the thigh, shank and foot of participants, represented by red, green and purple colours. The plots also represent the eight gait periods that composed the stance (period 1 to period 5) and swing (period 6 to period 8) phases of the gait cycle (see Figure 2D).

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

with locomotion classes summed over all gait period classes, and gait period classes summed over all locomotion classes.

Stop rule and decision making: the iterative accumulation of evidence, performed by the Bayesian update process, stops once a belief threshold $\beta_{\text{threshold}}$ is exceeded. This action enables the decision making process to estimate the perceptual class for locomotion mode and gait phase, using the *maximum a posteriori* (MAP) estimate as follows:

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

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

where the pair $(\hat{u}_k, \hat{v}_l)$, that represents the estimated class $\hat{c}_n$, provides the estimated locomotion mode and gait phase at time t. The belief threshold $\beta_{\text{threshold}}$ permits to adjust the confidence level of the probabilistic recognition method to achieve a desired accuracy for the decision making process. Here, we defined $\beta_{\text{threshold}} = [0.0, 0.5, \ldots, 0.99]$ to observe its effects on the performance in accuracy and decision time for recognition of locomotion mode and gait phases.

The simultaneous Bayesian recognition process is implemented with a layered architecture, composed of physical and cognitive layers, as shown in Figure 4. The physical layer contains the sensation process, while the cognitive layer contains perception and decision processes. The data from the IMU sensors, worn by humans, are sent to the sensation process. Its output is received by the perception process which implements the Bayesian formulation. The decision process allows the recognition system to decide whether there is enough evidence to make a decision about the current walking activity, or more measurements are needed from the sensors. The cognitive layer outputs the recognised locomotion mode and gait period, which can be used to monitor the state of the human body and control of wearable assistive devices.

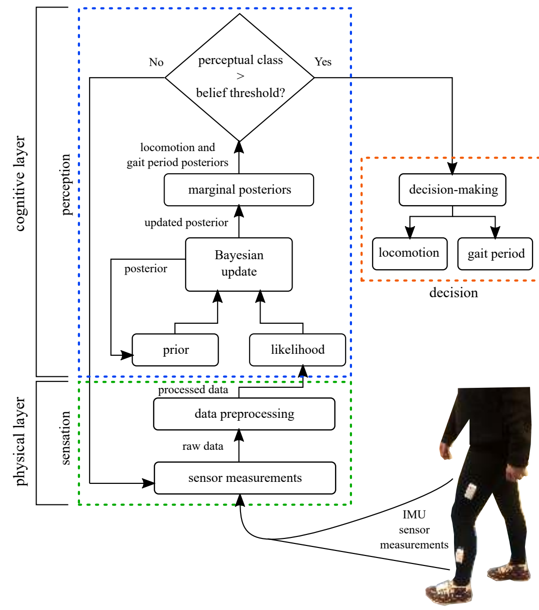


Fig. 4. Layered architecture composed of physical and cognitive layers to implement our method for recognition of locomotion mode and gait phases. The physical layer interacts directly with the environment through the sensation process, which receives data from wearable sensors. The cognitive layer is responsible for perception and decision making processes. They implement our Bayesian formulation to estimate the posterior probability and make a decision about locomotion mode and gait period once the belief threshold is exceeded. The locomotion is recognised as level-ground walking, ramp ascent or ramp descent, while recognition gait periods permits to know whether the participant is in stance or swing phase.

IV. Results

Multiple experiments were performed to validate our recognition method using real data and the locomotion activities described in Section III. The experiments were performed by training our method and randomly selecting sensor samples from the testing dataset with 10,000 iterations. The experiments and results are presented in the following sections.

A. Recognition of locomotion mode

First, we validated the accuracy for recognition of locomotion mode. For this process, we used three locomotion modes; level-ground walking, ramp ascent and ramp descent. The data from these locomotion modes measured from the thigh, shank and foot are shown in Figure 2. The data collected were grouped into multiple datasets, as described in Sections III-A and III-B, to build training and testing datasets for the proposed recognition method.

We configured the probabilistic recognition method with 24 perceptual classes c (3 locomotion modes $\times$ 8 gait periods). The performance, in recognition accuracy and decision time is evaluated using the belief threshold $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. This parameter also permits to observe and control the confidence level needed by the recognition system to achieve a specific accuracy. Accuracy recognition results of locomotion mode against belief threshold are shown in Figure 5A. The accuracy for recognition of locomotion mode is gradually improved from a mean error of 21% (accuracy of 79%) with $\beta_{\text{threshold}} = 0.0$, to a mean error of 0.13% (accuracy of 99.87%) with $\beta_{\text{threshold}} = 0.99$. This shows how our method is capable to reduce uncertainty and achieve better confidence for the decision making process. Our approach also permits to analyse the performance in decision time against belief threshold (see Figure 5B). Analysis of decision time is important given that recognition systems are required to make accurate decisions but also to respond in the appropriate time. Decision times gradually increased from a mean of 1 (for $\beta_{\text{threshold}} = 0.0$) to 25 (for $\beta_{\text{threshold}} = 0.99$) sensor samples. This behaviour was expected as more evidence is needed to achieve higher levels of confidence. The data from the IMU sensors were collected at a sampling rate of 1000 Hz (1 ms per sample), and thus, the Bayesian recognition method required a mean of 1 ms and 25 ms to achieve the recognition accuracies of 79% and 99.87% respectively.

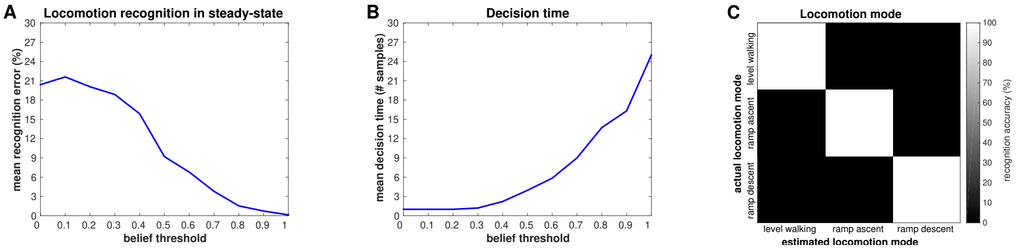


Fig. 5. Recognition results of locomotion activities. (A) Mean errors for recognition of locomotion mode gradually decrease for increasing belief thresholds achieving a mean error of 0.13% (accuracy of 99.87%). (B) Mean time to make a decision gradually increased for large belief thresholds, requiring a mean of 25 samples (25 ms) for the highest recognition accuracy. (C) Confusion matrix that shows the recognition accuracy for each locomotion mode, where level-ground walking, ramp ascent and ramp descent achieved a 100%, 99.84% and 99.78% accuracy respectively.

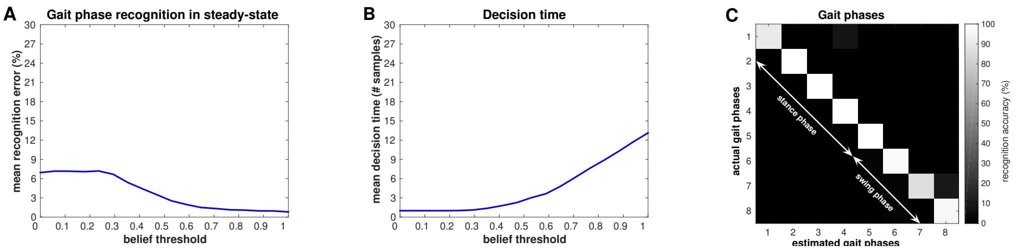


Fig. 6. Recognition results of gait period and phases. (A) Mean errors for recognition of gait phases gradually decrease for increasing belief thresholds. The lowest error of 0.8% (accuracy of 99.20%) was achieved for recognition of gait phases. (B) Gradual increments in the confidence level of our recognition system showed a gradual increment in the mean time to make a decision, where 13 samples (13 ms) were required to achieve the highest gait phase recognition accuracy. (C) Confusion matrix with accuracy of each gait period; 92.83%, 100%, 99.60%, 100%, 99.98%, 97.94%, 87.66% and 97.50% accuracy for periods 1 to 8 respectively. Stance and swing phases accuracies are 98.48% and 94.36% using periods 1 to 5 and periods 6 to 8 respectively.

The confusion matrix in Figure 5C shows the recognition accuracy for each individual locomotion mode. Black and white colours represent 0% and 100% accuracy respectively. These results show that level ground-walking, ramp ascent and ramp descent locomotion activities were successfully recognised with a 100%, 99.84% and 99.78% accuracy respectively. The analysis from these experiments shows that our method is capable to perform both, accurate and fast recognition processes, using a small number of wearable sensors.

B. Recognition of gait cycle phases

Recognition accuracy of gait phases and periods is also validated, which provides important information to know the state of the human body during the gait cycle for each locomotion activity. This experiment used the information from the eight gait periods in which the gait cycle was divided, where stance and swing phases are composed of gait periods 1 to 5 (initial contact, loading response, mid stance, terminal stance, pre-swing) and gait periods 6 to 8 (initial swing, mid swing, terminal swing) respectively (see Figure 2D).

In this experiment, recognition accuracy and decision time for different levels of confidence were analysed using the belief thresholds $\beta_{\rm threshold} = [0.0, 0.05, \ldots, 0.99]$. Recognition accuracy from gait periods and phases against belief thresholds are shown in Figure 6A. Our Bayesian approach was able to gradually improve the accuracy from a mean error of 7% (accuracy of 93%) with $\beta_{\rm threshold} = 0.0$, to 0.8% (accuracy of 99.20%) with $\beta_{\rm threshold} = 0.99$. This shows that high levels of confidence allow to achieve high accurate recognition of gait periods, as well as stance and swing phases. Results from decision time against belief threshold in Figure 6B show a gradual increment in decision time, requiring from 1 to 13 sensor samples to make a decision with $\beta_{\rm threshold} = 0.0$ and $\beta_{\rm threshold} = 0.99$ respectively. This means that our recognition method needs a mean of 1 ms and 13 ms to identify in which phase of the gait cycle the human body is, with an accuracy of 93% and 99.20% respectively.

The confusion matrix in Figure 6C presents the recognition accuracy for each gait period. Black and white colours represent 0% and 100% recognition accuracy. This result shows that the eight gait periods were identified with accuracies of 92.83%, 100%, 99.60%, 100%, 99.98%, 97.94%, 87.66% and 97.50% for periods 1 to 8 respectively. With these results, our approach was able to successfully recognise stance and swing phases with a 98.48% (gait periods 1 to 5) and 94.36% (periods 6 to 8) accuracy. Mean recognition of individual gait periods for level-ground walking, ramp ascent and ramp descent is shown in Figure 7A. Recognition accuracy for all gait periods in level-ground walking was highly accurate, successfully identifying stance and swing phases (see Figure 7B). Slightly less accuracy was observed in periods 1 and 7 for ramp ascent and ramp descent respectively, however, these results are compensated by the rest of gait periods to achieve accurate recognition of stance and swing phases (see Figure 7B).

Overall, all these experiments demonstrate the benefits offered by the simultaneous Bayesian recognition method. First, it allows to simultaneously recognise locomotion mode and gait phases. Second, this method responds fast, without highly compromising the recognition accuracy. Third, the accurate identification of periods permits to know the state of the human body during the gait cycle. Finally, all this information is essential to assist humans in walking activities, using wearable sensors and robots that respond fast and reliably.

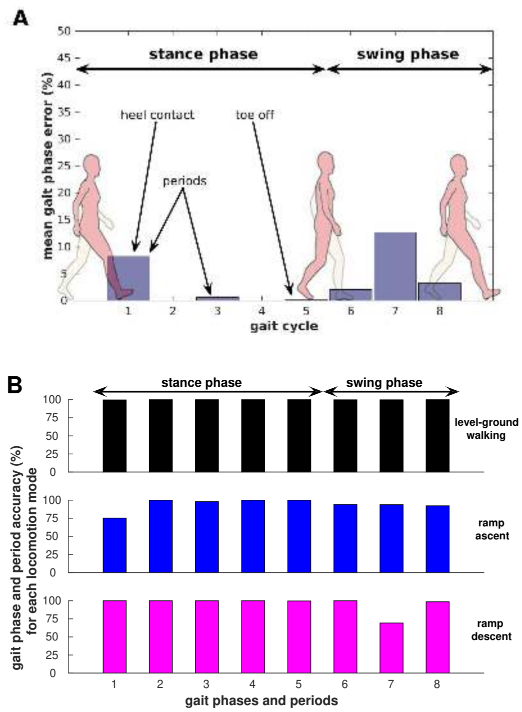


Fig. 7. (A) Representation of mean recognition errors for gait periods and phases from three locomotion activities. Stance and swing phases are composed of periods 1 to 5 (initial contact, loading response, mid stance, terminal stance, pre-swing) and periods 6 to 8 (initial swing, mid swing, terminal swing) respectively. (B) Recognition accuracy of the eight periods for each locomotion mode. All locomotion modes achieved high accuracy for all the periods, with a slightly decay in periods 1 and 7 for ramp ascent and descent respectively. This slightly decay is compensated with the high accuracy achieved by rest of the gait periods.

V. Discussion

High-level recognition methods play a key role to recognise movement intent and assist humans in ADLs. In this work, we presented a Bayesian formulation for simultaneous recognition of locomotion mode and gait phases. First, our probabilistic formulation successfully recognised multiple human locomotion modes with high accuracy. Second, stance and swing phases were recognised to identify the state of the human body for each walking activity. Third, the performance in accuracy and decision time was analysed for different levels of confidence employed by the recognition method.

The simultaneous recognition method was implemented using a Bayesian formulation together with a sequential analysis method. We found that our approach was able to deal with uncertainty from the wearable IMU sensors attached to the human body. Dealing with uncertainty is crucial in intelligent systems to make accurate decisions, provide assistance and act accordingly in the face of sensor noise and dynamics of the environment [30]. Our recognition method is capable to adapt to various sensor types and stimuli, which is extremely useful for implementation in assistive devices composed of different sensor technologies [7], [8], [39].

The performance of the simultaneous Bayesian method was analysed with the recognition of locomotion mode and gait phases. Level-ground walking, ramp ascent and ramp descent locomotion modes were successfully recognised with a mean accuracy of 99.87%. For recognition of gait phases, the gait cycle was segmented into eight periods to identify stance and swing phases [36]. Gait periods were recognised with a mean accuracy of 99.20%, while stance and swing phases achieved a mean accuracy of 98.48% (gait periods 1 to 5) and 94.36% (gait periods 6 to 8) respectively. Key events during the gait cycle, such as heel contact and toe off, were also recognised with small error from all locomotion activities. In general, identification of gait periods was successful with slightly less accuracy in periods 1 and 7 for ramp ascent and ramp descent. This small decrease in accuracy was compensated by the rest of gait periods that form the gait cycle, and still achieve high recognition accuracy. Previous works, using a variety of machine learning methods and sensor technologies, have been able to achieve accuracies of 65.8%, 73.83%, 95.2%, 99% and 100% for recognition of walking activities [5], [20], [29], [40]. However, they present limitations such as fixed sampling window size, large number of sensors, lack of analysis for decision time, gait phases and gait periods. Other works have addressed the recognition of gait phases, but they still use a fixed sampling window size [27], [36]. In contrast, our method achieved high accuracy for simultaneous recognition of locomotion and gait phases, while dealing with uncertainty and using only three inertial measurement units. These are important factors in sensor networks for recognition systems, –for instance, lightweight systems, reduction of energy consumption and computational complexity.

In these experiments we have made some assumptions such as the number of gait periods and the location of the wearable sensors. The segmentation of sensor signals from the gait cycle was based on studies from biomechanics, but a different number of segments could also be employed to perform the analysis. However, the larger the number of segments the less the data available for recognition, which could affect the accuracy. In this work, the wearable sensors were attached in the external side of the lower limbs based on previous studies on intent recognition, however, rearranging the location of sensors could also affect the performance of the recognition process. All these aspects can be analysed in future works to extend the present investigation.

Decision time to respond to an action or event is an important feature for recognition systems. Results showed that recognition of locomotion mode required a mean of 25 measurement samples (25 ms) to make a decision with the highest accuracy (Figure 5B), while for stance and swing phases a mean of 13 measurement samples (13 ms) were required for the highest recognition accuracy (Figure 6B). Interestingly, these decision times are below the average time required for intent recognition with imperceptible delay and without compromising the accuracy [27]. Other works have also achieved fast recognition processes, but using large number of sensors which affects the accuracy [36], [41]. Conversely, our method was able to react fast and with high accuracy to multiple walking activities, by adjusting the parameter $\beta_{\mathrm{threshold}}$ without a significant impact on the recognition accuracy. For instance, for a belief threshold from $\beta_{\mathrm{threshold}} = 0.9$ to $\beta_{\mathrm{threshold}} = 0.99$ it is required to have between 16 ms to 25 ms and 10 ms to 13 ms to make a decision for locomotion and gait phase respectively. With these parameters, it would be possible to achieve an accuracy from 99.10% to 99.87% for locomotion, and 99% to 99.20% for gait phases. This demonstrates the capability of the simultaneous Bayesian recognition to maximise the trade-off between accuracy and speed, taking the best from both worlds.

Interestingly, our high-level recognition system is able to autonomously determine when the evidence accumulated from sensor measurements is enough to make accurate decisions. This aspect is an improvement over previous works, which normally restrict the decision-making and recognition processes with a fixed and predefined number of sensor samples [27], [34], [42]. We consider that our work offers the potential to develop intelligent wearable robots, capable to recognise human movements and adapt their performance to provide fast and safe assistance in activities of daily living.

Even though this investigation focused on the processes that take place in the high-level layer, e.g., perception and decision-making, our recognition system offers the potential to interact with middle- and low-level layers for the control of assistive robots. This capability was illustrated in Figure 4 with a multi-layer architecture that could be extended to include middle- and low-level processes for robot control and assistance in real-time. This type of architecture is recognised to be essential for intelligent systems to perform robust data processing, perception, decision making and action at different levels of abstraction [10], [31]. There are important aspects that we plan to investigate in our future work: a) We plan to increase the sample size and variation of measurements including data from female and senior people. This aspect is important to achieve robust methods suitable to assist a large variety of people; b) Research on different approaches for segmentation of the gait cycle; c) Methods for prediction of gait periods and gait events; d) Rearrangement of wearable sensors; e) Integration of a larger number of ADLs. We also plan to investigate on middle- and low-level methods for control of assistive devices, which can be benefited by the functionalities offered by our high-level recognition method.

Intelligent systems, capable to assist humans, involve complex processes at different levels of control. Here, we presented a high-level method to simultaneously recognise walking activities and gait phases. This method has also the potential to perform cognitive capabilities such as interaction, perception and decision making, which are important for safe and adaptable systems that intelligently recognise human motions to provide reliable assistance in activities of daily living.

VI. Conclusion

In this work, a high-level method for simultaneous recognition of locomotion mode and gait phases was presented. Our approach was based on a probabilistic Bayesian formulation with a sequential analysis method. Angular velocity data, from three IMUs attached to the lower limbs of participants, were employed for recognition. Recursive accumulation of evidence allowed our method to achieve a mean accuracy of 99.87% and 99.20% for recognition of locomotion mode and gait phases. Our approach also showed to be fast without compromising its performance in accuracy. Furthermore, adaptability of performance, based on confidence levels and autonomous decisions, make our method suitable for intelligent recognition systems. Overall, the simultaneous Bayesian recognition method has the potential to perform fast and accurate recognition of walking activities, which is essential for intelligent systems capable to understand human movements and safely assist in activities of daily living.

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