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Adaptive Bayesian inference system for recognition of walking activities and prediction of gait events using wearable sensors

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Abstract

In this paper, a novel approach for recognition of walking activities and gait events with wearable sensors is presented. This approach, called adaptive Bayesian inference system (BasIS), uses a probabilistic formulation with a sequential analysis method, for recognition of walking activities performed by participants. Recognition of gait events, needed to identify the state of the human body during the walking activity, is also provided by the proposed method. In addition, the BasIS system includes an adaptive action-perception method for the prediction of gait events. The adaptive approach uses the knowledge gained from decisions made over time by the inference system. The action-perception method allows the BasIS system to autonomously adapt its performance, based on the evaluation of its own predictions and decisions made over time. The proposed approach is implemented in a layered architecture and validated with the recognition of three walking activities; level-ground, ramp ascent and ramp descent. The validation process employs real data from three inertial measurements units attached to the thigh, shanks and foot of participants while performing walking activities. The experiments show that mean decision times of 240 ms and 40 ms are needed to achieve mean accuracies of 99.87% and 99.82% for recognition of walking activities and gait events, respectively. The validation experiments also show that the performance, in accuracy and speed, is not significantly affected when noise is added to sensor measurements. These results show that the proposed adaptive recognition system is accurate, fast and robust to sensor noise, but also capable to adapt its own performance over time. Overall, the adaptive BasIS system demonstrates to be a robust and suitable computational approach for the intelligent recognition of activities of daily living using wearable sensors.

Keywords: Intent recognition, high-level control, Bayesian inference, action-perception architectures

1. Introduction

Recognition of human activities has played an important role for applications in healthcare, surveillance, human-computer interaction and teleoperation [1, 2]. In healthcare, recognition of activities of daily living (ADLs) is a key process to develop intelligent robots that understand human motion and provide reliable assistance [3, 4]. Particularly, activities that involve mobility such as walking in level-ground, ramps and stairs are essential for independence of living, transporting the human body safely and efficiently across terrains [5]. Even though walking activities are normally taken as granted, they require coordinated movements difficult to be performed by elderly people or those who have suffered a physical injury [6].

Recent advances in sensor technology have enabled the development of small size and low cost wearable devices for applications that require physiological, biomechanical and motion data, e.g., electromyography (EMG) and inertial measurement units (IMUs) [7, 8, 9]. Despite this progress, the design of reliable, fast and accurate computational methods, that exploit the benefits offered by wearable sensors for recognition of human walking activities still remain a challenge.

In this work, a Bayesian inference system (BasIS) for recognition of walking activities using wearable sensors is presented. The BasIS system uses a probabilistic formulation that, together with a sequential analysis method, iteratively accumulates sensor data to improve the recognition of walking activities. This approach is inspired by the *competing accumulators* model for decision-making proposed by neuroscientists [10, 11], and applied to robotics in tasks such as perception, learning, exploration and interaction [12, 13, 14]. In addition, the BasIS system is capable to recognise the gait events that compose the walking activity. These functionalities are essential to recognise the activity performed by a subject, but also to know the state of the human body during the walking cycle.

An adaptive action-perception method is presented to extend the BasIS system to improve the recognition accuracy and speed. This method uses a weighted combination of information sources, which is inspired by the way in that humans make decisions. Studies have shown that human decision-making combines prior knowledge and current expectations, weighted according to the accuracy of decisions made and reliability of information sources [15, 16]. Thus, the adaptive BasIS system performs a weighted combination of 1) prior knowledge and 2) predicted information from the observation of decisions made over time. The proposed combination of information sources initialises the recognition process with a certain amount of knowledge, which is adapted over time to make the BasIS system reliable to changes observed from sensor inputs.

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A layered architecture is developed to validate the adaptive BasIS system for the recognition of walking activities (level-ground walking, ramp ascent and descent) and gait events. The validation process uses real data collected from participants wearing IMU sensors attached to their lower limbs. Results show that the adaptive BasIS system is able to recognise walking activities and gait events with high accuracy and speed. In addition, significant improvement, in accuracy and speed, is observed using the prediction and weighted combination of information methods offered by the adaptive BasIS system. These results demonstrate the benefits of probabilistic methods for recognition of ADLs, but also show that the intelligent use of knowledge, gained over time, has the potential to improve the performance of autonomous inference systems.

Overall, the proposed probabilistic approach, together with wearable sensors, has shown to be a suitable high-level method for the development of intelligent and adaptable systems capable to recognise activities of daily living.

The remainder of this article is organised as follows: the literature review is described in Section 2. The method for recognition and prediction of walking activities and gait events is presented in Section 3. Experiments and validation of the proposed method are shown in Section 4. The discussion and conclusion of this research are presented in Sections 5 and 6 respectively.

2. Related work

A heuristic approach, with predefined rules and electromyography (EMG) signals from six muscles of participants, was used to recognise level-ground walking, ramp ascent and descent activities [17]. Ground reaction force, hip and knee joint angles were used, together with a predefined set of rules and Finite State Machine (FSM), to identify sitting, standing and level-ground walking [18]. These hard-coded methods are able to recognise ADLs, however, they do not take into account the uncertainty from sensor measurements, making these methods susceptible to fail for slight changes in the environment [19].

Machine learning algorithm have played an key role in different disciplines, and it has not been the exception for the development of intent recognition methods. Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN) have been widely used to identify ADLs with EMGs [20], time-domain and frequency domain features [21]. These works achieved accuracies from 80.0% to 94.1% for recognition of level-ground walking, stair ascent/descent and standing with a sampling window of 150 ms. A combination of ANN and heuristic methods identified walking, running, stair ascent and descent activities with accuracies ranging from 88.8% to 99% [22, 23]. A drawback of these methods is the need for a large number of sensors, which makes the calibration, synchronisation and data collection complicated processes that impact on the computational cost and speed. An adaptive algorithm, based on decision trees and four sensors attached to the human body, was implemented for recognition of walking, standing and sitting with an accuracy of 99.0% [24]. Information from hip angle and pressure sensors was used with Fuzzy Logic (FL) methods for recognition of walking and stair ascent/descent, achieving an accuracy from 99.67% to 99.87% [25, 26]. High accurate identification of ADLs was achieved using a combination of FL and ANN methods with EMG signals [27, 28, 29]. Neuromuscular-mechanical signals with Support Vector Machines (SVM), and fixed sampling window of 150 ms, were able to identify walking activities and gait phases (stance and swing) with accuracies of 97.0% and 99.0%, respectively [30]. Multiple human activities were recognised with accuracies between 77.3% and 99.0% using SVMs with EMG and vision sensors. A drawback of this approach was the limitation to indoor applications [31]. SVM and k-nearest neighbour (kNN) algorithms, together with 9 accelerometers distributed from the torso to the ankle, achieved an accuracy of 97.6% for the recognition of ADLs [32]. Despite the high accuracy achieved by ANN and SVM methods, they produce black box models, which do not provide any measure of confidence or uncertainty of the decisions and actions made.

Probabilistic methods offer well-defined mathematical models for perception and learning, but also to handle sensor limitations and noise [19, 33, 34]. Bayesian formulations have demonstrated to be reliable for perception and control in robotics while dealing with uncertainty from sensors and the environment [12, 35, 36]. Gaussian Mixture Models (GMM) achieved a high accuracy of 100% with a decision time of 100 ms for identification of three locomotion activities [37]. Walking activities on different terrains were successfully recognised using a Naïve Bayesian classifier trained with signals from IMU sensors [38]. Mechanical and EMG sensors have been used to train Dynamic Bayesian Networks (DBNs) for recognition of level walking, ramps and stairs, achieving recognition accuracies between 86.0% and 99.87% [39, 40, 41]. History information was employed, together with DBNs, to recognise walking activities and gait phases (stance and swing) with accuracies of 98.0% and 95.25%, respectively [42]. This work was limited by the predefined and fixed amount of history or prior data for each new decision process. Even though the high accuracy achieved by the works previously described, they do not provide information about recognition of gait events. The recognition of walking activities, gait periods and events is crucial to develop systems capable to improve their decisions made over time. It has been shown that humans combine multiple source of information in decision-making processes, in order to make accurate decisions and actions [43]. This combination of information has also been studied with humans and robots with multiple applications [16, 12]. These works showed that when the combination is appropriately weighted, according to the reliability of each information source, it is possible to achieve more robust and adaptable autonomous systems.

In this work an adaptive Bayesian inference approach is proposed for recognition of walking activities and gait events using IMUs. This approach uses an adaptive action-perception method, that allows the Bayesian process to understand its decisions and actions made over time, and thus, to adapt and improve the recognition accuracy. The adaptive functionality also allows to predict the next probable gait periods and events during walking activities, improving the speed and accuracy of the decision-making process. A detailed description of the adaptive Bayesian inference system is presented in the next sections.

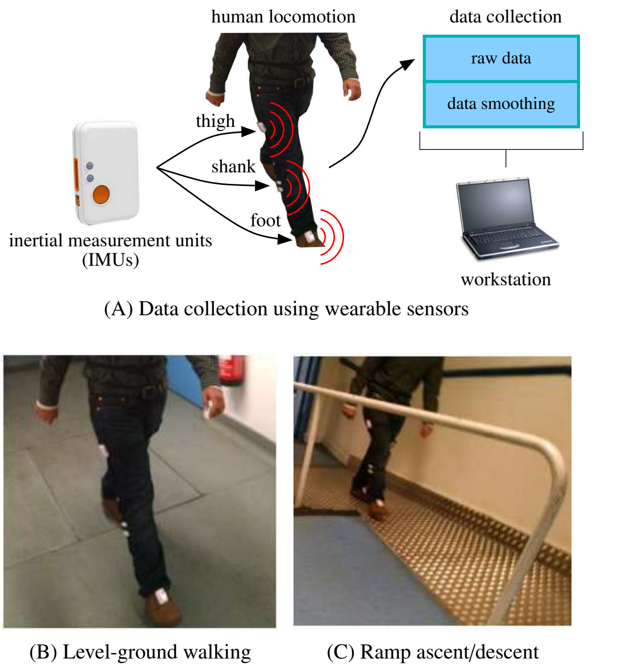


Figure 1: Human participants performing multiple walking activities for data collection. (A) IMU sensors attached to the thigh, shank and foot of healthy participants. (B) Level-ground walking activity on a flat cement surface. (C) Ramp ascent and descent activities on a metallic ramp with a slope of 8.5 deg. Participants were asked to repeat ten times each of walking activity.

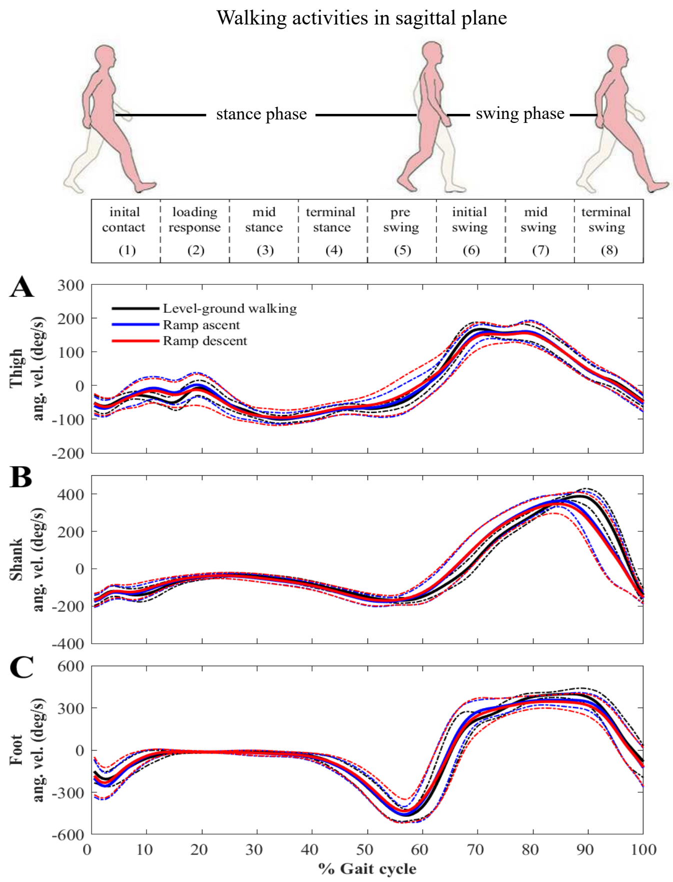


Figure 2: Angular velocity signals from level-ground walking, ramp ascent and descent activities, represented by black, blue and red colour curves. The data were collected from three IMUs attached to (A) the thigh, (B) shank and (C) foot of healthy participants. Solid lines show the mean angular velocities for each walking activity, while dashed-lines represent the standard deviation. (top) Gait cycle divided into eight events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing. These gait events are employed to determine the state of the human body during the gait cycle of the walking activity.

3. Methods

3.1. Participants and measurements

Twelve healthy male subjects were recruited to participate in this investigation. These subjects did not present any gait abnormality, orthopedic and neurological pathology. Subjects' ages ranged between 24 and 34 years old, heights between 1.70 m and 1.82 m, and weights between 75.5 kg and 88 kg.

Angular velocity signals were employed for training and testing the proposed adaptive BasIS system. These signals were collected from three IMUs, from Shimmer Inc., attached to the thigh, shank and foot of participants. Here, the angular velocity signals are processed and analysed by a workstation connected to the IMU sensor through wireless communication. In addition, two foot pressure insoles, built with piezoresistive sensors, were used to detect the beginning and end of gait cycles. Figure 1A depicts the data collection process using multiple IMUs attached to lower limb of participants. This type of wearable sensors provide a suitable platform for both, monitoring of human motion and development of assistive and rehabilitation devices, e.g., wearable soft ankle-foot robots [44].

Participants were asked to walk at their self-selected walking speed while wearing three IMUs attached to their lower limbs. Each participant completed ten repetitions of three locomotion modes; level-ground walking, ramp ascent and ramp descent. For level-ground walking, a flat cement surface was employed, while ramp ascent and descent were performed on a metallic ramp with a slope of 8.5 deg (see Figures 1B and 1C). Angular velocity signals were systematically collected with a sampling rate of 100 Hz from each IMU. These signals were prepared and stored in an appropriate format for their analysis using the proposed method for recognition of walking activities.

3.2. Signal processing and data preparation

Angular velocity signals, collected from all walking activities, were preprocessed by a second-order Butterworth filter with a cut-off frequency of 10 Hz. The gait cycles were segmented using a combination of foot pressure insoles and a threshold crossing method. Figure 2 shows the angular velocities measured from the thigh, shank and foot for level-ground walking, ramp ascent and descent. Solid and dashed lines represent mean angular velocities and standard deviations, respectively.

The filtered data from the thigh, shank and foot were concatenated into column format to build training and testing datasets for their subsequent analysis. An example of filtered data from a gait cycle is shown in Figures 2A, 2B and 2C, which were used for training the adaptive BasIS method for recognition of walking activities. The gait cycle was also divided into eight events (initial contact, loading response, mid stance, terminal

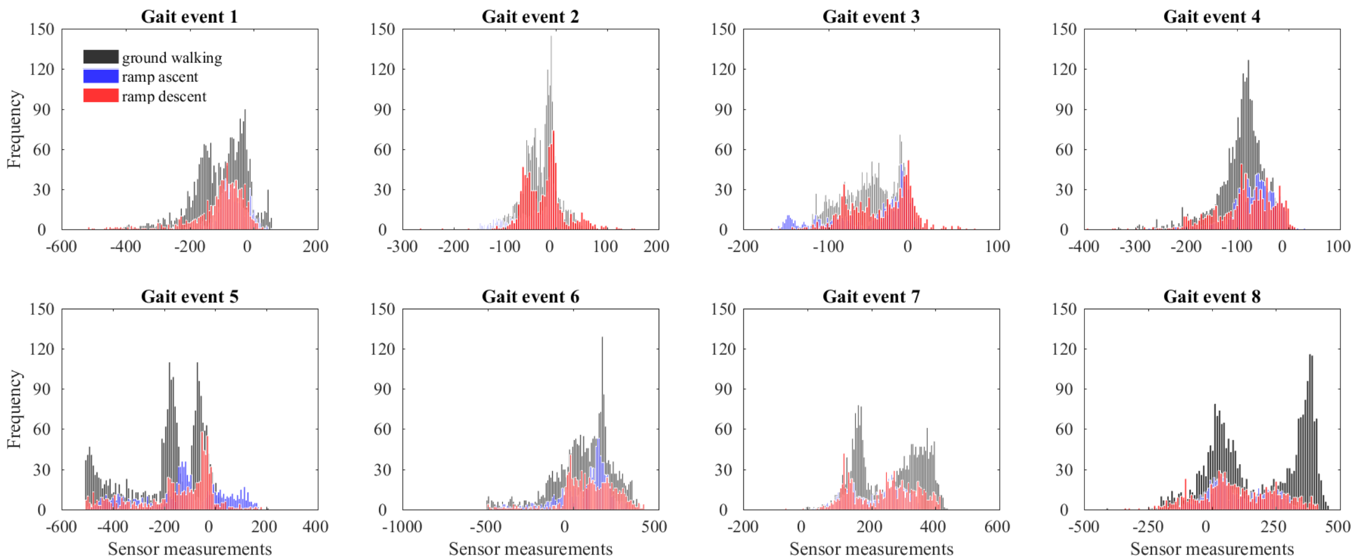


Figure 3: Histograms used by the method for recognition of walking activities and gait phases. These plots show the histograms from three walking activities performed by participants wearing IMU sensors attached to their lower limbs. Level-ground walking, ramp ascent and ramp descent activities are represented by black, blue and red colours. These plots represent the eight gait events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing) that compose the stance (event 1 to event 5) and swing (event 6 to event 8) phases of the gait cycle (see Figure 2).

stance, pre-swing, initial swing, mid swing and terminal swing) and two phases (stance and swing), for recognition of the state of the human body at specific moments during the walking activity (see Figure 2). This data format was employed for training the recognition method described in Section 3.3.

3.3. Bayesian inference system

A Bayesian Inference System (BasIS), composed of a probabilistic formulation and a sequential analysis method, is developed to accurately recognise different walking activities and gait events performed by humans.

3.3.1. Bayesian update

The inference system uses a Bayesian formulation that recursively updates the posterior probability from the product of the prior probability and likelihood estimated over time. Here, the following notation is used:

- $c_n \in C$ is a class from the set C composed of a walking activity and gait event pair.
- n denotes a specific perceptual class from the total number of classes N.
- z represents the measurements collected from the wearable sensors attached to the human body.

Then, the Bayesian formulation for recognition of walking activities and gait events is as follows:

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

where $P(c_n|z_t)$ and $P(z_t|c_n)$ are the posterior probability and likelihood at time t. The prior probability for time $t > 0$, represented by $P(c_n|z_{t-1})$, is updated with the posterior probability estimated at time $t-1$. Each class c_n is defined by a (u_k, v_l) pair, where u_k with $k = 1, 2, \dots, K$ and $l = 1, 2, \dots, L$ are walking activities and gait events, respectively. Here, $K = 3$ and $L = 8$ represent the three walking activities (level-ground walking, ramp ascent and ramp descent) and eight gait events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing) that compose the gait cycle. The measurements z_t are collected from the wearable sensors attached to the lower limbs of participants.

3.3.2. Prior

The prior probability distribution for the initial time $t = 0$ is assumed to be uniformly distributed for all the walking activities and gait events. The prior is defined as follows:

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

where $P_{\text{flat}}(c_n)$ is the flat or uniform distribution probability with sensor observations z_0 at time $t = 0$. The number of classes c_n or (u_k, v_l) pairs is represented by the variable N.

3.3.3. Likelihood estimation

Angular velocity signals are acquired from three IMU sensors $S_{\text{sensors}} = 3$ attached to the thigh, shank and foot of participants. These signals are used to construct the measurement model with a nonparametric approach based on histograms. Figure 3 shows the built histogram used to evaluate each observation z_t at time t, and estimate the likelihood of a perceptual class c_n. The measurement model is represented as follows:

$$P_s(b|c_n) = \frac{h_{s,n}(b)}{\sum_{b=1}^{N_{\text{bins}}} h(b)} \tag{3}$$

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 angular velocity information into $N_{\text{bins}} = 100$ intervals. The values are normalised by $\sum_{b=1}^{N_{\text{bins}}} h(b)$ to have proper probabilities that sum to 1.

The likelihood of the observation z_t at time t, by evaluating Equation (3) over all sensors, is obtained as follows:

$$\log P(z_t|c_n) = \sum_{s=1}^{S_{\text{sensors}}} \frac{\log P_s(l_s|c_n)}{S_{\text{sensors}}} \tag{4}$$

where l_s is the sample from sensor s, and $P(z_t|c_n)$ is the likelihood of the observation z_t given a perceptual class c_n. Properly normalised values are ensured using the marginal probabilities conditioned on previous observations as follows:

$$P(z_t|z_{t-1}) = \sum_{n=1}^{N} P(z_t|c_n)P(c_n|z_{t-1}) \tag{5}$$

3.3.4. Marginal walking activity and gait events

The posterior probabilities for the perceptual class c_n, that corresponds to a (u_k, v_l) pair, are the joint distributions over walking activities u_k and gait events v_l joint classes. Then, the beliefs over individual walking activity and gait event perceptual classes are given by the following marginal posteriors:

$$P(u_k|z_t) = \sum_{l=1}^{L} P(u_k, v_l|z_t) \tag{6}$$

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

with the posterior for walking activity classes, $P(u_k|z_t)$, summed over all gait event classes, and the posterior for gait event classes, $P(v_l|z_t)$, summed over all walking activity classes.

3.3.5. Stop rule and decision making

The recursive accumulation of evidence performed by the BasIS system, stops once a belief threshold is exceeded. This action triggers the decision making process to estimate the perceptual class $\hat{c}$ at time t, represented by the estimated walking activity and gait event $(\hat{u_k}, \hat{v_l})$ pair. This process is performed using the *maximum a posteriori* (MAP) estimate as follows:

$$\begin{aligned} &\text{if any } P(u_k|z_t) > \beta_{\text{threshold}} \text{ then} \\ &\quad \hat{u_k} = \arg\max_{u_k} P(u_k|z_t) \end{aligned} \tag{8}$$

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

where the belief threshold $\beta_{\text{threshold}}$ is employed to control the confidence of the BasIS system and the desired accuracy for the recognition process. The MAP estimate takes the class with the maximum value from the posterior probability distribution. Here, the set of belief thresholds $\beta_{\text{threshold}} = [0.0, 0.5, \ldots, 0.99]$ is used to observe their effects on both, the accuracy and decision time for recognition of walking activities and gait events.

The processes of the BasIS system are shown in Figure 4A with a layered control architecture composed of physical, perception and decision layers. The physical layer contains the sensation and data preparation processes, which receive data from IMU sensors. Next, the perception layer processes and analyses the data using the Bayesian formulation. This process iteratively accumulates evidence until the belief threshold is exceeded. Then, a decision for the most probable class is made by the decision layer. The decision from the BasIS system can be used to control tasks and actions performed by autonomous systems, e.g., assistive robots, human-robot interaction and robot manipulation. Robot control requires the interaction of high-level controllers, e.g., perceptual and decision systems, with low-level controllers. Nevertheless, this work has been focused on the research of high-level controllers only.

The BasIS system assumes an initial uniform prior probability distribution (all classes are equally probable) for each decision process. However, decisions also use information and knowledge learned from previous events, generating a non-uniform initial prior. This process contributes to attain accurate and fast decisions. In Section 3.4 the BasIS system is extended with an approach to initialise the prior probability with a non-uniform distribution, based on the information and knowledge learned from decisions made over time.

3.4. Adaptive action-perception

The BasIS method, presented in Section 3.3, is extended with an adaptive action-perception loop for recognition and prediction of gait events. Thus, an adaptive BasIS method, using a weighted combination of current observations and information learned from previous events, is proposed to initialise the prior probability for each decision process as follows:

$$P(c_n|z_\tau) = \alpha_\tau P_{\text{predicted}}(c_n|z_\tau) + (1 - \alpha_\tau)P_{\text{flat}}(c_n) \tag{10}$$

where the combination of the predicted and uniform probability distributions, $P_{\text{predicted}}(c_n|z_\tau)$ and $P_{\text{flat}}(c_n)$, is weighted by the parameter $\alpha \in \{0, \ldots, 1\}$. This weighted combination provides the prior distribution $P(c_n|z_\tau)$ that initialises the new decision process τ for recognition of gait events. The parameter α, in Equation (10), controls the contribution from each information source, allowing the BasIS method to autonomously adapt according to the accuracy of predictions and decisions made.

The predicted probability distribution is estimated by the observation of transitions between gait events (eight events, see Figure 2) for each walking activity, as follows:

$$P_{\text{predicted}}(c_n|z_\tau) = P(u_k, v_l + \Delta|z_{\tau-1}) \tag{11}$$

$$\Delta = \hat{c}_\tau - \hat{c}_{\tau-1} \tag{12}$$

where $\Delta \in \{0, \ldots, 8\}$ is the learned parameter that observes how transitions of gait events occur between previous, $(\hat{c}_{\tau-1})$, and

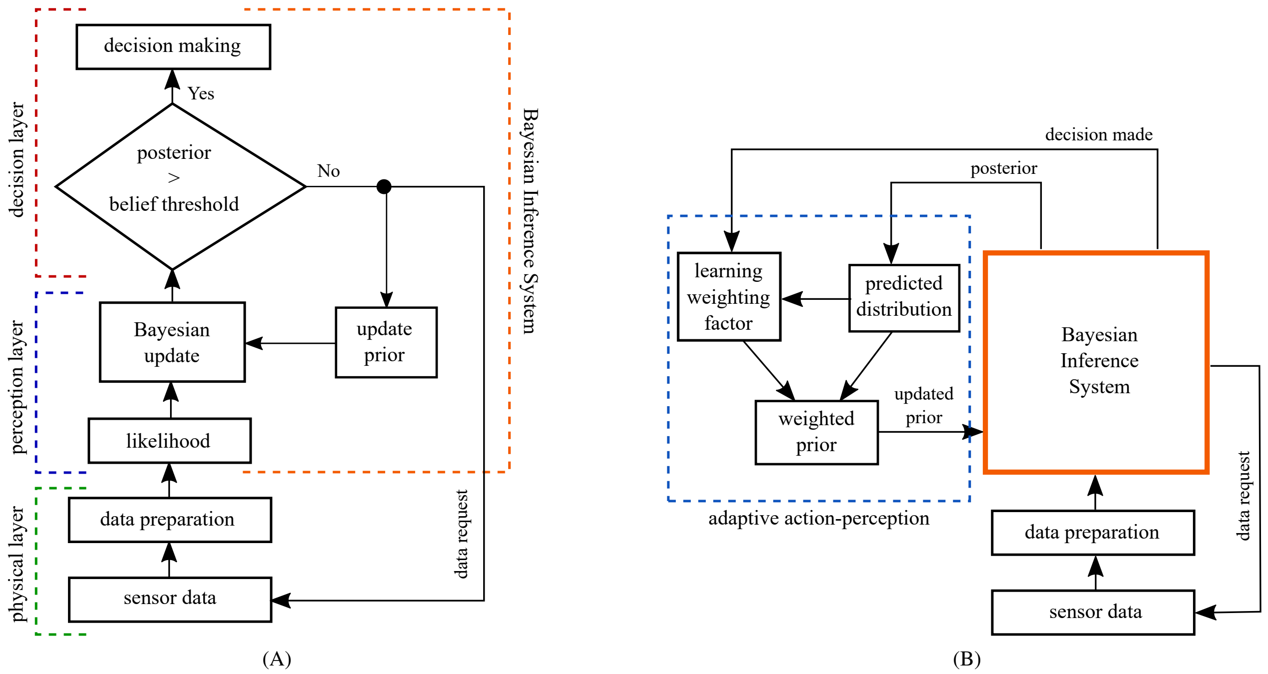


Figure 4: (A) Layered control architecture that implements the BasIS system for recognition of walking activities and gait events. This architecture is divided into physical, perception and decision layers. The physical layer interacts directly with the environment, e.g., the human and wearable devices, and it is responsible for data collection. The data received from IMU sensors are prepared in the appropriate format for their analysis. The perception layer implements the Bayes update process based on the combination of prior knowledge and the likelihood. The decision layer evaluates the posterior probability at each time step, in order to evaluate whether more sensor measurements are required or there is enough information to made a decision. (B) Adaptive BasIS system that, based on the implementation of the adaptive action-perception approach, allows to make predictions and perform a weighted combination of information sources to improve both accuracy and speed for recognition of ADLs. The weighting factor is learned based on the accuracy of decisions made by the inference system. Thus, the adaptive action-perception module allows the BasIS system to autonomously adapt its performance according to the observed accuracy of decisions made over time.

current, ($\hat{c}_\tau$), decisions made, estimating the probability distribution for the next gait events. Then, the MAP estimate is used to obtain the most probable predicted class, $\tilde{c}_\tau$, from the predicted distribution $P_{\text{predicted}}(c_n|z_\tau)$ as follows:

$$\tilde{c_\tau} = \arg\max_{c_n} P_{\text{predicted}}(c_n|z_\tau) \tag{13}$$

The accuracy of the predicted class, $\tilde{c}_\tau$, is evaluated to control the amount of evidence to be used from the predicted and uniform probability distributions. The resulting combination of information is used initialise the prior distribution for the new decision process (see Equation (10)). The evaluation of the predicted class is as follows:

$$\xi_\tau = (\beta_{\text{threshold}} - (\hat{c}_\tau - \tilde{c}_{\tau-1})) \tag{14}$$

where ξ_τ is the predicted distribution accuracy, which is the difference between the predicted class at previous decision process, $\tilde{c}_{\tau-1}$, and the actual perceived class, $\hat{c}_\tau$, bounded by the belief threshold $\beta_{\text{threshold}}$. Then, ξ_τ is employed to adapt the weighting parameter α_τ as follows:

$$\alpha_\tau = \left(\frac{\tau-1}{\tau}\right)\alpha_{\tau-1} + \left(\frac{1}{\tau}\right)\xi_\tau \tag{15}$$

Thus, the updated weighting parameter α_τ is used to assign or give more relevance to the source of information that is expected to provide more accurate results. This means that the updated prior in Equation (10) will depend more on the predictions if they have been reliable in previous decisions made. Otherwise, the updated prior will approximate to a uniform distribution (similar to the prior used in Section 3.3) reducing the probability to make inaccurate decisions. Overall, this approach extends the BasIS system by intelligently using information and knowledge learned from previous events. This process allows the recognition system to properly behave according to the iterative observation and interaction with the environment. Figure 4B shows the steps performed by the adaptive action-perception method and their integration with the BasIS system.

4. Results

The BasIS system and the adaptive action-perception method are validated with experiments for recognition of walking activities and prediction of gait events. These experiments use training and testing datasets from IMU sensors attached to the lower limbs of participants (see Section 3.1).

4.1. Recognition of walking activities and gait events

The first experiment validates the accuracy and speed of the BasIS system for recognition of three walking activities; level-ground walking, ramp ascent and ramp descent. In addition, the gait cycle from each walking activity is divided into eight segments for recognition of gait events. Angular velocity signals, employed for training and testing the proposed method,

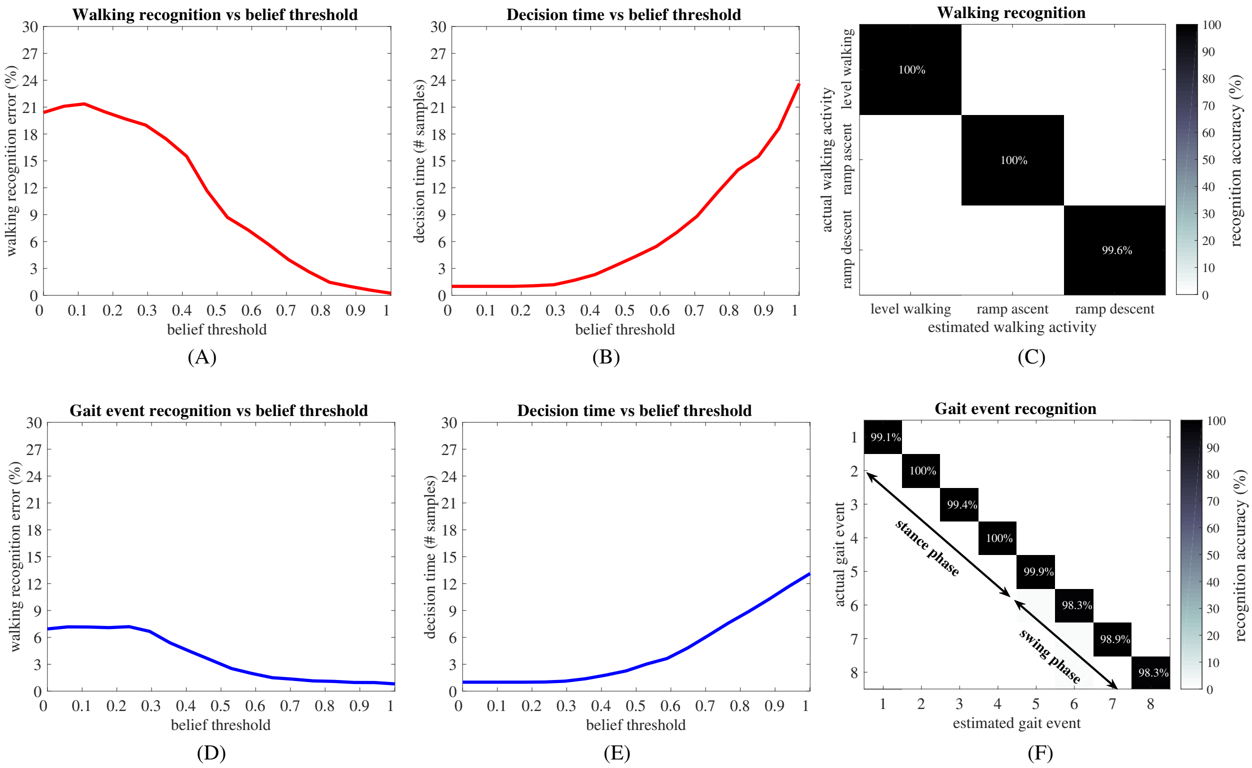


Figure 5: Recognition of walking activities and gait events with the BasIS system. (A) Mean error of 0.13% for recognition of walking activities (red colour curve). (B) Mean decision time for recognition of walking activities (red colour curve), with 24 sensor samples (240 ms) needed to achieve the highest accuracy. (C) Confusion matrix with the recognition accuracy for each walking activity (level walking, ramp ascent and ramp descent). (D) Mean error of 0.80% for recognition of gait events (blue colour curve). (E) Mean decision time for recognition of gait events (blue colour curve), where 13 sensor samples (130 ms) are required for the highest accuracy. (F) Confusion matrix for recognition of stance and swing phases composed of eight gait events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing.

are collected from three IMU sensors attached the thigh, shank and foot of participants while walking (see Figure 2).

For recognition of walking activities and gait events the BasIS system was prepared with the variables $K = 3$ and $L = 8$, respectively. The belief threshold, $\beta_{\text{threshold}}$, was used to evaluate the accuracy and decision time for different levels of confidence employed by the recognition method. The accuracy and speed of the BasIS system were tested by randomly drawing samples from the testing datasets. This process was repeated 10,000 times for each threshold value in $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. The results of recognition accuracy for walking activities against belief threshold are shown in Figure 5A. The recognition accuracy (red colour curve) is gradually improved from a mean error of 21% to a mean error of 0.13% with thresholds $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$, respectively. The plot of decision time against belief threshold, in Figure 5B, shows the speed of the recognition method to make a decision. The results show that decision time (red colour curve) gradually increases from a mean of 1 to 24 sensor samples with $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$, respectively. The data collected at a sampling rate of 100 Hz (10 ms per sample), indicate that the BasIS system requires a mean of 240 ms to achieve the highest accuracy of 99.87% for recognition of walking activities.

Recognition results for gait events against belief threshold are shown in Figure 5D, where a gradual improvement from a mean error of 7% to 0.8% is observed with $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$, respectively. The results of decision time against belief threshold, show a gradual increment in the time needed to make a decision with large belief thresholds (Figure 5E). The BasIS method requires a mean of 13 sensor samples, with $\beta_{\text{threshold}} = 0.99$, to achieve the highest accuracy of 99.20,% for recognition of gait events. Thus, the proposed recognition method needs a mean of 130 ms to identify the gait event for the current walking activity. The accuracy for recognition of individual walking activities and gait events is shown by the confusion matrices in Figures 5C and 5F, where white and black colours represent low and high accuracy, respectively.

The experiments for recognition of walking activity and gait event were repeated adding Gaussian noise to sensor measurements, with a signal-to-noise ratio of 50 dB. The noise was added to a sensor randomly selected for each decision process performed during the walking activity. This means that the Gaussian noise was not applied to the same sensor during the walking cycle, but randomly applied through all sensors. This process is important to observe the impact, in accuracy and speed, of the recognition method when a sensor is noisy or presents a malfunction. Figures 6A and 6B show the results in accuracy and speed against belief threshold for recognition of walking activities. These plots present the minimum recognition error of 0.33% (accuracy of 99.67%) and decision time

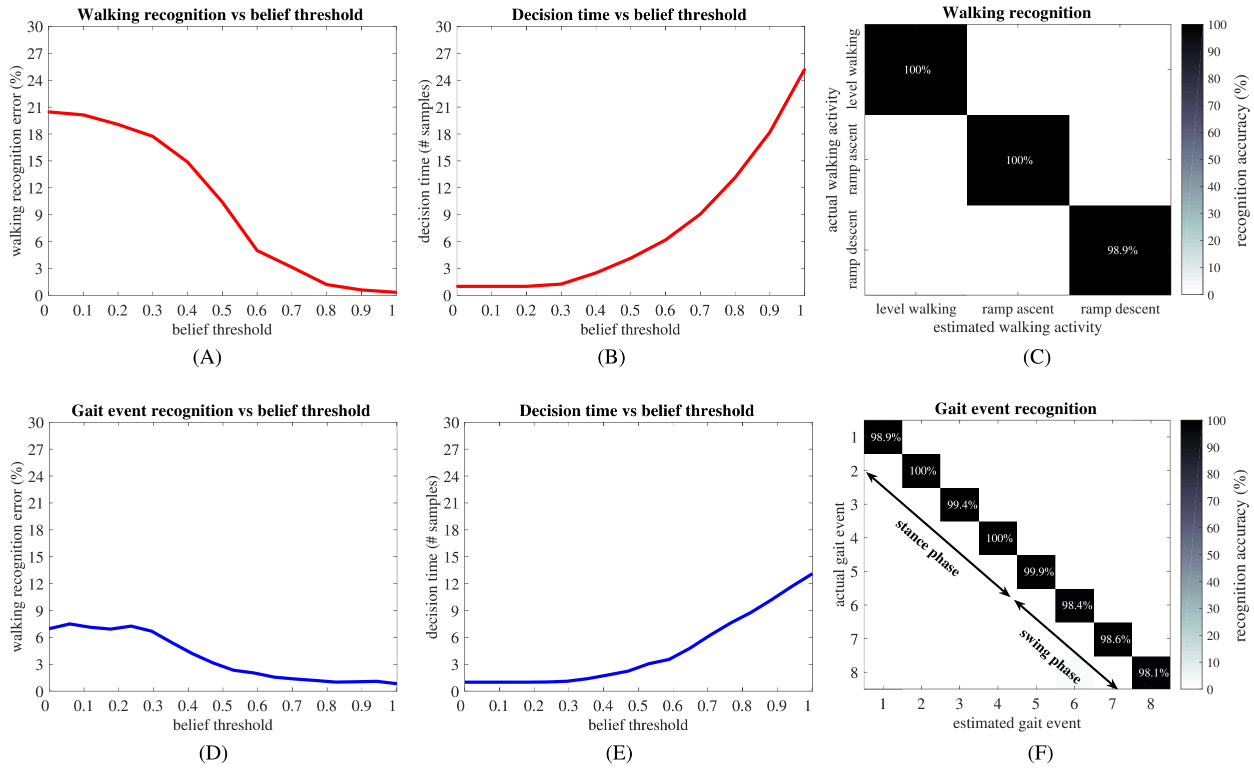


Figure 6: Recognition of walking activities and gait events with Gaussian noise, and signal-to-noise ratio of 50 dB, added to sensor measurements. For this analysis, the noise was added to a sensor randomly selected for each decision process performed during the walking activity. (A) Mean error of 0.33% for recognition of walking activities (red colour curve). (B) Mean decision time for recognition of walking activities (red colour curve), with 25 sensor samples (250 ms) needed to achieve the highest accuracy. (C) Confusion matrix with the recognition accuracy of each walking activity (level walking, ramp ascent and ramp descent). (D) Mean error of 0.82% for recognition of gait events (blue colour curve). (E) Mean decision time for recognition of gait events (blue colour curve), where 13 sensor samples (130 ms) are required for the highest accuracy. (F) Confusion matrix for recognition of stance and swing phases composed of eight gait events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing, 8) terminal swing.

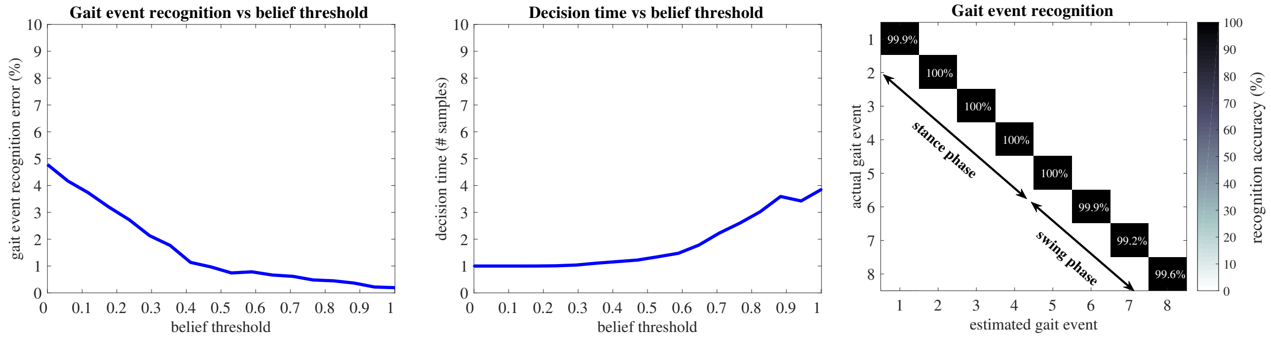
of 25 samples (250 ms). The confusion matrix in Figure 6C shows that the ramp descent activity was slightly affected by noisy measurements. Figures 6D and 6E present the accuracy and speed against belief threshold for recognition of gait events, where the minimum error of 0.82% (accuracy of 99.18%) and decision time of 13 samples (130 ms) were achieved. Figure 6F shows a slight reduction in accuracy for the initial contact, mid swing and terminal swing events. Overall, these results demonstrate the capability of the BasIS system to keep a robust performance in the presence of noisy sensor measurements.

4.2. Recognition and prediction of gait events

The adaptive BasIS system is validated with experiments for recognition and prediction of gait events. For these experiment, random samples were drawn from the testing datasets obtained from IMU sensors attached to the lower limbs of participants. This process was repeated 10,000 times for each threshold in $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. For each walking cycle, the adaptive BasIS system observed the behaviour of the signals from the IMUs. This observation process allowed to autonomously decide how to update the prior distribution (learning the parameters Δ and α) for each gait event.

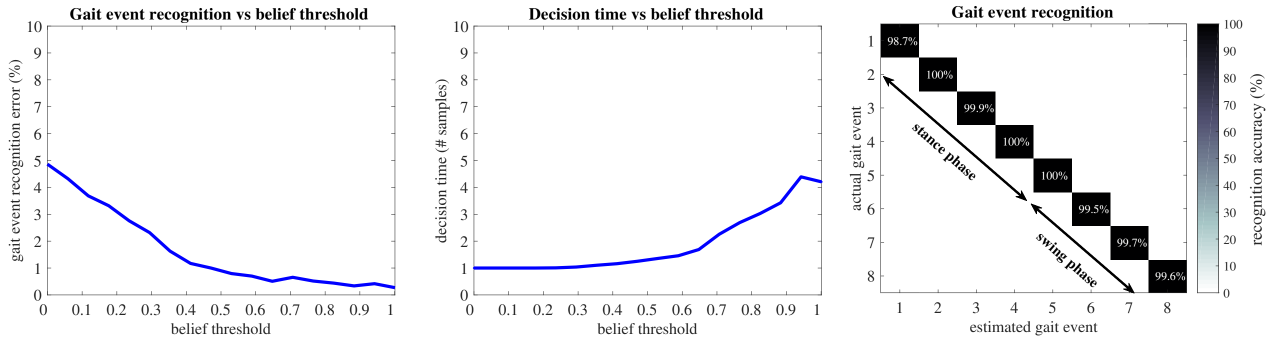
The results of gait event recognition against belief threshold are shown in Figure 7A. The adaptive BasIS system achieved high recognition accuracy with small threshold values. Here, $\beta_{\text{threshold}} = 0.5$ was enough to obtain an accuracy of 99.25% (error of 0.75%), while the highest accuracy of 99.82% (error of 0.18%) required $\beta_{\text{threshold}} = 1.0$. An improvement in recognition speed was also achieved, where only a mean of 4 sensor samples (40 ms) was required for the highest accuracy of 99.82% (see Figure 7B). These results indicate that the adaptive BasIS approach improves both, accuracy and decision time, over the results obtained with the non-adaptive BasIS system presented in Section 4.1. The recognition accuracy for individual gait events is shown in Figure 7C, where white and black colours represent low and high accuracy, respectively.

The recognition of gait events, with the adaptive BasIS method, was repeated adding Gaussian noise to sensor measurements, with a signal-to-noise ratio of 50 dB. The noise was added to a sensor randomly selected for each decision process during the walking activity. This means that the Gaussian noise was randomly moved through all the sensors during the walking cycle. This process permitted to observe the performance of the adaptive BasIS method in the presence of noisy measurements. The results in Figure 8A show the accuracy for recognition of gait events with a minimum error of 0.27% (accuracy of 99.73%), which presents a slight accuracy reduction of 0.09%. The noise added to sensor measurements did not affect the decision time



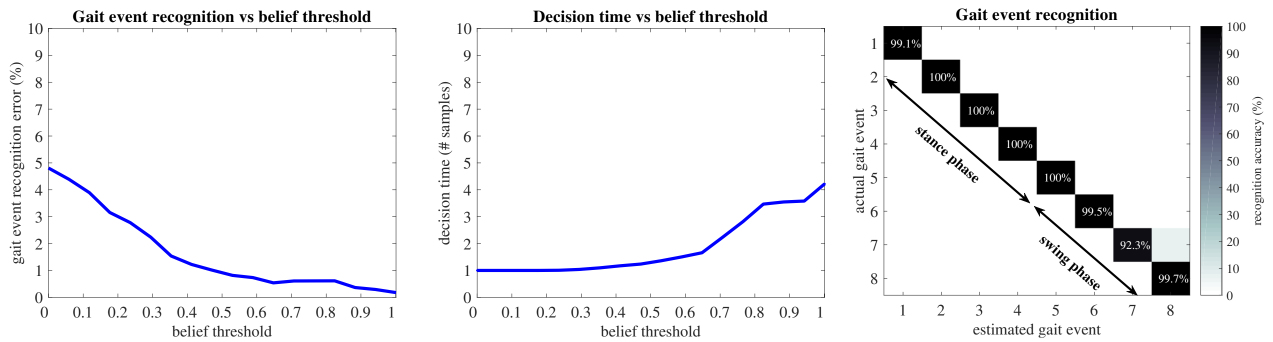
(A) (B) (C)

Figure 7: Recognition of gait events with the adaptive BasIS system. (A) The mean recognition error gradually decreases for large belief thresholds achieving the smallest error of 0.18%. (B) Large confidence levels show a gradual increment in decision time, where 4 samples (40 ms) are needed for the highest recognition accuracy. (C) Confusion matrix for recognition of stance and swing phases composed of eight gait events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing.



(A) (B) (C)

Figure 8: Recognition of gait events with the adaptive BasIS system employing Gaussian noise, with signal-to-noise ratio of 50 dB, to generate noisy sensor measurements. For this analysis, the noise was added to a sensor randomly selected for each decision process during the walking cycle. (A) The mean recognition error gradually decreases for large belief thresholds achieving the smallest error of 0.27%. (B) Large confidence levels show a gradual increment in the decision-making time, where 4 samples (40 ms) are needed for the highest recognition accuracy. (C) Confusion matrix for recognition of stance and swing phases composed of eight gait events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing, 8) terminal swing.



(A) (B) (C)

Figure 9: Recognition of gait events with the adaptive BasIS system using Gaussian noise to generate noisy sensor measurements. In this experiment, the noise was added to one sensor randomly selected for the complete walking cycle. This means that the Gaussian noise was applied to the same sensor during all the walking cycle, and then, another sensor was randomly selected for the next walking cycle. (A) The mean recognition error gradually decreases to the smallest error of 0.178% for large belief thresholds. (B) Large confidence levels show a gradual increment in the mean decision time, requiring 4 samples (40 ms) to achieve the highest recognition accuracy. (C) Confusion matrix for recognition of stance and swing phases composed of eight gait events; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing, 8) terminal swing.

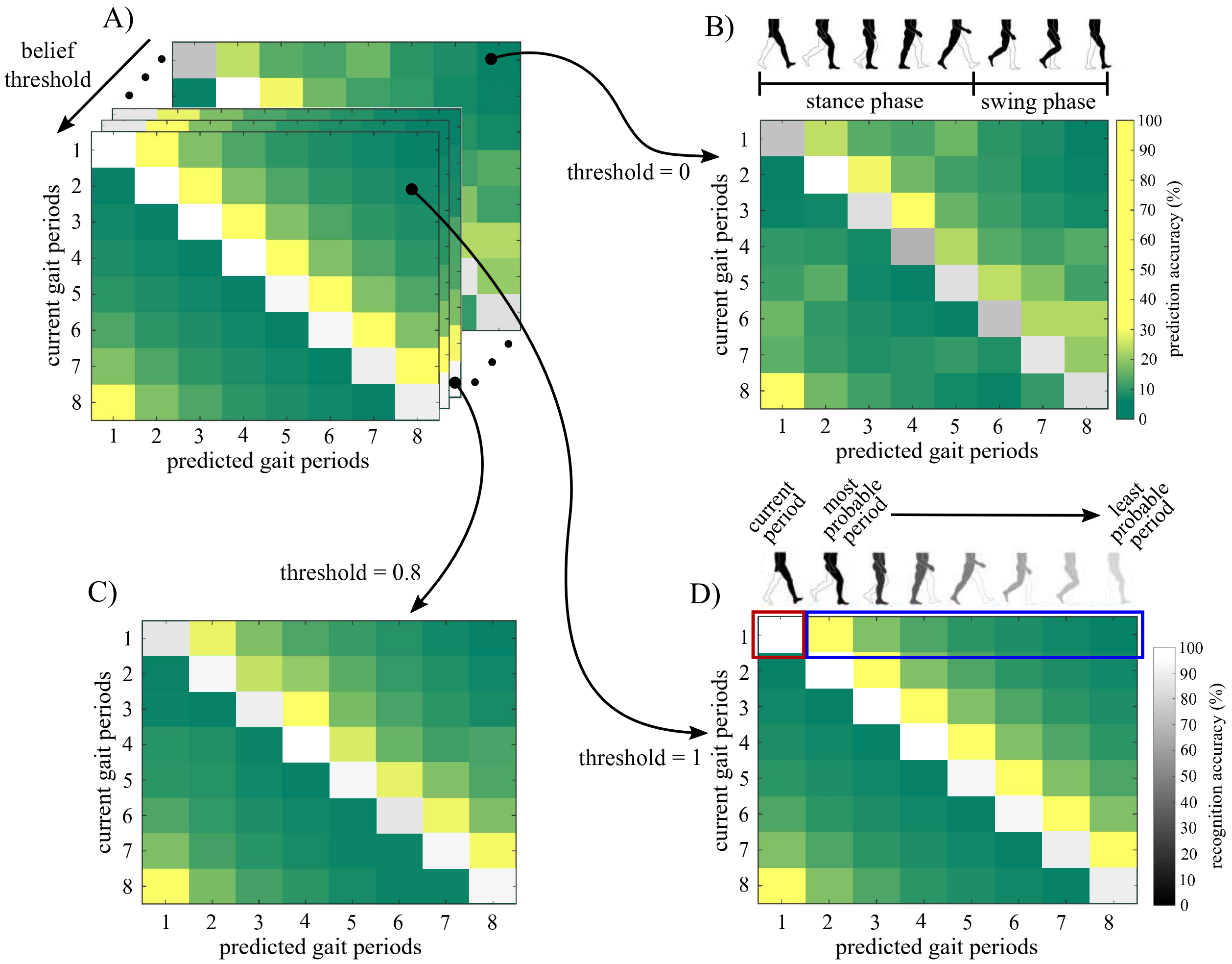


Figure 10: Confusion matrices with the mean recognition and prediction accuracy of each gait event; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing. Recognition of current gait events is shown in the main diagonal of each confusion matrix, where black and white colours represent low and high accuracies. Prediction of the next most probable gait events, for three walking activities, is shown in green and yellow colours, which represent low and high accuracies. (A) Recognition and prediction results of gait events for different belief thresholds, where y axis represents the current gait event, and x axis represents the next probable gait event. (B) Very low accuracy prediction results, which is related to the low accuracy for recognition of the current gait event achieved with the belief threshold $\beta_{\text{threshold}} = 0$. (C) Both recognition and prediction of gait events are improved with the belief threshold $\beta_{\text{threshold}} = 0.8$. (D) Highly accurate recognition and prediction of gait events with a belief threshold $\beta_{\text{threshold}} = 1$. Plot D also shows the current event (red colour box) and the most and least probable gait events (blue colour box). For instance, in plot D when the current gait event is recognised as event 1, the next most probable gait event predicted is event 2, then event 3, then event 4 until the least probable event 8. This contrasts with the low accuracy results for recognition and predictions observed in plot B, given the low confidence of the inference system.

for recognition of gait events. Then, 4 sensor samples (40 ms) were required to achieve the highest recognition accuracy (Figure 8B). The confusion matrix in Figure 8C presents the accuracy for recognition of individual gait events. These experiments demonstrate the robustness of the adaptive BasIS system in the presence of noisy measurements.

Another experiment, where noise was added to the same sensor during the walking cycle, was performed for recognition of gait events. This time, Gaussian noise was not randomly applied through all the sensors, but applied to one sensor for the complete gait cycle. Then, the noise was added to another sensor randomly selected for the next gait cycle. The recognition of gait events achieved an error of 0.178% (accuracy of 99.82%) for the largest belief threshold (Figure 9A). A mean of 4 sensor samples (40 ms) were required to make a decision with the highest accuracy (Figure 9B). The recognition accuracy for each gait event is presented in Figure 9C. This experiment shows that the adaptive BasIS system performs accurately and fast in the presence of noisy measurements.

Prediction of gait events for different belief thresholds, averaged over all walking activities, is presented in Figure 10A. These results show the accuracy of the adaptive BasIS system to predict the next most probable gait event given the current recognised event. Rows show the current recognised event, while columns present the prediction of the next most (yellow colour) and least (green colour) probable gait events. Prediction results with $\beta_{\text{threshold}} = 0.0$ are shown in Figure 10B, where low prediction accuracy is observed. This result is related to the low accuracy achieved for recognition of current gait events, given the low confidence of the system to make a decision. In

Table 1: Comparison of the performance and capabilities offered by the adaptive BasIS system and state-of-the-art methods for recognition of walking activities and prediction of gait events

Method	Activity	# Sensors	Recognition activity		Recognition gait event		Prediction gait event	
			accuracy (%)	decision time (ms)	accuracy (%)	decision time (ms)	accuracy (%)	decision time (ms)
K-NN [45]	Level walking	2	65.85	-	-	-	-	-
Log-sum distance [46]	Level walking, ramps, stairs, sitting	9	99.0	-	-	-	-	-
Ensemble of classifiers [32]	Level walking, ramps, stairs	9	97.60	-	-	-	-	-
GMM [37]	Level walking, standing, sitting	4	100	100	-	-	-	-
SVM [30]	Level walking, ramp ascent/descent, stair	9	99	150	97	-	-	-
DBN [42]	Level walking, ramp ascent/descent, stair	13	98	300	95.25	-	-	-
ANN [47]	Level walking	32	98.78	-	-	-	-	-
LDA+DBN [48]	Level walking, ramp ascent/descent, stair	13	99.5	300	-	-	-	-
Adaptive BasIS method	Level walking, ramp ascent/descent	3	99.87	240	99.20	130	99.82	40

contrast, increments in the confidence with $\beta_{\text{threshold}} = 0.8$ and $\beta_{\text{threshold}} = 1.0$ allow the adaptive BasIS system to gradually improve the accuracy for both, recognition and prediction of gait events, as shown in Figures 10C and 10D. The red colour box in Figure 10D shows the current recognised gait event, e.g., event 1 or initial contact, while the blue colour box shows the prediction of the next most and least probable gait events. These results validate the adaptive action-perception method that, adapting the prior distribution of the BasIS system by learning the parameters Δ and α, improves the performance for recognition and prediction of gait events during the walking cycle. The predictive functionality, offered by the adaptive BasIS system, has the potential to prepare low-level controllers to act according to expected or anticipated gait events.

Similar to the adaptive BasIS system, there are some works that have achieved accurate recognition of walking activities. Table 1 summarises the performance, in accuracy and decision time, offered by state-of-the-art recognition methods. GMM achieved a recognition accuracy of 100% using 4 sensors and fixed sampling window of 100 ms. A combination of LDA and DBN achieved an accuracy of 99.5%, employing a large number of sensors and sampling window of 300 ms. Recognition of walking activity and gait event with SVM achieved accuracies of 99% and 97%, respectively. DBN, together with 13 sensors, obtained accuracies of 98% and 95.5% for recognition of activities and gait events. Even though all these methods obtained good results, the adaptive BasIS system offers the following functionalities not observed in previous works; 1) in-depth analysis for recognition of walking activities and gait events, and prediction of gait events, 2) analysis of decision time for recognition of walking activities and gait events, 3) high recognition accuracy and fast decisions, 4) small number of wearable sensors and 5) adaptive recognition of gait events based on the combination of information sources. These functionalities make the adaptive BasIS system suitable for the development of intelligent wearable robots, capable to recognise movement intent and assist humans in ADLs.

5. Discussion

Wearable robots capable to provide assistance to humans in activities of daily living, require sophisticated sensors and computational algorithms. In recent decades, sensor technology has shown a rapid progress in the development of wearable devices for collection of large and rich datasets. However, intelligent algorithms needed for fast and accurate recognition of human motion is an ingredient that still remain a challenge.

A Bayesian inference system (BasIS), together with a sequential analysis approach, was presented in this work for recognition of walking activities and gait events. This approach, inspired by studies on psychology and neuroscience, proposes that humans improve their decision accuracy by observation and accumulation of evidence [11]. Various experiments were performed with the BasIS system to validate its accuracy and speed for recognition and decision making. These aspects are important in autonomous systems, which need to be fast but also accurate. The BasIS system was able to gradually achieve high recognition accuracy of walking activities and gait events with large belief thresholds (Figure 5A and 5D). The speed needed to make a decision was also gradually increased for large belief threshold (Figure 5B and 5E). It is important to observe that the BasIS system can obtain a very high recognition accuracy but it would require more sensor measurements, which affect the speed to make a decision. Interestingly, the decision time required by the BasIS system, to achieve high accuracy, is still under the maximum time allowed for intent recognition systems [30]. The robustness of the BasIS system in the presence of noisy measurements was also tested using Gaussian noise with signal-to-noise ratio of 50 dB. In this analysis, the noise was randomly added to all sensors for each decision process during the walking cycle. High recognition accuracy and fast decision times were achieved, demonstrating the capability of the recognition method to deal with sensor noise (Figure 6). Some other advantages offered by the BasIS system are the use of non-fixed sampling windows, autonomous accumulation of evidence and decision making, recognition of gait events and phases, and the capability to deal with uncertainty from the environment. All these aspects permit to the BasIS system to be adaptable for recognition of walking activities at different speeds, but also to make fast and robust decisions in the presence of uncertainty from the changing environment [19]. It is important to note that the proposed recognition method estimates the likelihood using a nonparametric approach and raw data from wearable sensors. However, this process also can be investigated using methods for selection of key features and metric learning, with the potential to improve the likelihood estimation and recognition accuracy. For this purpose, the Logdet divergence-based metric learning (LDMLT) method offers an approach for feature selection and classification tasks, which we plan to investigate in the future work [49].

Normally, humans make sensory predictions based on what they learned from events or actions performed previously. The combination of predictions with current sensory observations allows humans to make better decisions, compared to the case when decisions rely on current sensory information alone [50]. For that reason, the BasIS system was extended with an action-perception method to make predictions of next events, based on the observation of previous events. This approach also performs a weighted combination of predictions and current sensor observations. This novel adaptive BasIS system was implemented to recognise and predict gait events for different walking activities. This method was capable to both, observe its decisions made and learn the transition of gait events over time, which were used for prediction of the next most probable gait event during the walking cycle. Learning the appropriate weighting value for combination of predictions and current observations is essential, given that the weight should be higher for the source of information that is more reliable. For this learning process, the adaptive BasIS system evaluates the distance between the decision made, at current time, and the prediction made at previous time. In other words, the more accurate the predictions the smaller the distance value. This process continually evaluates the performance of predictions, assigning more weight to the source of information that shows to be more reliable.

The validation of the adaptive BasIS system provided interesting results. First, the recognition accuracy was improved, obtaining higher accuracy with smaller belief thresholds (Figure 7A). Second, the speed for decision-making was improved requiring a mean of 4 samples only (Figure 7B). Third, the adaptive BasIS system was able to evaluate its decisions and adapt over time to ensure the best performance, making the recognition system capable to autonomously observe, predict and learn. These features permit to have a recognition system that intelligently decides what information and how much information need to be used from previous events, in order to make highly accurate decisions. The robustness of the adaptive BasIS system was also tested adding Gaussian noise with signal-to-noise ratio of 50 dB. For this experiment, the noise was randomly added to all sensors for each decision process during the walking cycle. The experiments showed that the accuracy and decision time were not highly affected, ensuring a reliable prediction of gait events during the gait cycle (Figure 8). In another experiment, the adaptive BasIS system was tested adding noise to one sensor randomly selected for the walking cycle. Then, for the next walking cycle, the noise was added to another randomly selected sensor. The results demonstrated that the performance of the adaptive BasIS system, in accuracy and decision time, was not affected compared to the case where noise was not added to sensor measurements (Figure 9).

Interestingly, predictions obtained with the adaptive BasIS system not only allow to know what is the next most probable gait event, but also to know the probability for all next gait events for the complete walking cycle. The accuracy of predictions is also related to the belief threshold –for instance, low and high accuracy predictions are achieved with belief thresholds 0 and 1 respectively (Figures 10B and 10D). These results show that the adaptive BasIS system has the potential to prepare robotic systems to recognise movement intent, but also to react to anticipated events with high accuracy and speed. It is worth mentioning that the complexity of the proposed recognition method grows exponentially for very large number of classes. This is a characteristic of Bayesian methods, which is also related to the nonparametric approach used for likelihood estimation. However, previous studies have successfully demonstrated the use of Bayesian methods for exploration and recognition tasks, implemented in real time and using larger number of classes [12, 36, 51, 52]. For that reason, we consider that the high-level adaptive BasIS system, coupled to low-level and robust control approaches such as wavelet-based methods, is suitable for the development of intelligent assistive and rehabilitation robots. Specially, Haar wavelet has shown to be a robust control approach for approximation to a natural and optimal walking trajectory [53, 54]. Morlet wavelet is another method that, connected to the adaptive BasIS system, offers a tool for the design of low-level controllers to provide assistance to humans in real-time [55]. For example, the Omnidirectional Rehabilitative Training Walker offers a stable platform that, taking advantage of the adaptive BasIS system and wavelet-based methods, can provide autonomous and reliable assistance to humans according to the recognised walking activity [56].

All in all, intelligent assistive robots capable to assist humans involve complex processes with different levels of control. Here, a probabilistic and adaptive action-perception inference framework was presented for recognition of walking activities and gait events. This method has the potential to develop cognitive capabilities such as interaction, perception and decision-making, which are essential to deploy safe and reliable wearable robots to predict, adapt and assist humans in ADLs.

6. Conclusion

In this work an adaptive Bayesian inference system (BasIS), together with an action-perception method, was presented for recognition and prediction of walking activities and gait events. The adaptive BasIS system autonomously evaluates its behaviour, and adapts during walking activities, to obtain the best performance in recognition accuracy and decision time. Experiments with participants wearing IMU sensors were performed with three walking activities. The results showed that the adaptive BasIS system improves its recognition accuracy and decision time over the results achieved by a non-adaptive system. Furthermore, the proposed approach provides the prediction of the most probable gait events during walking activities. These high-level features, offered by the adaptive BasIS system, have the potential to control low-level layers, and thus, to advance the development of intelligent wearable robots that safely assist humans in their activities of daily living.

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