Proceedings Paper:

Martinez Hernandez, U orcid.org/0000-0002-9922-7912, Rubio-Solis, A, Panoutsos, G et al. (1 more author) (2017) A combined Adaptive Neuro-Fuzzy and Bayesian strategy for recognition and prediction of gait events using wearable sensors. In: IEEE International Conference on Fuzzy Systems (Fuzz-IEEE). 2017 IEEE Conference on Fuzzy Systems (Fuzz-IEEE 2017), 09-12 Jul 2017, Naples, Italy. Institute of Electrical and Electronics Engineers . ISBN 978-1-5090-6034-4

https://doi.org/10.1109/FUZZ-IEEE.2017.8015447

A combined Adaptive Neuro-Fuzzy and Bayesian strategy for recognition and prediction of gait events using wearable sensors

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***Abstract*— A robust strategy for recognition and prediction of gait events using wearable sensors is presented in this paper. The strategy adopted here uses a combination of two computational intelligence approaches: Adaptive Neuro-Fuzzy and Bayesian methods. Recognition of gait events is performed by a Bayesian method which iteratively accumulates evidence to reduce uncertainty from sensor measurements. Prediction of gait events is based on the observation of decisions and actions made over time by our perception system. An Adaptive Neuro-Fuzzy system evaluates the reliability of predictions, learns a weighting parameter and controls the amount of predicted information to be used by our Bayesian method. Thus, this strategy ensures the achievement of better recognition and prediction performance in both accuracy and speed. The methods are validated with experiments for recognition and prediction of gait events with different walking activities, using data from wearable sensors attached to lower limbs of participants. Overall, results show the benefits of our combined Adaptive Neuro-Fuzzy and Bayesian strategy to achieve fast and accurate decisions, but also to evaluate and adapt its own performance, making it suitable for the development of intelligent assistive and rehabilitation robots.**

I. INTRODUCTION

Robust autonomous systems, capable to understand human motion to provide safe and appropriate assistance, require methods for recognition of activities of daily living (ADL) [1], [2]. Walking, ramp ascent and descent activities are of particular importance, because they provide humans with independence of living and transportation to different locations across various terrains and environments [3], [4]. However, these activities require coordinated movements that become difficult to execute by elder people [5].

In recent years sensor technology and computational intelligence methods, needed to achieve robust and reliable human motion analysis, have shown rapid progress. Specifically, large progress has been observed in wearable sensors –for instance, lightweight and fast inertial measurement units (IMUs) and soft kinematic sensors [6], [7], [8]. In contrast, the deployment of computational methods that permit to perform fast and accurate human motion analysis, recognition of walking activities and prediction of gait events are still under development [9], [10], [11].

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

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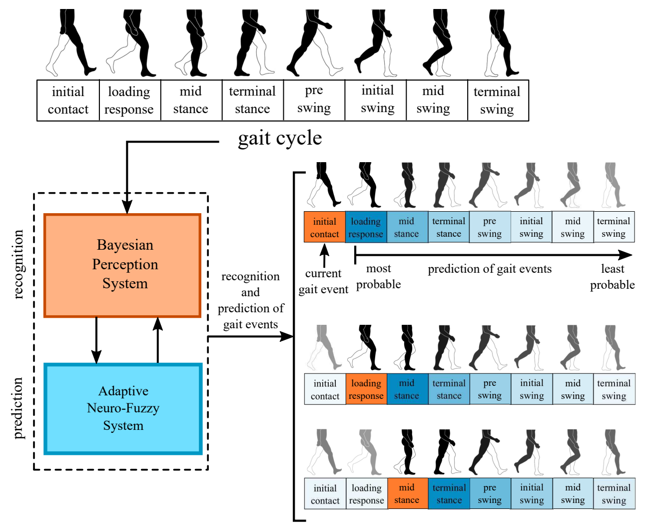


Fig. 1. Combined Adaptive Neuro-Fuzzy and Bayesian strategy for recognition and prediction of gait events in multiple walking activities.

In this work, we present a novel strategy for recognition and prediction of gait events, that combines two computational intelligence approaches: Adaptive Neuro-Fuzzy and Bayesian methods (Figure 1). This strategy extends our previous work for recognition of walking activities [12]. First, recognition of gait events is performed with a Bayesian method that has demonstrated to be robust with different applications [13], [14]. Second, prediction of gait events is based on the observation of decisions and actions made over time [15], [16], [17], which is motivated by the way in that humans make predictions according to the changes observed from their surrounding environment [18], [19]. An Adadptive Neuro-Fuzzy system is used to learn a weighting parameter, to control the amount of predicted information to be used by our Bayesian approach. Adaptive Neuro-Fuzzy systems have demonstrated to be a robust tool for fast learning and control in a large number of applications [20], [21], [22], [23]. Thus, a combination of both Adaptive Neuro-Fuzzy and Bayesian approaches, provides a reliable system that autonomously evaluates its performance to adapt to changes from the environment, and achieve better recognition and prediction results in accuracy and speed.

Our methods are implemented in a layered architecture composed of physical, perception and prediction layers. These architectures have shown to be a better approach for the development of modular, autonomous and scalable robotic systems [24]. We use this architecture to validate the performance of our method with experiments for recognition and prediction of eight gait events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing) from multiple walking activities. For these experiments we employed data collected from multiple human participants wearing three inertial measurement unit sensors, attached to their lower limbs and performing three different walking activities. Results from our experiments demonstrate the capability of our proposed strategy to both, recognise and predict gait events with high accuracy and small decision time from ADLs.

Overall, our combined Adaptive Neuro-Fuzzy and Bayesian strategy is robust, accurate and fast, which makes it suitable for wearable robots to provide safe and reliable assistance to humans in their activities of daily living.

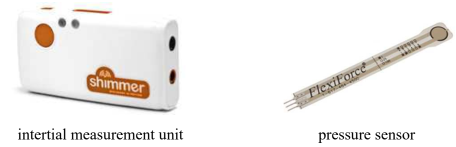
II. METHODS

A. Experimental protocol and data collection

For our investigation we used angular velocity data from multiple IMU sensors worn by twelve healthy human participants. Anthropometric data from participants are as follows: ages between 24 and 34 years old, heights between 1.70 m and 1.82 m, and weights between 75.5 kg and 88 kg.

Data from IMU sensors were systematically collected from each participant to train and test our proposed method. We employed three IMUs (Shimmer Inc.) attached to the thigh, shank and foot of participants. We also used two foot pressure insoles sensors to detect the beginning and end of each gait cycle. A sampling rate of 100 Hz was used for data collection from these sensors attached to the human body. Both wearable devices, IMU and foot pressure sensors, provide a lightweight and low cost platform for the investigation and development of human-robot interaction, assistive and rehabilitation robotic systems [25], [26]. Figure 2A shows the sensors used for systematic data collection.

Participants were asked to walk normally at their self-selected walking speed. Here, we asked the participants to perform ten repetitions of three different walking activities; level-ground walking, ramp ascent and ramp descent. Level-ground walking was performed on a flat cement surface (see Figure 2B). Both ramp ascent and descent were performed on a metallic ramp with a slope of 8.5 deg (see Figure 2C). The signals collected were processed by a second-order Butterworth filter with a cut-off frequency of 10 Hz. Figures 3A,B,C show the angular velocities from lower limbs for level-ground walking (black colour curves), ramp ascent (blue colour curves) and ramp descent (green colour curves). Solid and dashed lines represent mean angular velocities and standard deviations respectively. We divided the gait cycle for each walking activity into stance and swing phases, and eight events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing) as shown in Figure 3D. The segmentation of the gait cycle, together with our proposed strategy presented in Section II-B, allows to recognise and predict the state of the human body during a walking activity.



(A) Wearable sensors for systematic data collection

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

Fig. 2. Human performing walking activities using wearable sensors. (A) IMU and pressure sensors used for data collection. (B) Level-ground walking on a flat cement surface. (C) Ramp ascent and descent on a ramp with a slope of 8.5 deg. Participants repeated ten times each walking activity.

B. Bayesian perception system

In this work we have extended our method for recognition of walking activities presented in [12] with a set of prediction and learning modules. Recognition of gait events is performed with a Bayesian formulation together with a sequential analysis method. We use the following notation:

- C, a finite set of classes or events $N = |C|$, e.g., here it denotes set of the gait events.
- z, measurements from the wearable sensors.
- n, denotes a specific gait event from the set N.

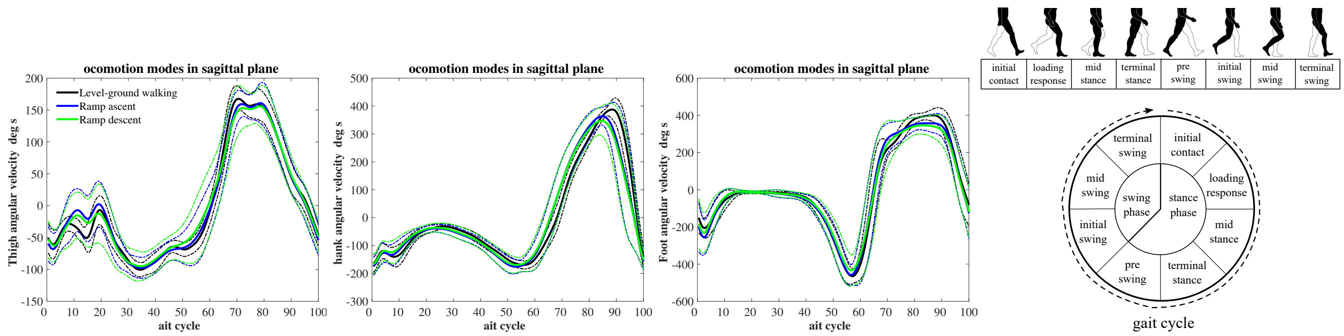
The Bayesian formulation for recognition of gait events is defined as follows:

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

where $P(c_n|z_t)$ is the posterior probability of a gait event c_n given the sensor measurements z_t at time t, and $P(z_t|c_n)$ is the likelihood of the sensor measurements z_t. We use an initial uniform prior $P(C_n|z) = 1/N$ at $t = 0$, which is updated by the posterior $P(c_n|z_{t-1})$ estimated at time $t-1$. Here, $n = 1, 2, \ldots, N$ with $N = 8$ are the gait events (see gait events in Figure 3D). The posterior in Equation 1 is used to make a decision about the gait event once a belief threshold $\beta_{\text{threshold}}$ is exceeded. The decision-making process to recognise a gait event is performed as follows:

$$\begin{gathered}\text{if any } P(c_n|z_t) > \beta_{\text{threshold}} \text{ then} \\ \hat{c} = \arg\max_{c_n} P(c_n|z_t)\end{gathered} \tag{2}$$

where the gait event $\hat{c}$ at time t is obtained using the *maximum a posteriori* (MAP) estimate. The confidence of our Bayesian system can be adjusted with the belief threshold $\beta_{\text{threshold}}$ parameter, which allows to control the recognition accuracy. The physical and perception layers in Figure 6 contain the processes for sensor data collection and Bayesian perception. For more details about the estimation of the parameters of our Bayesian perception system and its application for different tasks see [12], [27].



(A) (B) (C) (D)

Fig. 3. Angular velocity data collected from three locomotion modes; level-ground walking, ramp ascent and ramp descent represented by black, blue and green colour curves. The data were collected using three inertial measurement units (IMUs) attached to (A) the thigh, (B) shank and (C) foot of healthy human participants. Solid lines show the mean angular velocities for each locomotion mode, while dashed-lines represent the standard deviation.

Our Bayesian approach assumes an initial uniform prior for each new decision process. However, humans make decisions using knowledge and observations learned from previous events, which generate non-uniform initial priors. This contributes to attain more accurate and fast decisions, but also to predict next events. For that reason, we have extended our work with a prediction layer and an Adaptive Neuro-Fuzzy system described in the following sections.

C. Prediction of gait events

For prediction of gait events we obtain a predicted probability distribution from the observation of transitions between gait events (see Figure 3D) over time as follows:

$$P_{\text{predicted}}(c_n|z_\tau) = P(c_n + \delta|z_{\tau-1}) \tag{3}$$

where $P_{\text{predicted}}(c_n|z_\tau)$ is the predicted probability used for initialisation of the new decision-making process at time τ. $P(c_n + \delta|z_{\tau-1})$ is the posterior from the previous decision made by our Bayesian method and shifted by the parameter δ. The parameter δ is learned by observation of how transitions between gait events occur from previous $\hat{c}_{\tau-1}$ and current $\hat{c}_\tau$ decisions made over time τ. This process is performed as follows:

$$\delta = \hat{c}_\tau - \hat{c}_{\tau-1} \tag{4}$$

where $\delta \in \{0, \dots, 7\}$ according to the segmentation of the gait cycle into eight events. We use the MAP estimate to obtain the most probable predicted class $\tilde{c}_\tau$ from Equation (3) as follows:

$$\tilde{c_\tau} = \underset{c_n}{\arg\max}\, P_{\text{predicted}}(c_n|z_\tau) \tag{5}$$

To ensure reliable predictions and decisions, the accuracy of the predicted class or gait event is evaluated as follows:

$$\xi_\tau = (\beta_{\text{threshold}} - (\hat{c}_\tau - \tilde{c}_{\tau-1})) \tag{6}$$

where ξ_τ represents the accuracy of the predicted gait event estimated at previous decision time $\tau - 1$.

D. Adaptive Neuro-Fuzzy system

We implement an Adaptive Neuro-Fuzzy system, based on the ANFIS model [20] and the Takagi-Sugeno inference engine, to learn the weighting parameter α. This parameter is required to combine two sources of information and obtain the new updated prior for the initialisation of our perception system. Figure 4 shows the structure of our inference system. To speed up the learning process, the Adaptive Neuro-Fuzzy system is trained with an Adaptive Back Error Propagation (ABEP) technique and a cross-validation method using the following *ith*-membership function updating rules [21]:

$$\Delta w_i(\tau+1) = -\eta_1 \frac{\partial E_l}{\partial w_i} + \gamma \Delta w_i(\tau) \tag{7}$$

$$\Delta \sigma_i(\tau+1) = -\eta_2 \frac{\partial E_l}{\partial \sigma_i} + \gamma \Delta \sigma_i(\tau) \tag{8}$$

$$\Delta m_k^i(\tau+1) = -\eta_3 \frac{\partial E_l}{\partial m_k^i} + \gamma \Delta m_k^i(\tau) \tag{9}$$

where m, w and σ are the centre, width and fuzzy weight for the *ith*-fuzzy rule, while $E_l = \frac{1}{2}\sum_{\tau=1}^{M} (\alpha_\tau - S(x)\beta_{threshold})^2$ is the cost function error and $S(x)$ is a sigmoid function. A performance index $\Gamma_i(\tau+1) = \frac{1}{\Gamma}\sum_{l=1}^{L} E_l^2$ that monitors the adaptive approach is defined as follows:

- if $\Gamma_i(\tau+1) \geq \Gamma_i(\tau)$ Then

$$\eta(\tau+1) = h_d \eta(t), \qquad \gamma(\tau+1) = 0$$

- if $\Gamma_i(\tau+1) < \Gamma_i(\tau)$ and $\left|\dfrac{\Delta\Gamma_i}{\Gamma_i(\tau)}\right| < \theta$ Then

$$\eta(\tau+1) = h_i \eta(t), \qquad \gamma(\tau+1) = \gamma_0 \tag{10}$$

- if $\Gamma_i(\tau+1) < \Gamma_i(\tau)$ and $\left|\dfrac{\Delta\Gamma_i}{\Gamma_i(\tau)}\right| \geq \theta$ Then

$$\eta(\tau+1) = \eta(\tau), \qquad \gamma(\tau+1) = \gamma(\tau)$$

where h_d $(0 < h_d < 1)$ and h_i $(1 < h_i)$ are the decreasing and increasing factors, and θ is the threshold for the rate of

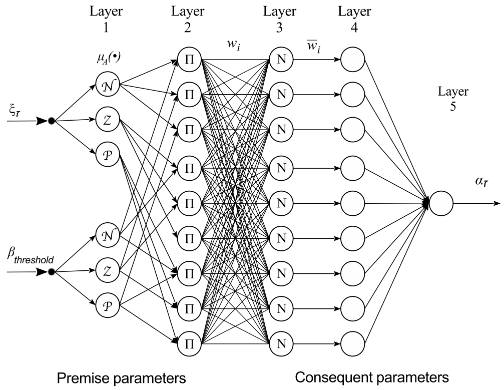


Fig. 4. Adaptive Neuro-Fuzzy system used to learn the weighting parameter α. It is composed of two inputs, one output and four hidden layers.

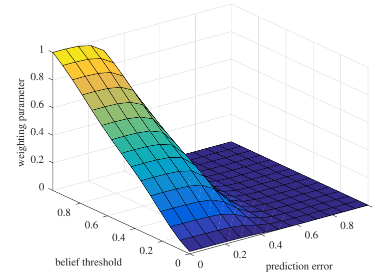


Fig. 5. Output surface obtained from the Adaptive Neuro-Fuzzy system. Our system receives two inputs, ξ_τ (prediction error) and $\beta_{\text{threshold}}$ (belief threshold), and one output α (weighting parameter).

the relative index based on the Root-Mean-Square Error. The behaviour of our inference system, given the inputs ξ_τ (prediction error) and $\beta_{\text{threshold}}$ (belief threshold), is shown by the surface plot in Figure 5. Then, the output parameter α is used to weight the combination of the predicted distribution ($P_{\text{predicted}}(c_n|z_\tau)$) and the uniform distribution ($P_{\text{flat}}(c_n)$) to obtain the new updated prior as follows:

$$P(c_n|z_\tau) = \alpha_\tau P_{\text{predicted}}(c_n|z_\tau) + (1-\alpha_\tau)P_{\text{flat}}(c_n) \quad (11)$$

where $P(c_n|z_\tau)$ is the prior distribution that initialises the new decision process performed by our Bayesian method at time τ. Equation 11 shows that our probabilistic system autonomously uses more information from the information source that is more accurate. For example, our method relies more on $P_{\text{predicted}}$ when predictions are accurate, reducing the contribution from the uniform distribution and vice versa. Notice that when $\alpha = 0$ our method behaves as our initial Bayesian method described in Section II-B. Figure 6 shows a description of our combined Adaptive Neuro-Fuzzy and Bayesian strategy using a layered control architecture composed of physical, perception and prediction layers.

III. RESULTS

We validate the performance in both, accuracy and speed, of our combined strategy with the recognition and prediction of gait events. For these experiments we use training and testing datasets collected from IMU sensors attached to the lower limbs of human participants (see Section II-A).

A. Recognition of gait events

First, we validate the accuracy and speed of our combined system with recognition of gait events for different walking activities. For this experiment we use angular velocity signals from level-ground walking, ramp ascent and ramp descent. These signals collected from the thigh, shank and foot of human participants are shown in Figure 3. The eight segments in which the gait cycle is divided, for recognition of gait events, are shown in Figure 3D.

Our combined strategy is configured with the classes C ={initial contact, loading phase, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing} and $N = 8$ that represent the gait events. We set $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$ to evaluate the recognition accuracy and decision time for different levels of confidence used by our perception method. In this experiment for recognition accuracy and speed, our method randomly draw samples from the testing dataset with 10,000 iterations for each belief threshold value in $\beta_{\text{threshold}}$. Averaged gait event recognition results over all walking activities against belief threshold are shown in Figure 7A. The recognition accuracy for gait events is gradually improved, starting with a mean error of 7% and reaching a small mean error of 0.52% using threshold values of $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$ respectively. Decision time results against belief threshold in Figure 7B shows the speed of our combined strategy to make a decision. The decision time gradually increases from a mean of 1 (10 ms) to 10 (100 ms) sensor samples with $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$ respectively. These results show that

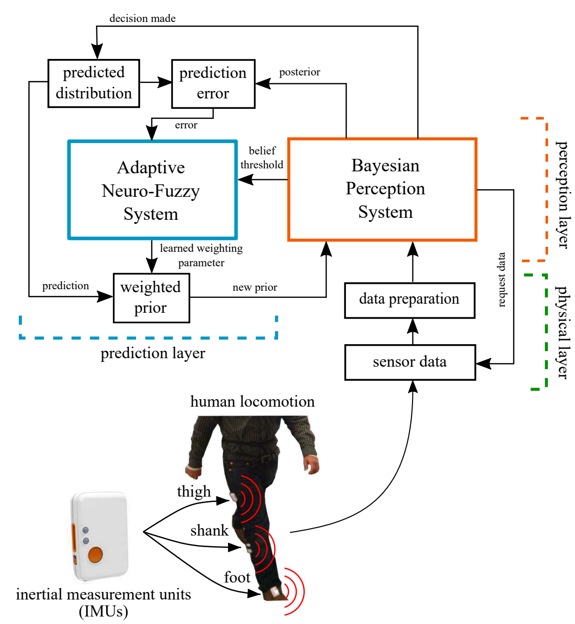
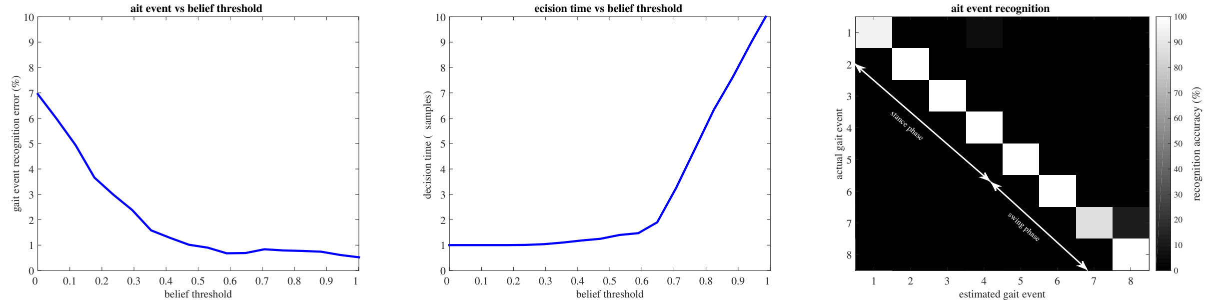
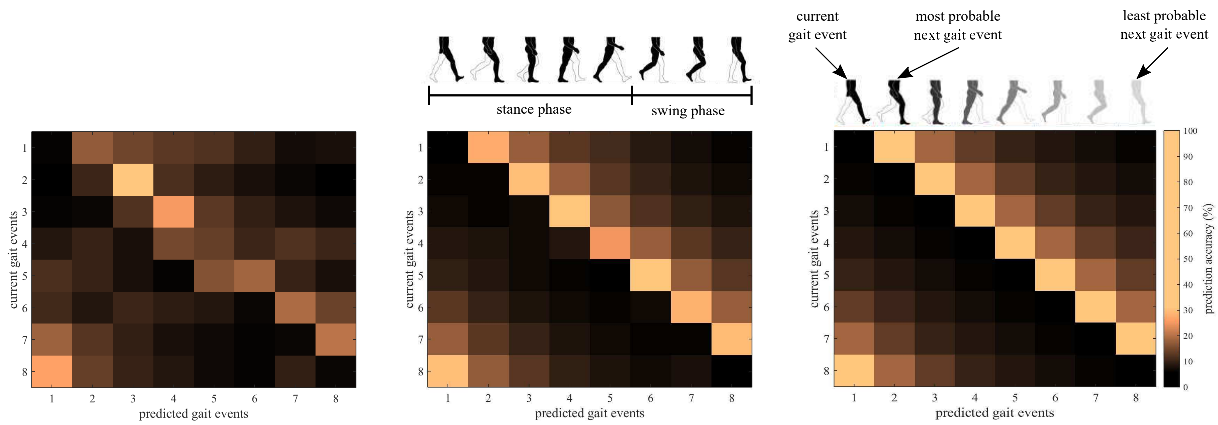


Fig. 6. Control architecture that implements our combined Adaptive Neuro-Fuzzy and Bayesian strategy. This architecture is divided in physical, perception and prediction layers. The physical layer interacts with the environment for data collection, e.g., the human and wearable devices. The data received from IMU sensors are prepared with the appropriate format for their subsequent analysis. The perception layer implements our Bayesian method to update a posterior from the prior and likelihood. The prediction layer provides the predicted probability and adapts the prior probability with our Adaptive Neuro-Fuzzy system which learns a weighting parameter for the combination of information sources.



(A) (B) (C)

Fig. 7. Recognition of gait events with our combined Adaptive Neuro-Fuzzy and Bayesian strategy. (A) Mean recognition error of gait events gradually decrease for large belief thresholds achieving the smallest error of 0.52%. (B) Increments in the confidence level of our perception system also shows a gradual increment in the mean time to make a decision, where 10 samples (100 ms) are required to achieve the highest gait event recognition accuracy. (C) Confusion matrix with accuracy recognition results for each gait event, stance and swing phases.



(A) (B) (C)

Fig. 8. Confusion matrices with prediction accuracy of the eight gait events that composed the gait cycle: (1) initial contact, (2) loading phase, (3) mid stance, (4) terminal stance, (5) pre-swing, (6) initial swing, (7) mid swing, (8) terminal swing. The accuracy for prediction of the most probable gait events, for three walking activities, are shown in black and light brown colours, which represent low and high probability respectively. (A) Very low accurate prediction results (x axis) that correspond to $\beta_{\text{threshold}} = 0$ and the low accurate recognition of current gait events (y axis). (B) Accurate recognition and prediction of gait events with $\beta_{\text{threshold}} = 0.8$. (C) Highly accurate recognition and prediction of gait events achieved with $\beta_{\text{threshold}} = 0.99$.

our proposed system is not only highly accurate (99.48%), but also it is capable to perform fast decisions (100 ms), which is important in robotics and autonomous systems.

Recognition accuracy for each individual gait event is shown by the confusion matrix in Figure 7C, where black and white colours represent low and high accuracy respectively. These results show the high accuracy achieved for recognition of each gait event, but also they show that it is possible to determine in which gait phase is the human during the walking activity, e.g., stance or swing phase. This information from both, gait event and gait phase, provide a better knowledge about the state of the walking activity, which can be used to develop more robust and intelligent autonomous devices that safely assist humans in ADLs.

B. Prediction of gait events

Prediction results of gait events for different belief threshold values $\beta_{\text{threshold}}$, and averaged over all walking activities are presented by confusion matrices in Figure 8. These results show the accuracy of our combined Adaptive Neuro-Fuzzy and Bayesian strategy to predict the next most probable gait event based on the recognition of the current event and observation of previous decisions. Rows of each confusion matrix show the current recognised event, while columns show the most (light brown colour) and least (black colour) probable gait event. Figure 8A shows the confusion matrix obtained with $\beta_{\text{threshold}} = 0.0$, which achieved low prediction accuracy results. This behaviour is related to the low accuracy for recognition of current gait events that, given the belief threshold value $\beta_{\text{threshold}} = 0.0$, affects the performance of predictions. Figure 8B shows the results when the confidence of our perception system is increased using $\beta_{\text{threshold}} = 0.8$. From this confusion matrix, we observe that our combined strategy is capable to achieve better predictions for gait events, which also improves the accuracy to recognise whether the human is in stance or swing phase. Our proposed strategy achieved its highest accuracy with $\beta_{\text{threshold}} = 0.99$ as shown by the confusion matrix in Figure 8C. Here, again we observe that high accuracy was achieved for both recognition of current gait events and prediction of the most probable gait events using our combined Adaptive Neuro-Fuzzy and Bayesian strategy. Interestingly, our proposed strategy is able to achieve not only highly accurate recognition and prediction results, but also it demonstrated to be fast, requiring a mean of 10 sensor samples (100 ms) to make a decision (see Figure 7C). Results from all experiments validate our proposed combined strategy which, learning how to combine information sources using an Adaptive Neuro-Fuzzy system to adapt the prior distribution of a Bayesian perception system, improves the accuracy and speed for recognition and prediction of gait events. Furthermore, this predictive functionality offered by our combined strategy, at high-level layer, can be used to prepare low-level controllers of robotic devices to respond according to the predicted or anticipated gait events for safe assistance to humans in their activities of daily living.

IV. CONCLUSIONS

In this work we presented a combined Adaptive Neuro-Fuzzy and Bayesian strategy for recognition and prediction of gait events. This strategy extends our previous study for recognition of walking activities. For recognition of gait events, we used a Bayesian perception system that, together with a sequential analysis method, achieves highly accurate results. Prediction of gait events was implemented with a method based on the observation of actions and decisions made by our perception system over time. This observation provides a transition parameter that is used to obtain a predicted probability distribution. We used an Adaptive Neuro-Fuzzy system to learn how to use the predicted information for new decisions tasks performed by our Bayesian method. This learning process allows our combined strategy to autonomously evaluate and adapt its own performance, ensuring the best recognition and prediction results in accuracy and speed. We validated our methods with experiments for recognition and prediction of gait events during walking activities using three wearable sensors attached to the lower limbs of participants. Results showed that combining the benefits from both, Adaptive Neuro-Fuzzy and Bayesian methods, it is possible to achieve fast and highly accurate recognition and prediction of gait events.

Overall, our combined Adaptive Neuro-Fuzzy and Bayesian strategy demonstrated to be robust for the analysis of human movements using wearable sensors. Furthermore, the features offered by our work, integrated to low-level controllers, provide a reliable approach to develop intelligent robotic devices that safely assist humans in their ADLs.

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