UNIVERSITY OF LEEDS

This is a repository copy of *Learning architecture for the recognition of walking and prediction of gait period using wearable sensors*.

White Rose
university consortium
Universities of Leeds, Sheffield & York

eprints@whiterose.ac.uk
https://eprints.whiterose.ac.uk/

Learning architecture for the recognition of walking and prediction of gait period using wearable sensors

Uriel Martinez-Hernandez[a,*], Mohammed I. Awad[b], Abbas A. Dehghani-Sanij[c]

[a]*Centre for Autonomous Robotics (CENTAUR), Department of Electronic and Electrical Engineering, University of Bath, Bath, BA2 7AY, UK.*
[b]*Department of Mechatronics Engineering, Ain Shams University, Cairo, Egypt.*
[c]*School of Mechanical Engineering, University of Leeds, Leeds, UK.*

Abstract

This work presents a novel learning architecture for the recognition and prediction of walking activity and gait period, respectively, using wearable sensors. This approach is composed of a Convolutional Neural Network (CNN), a Predicted Information Gain (PIG) module and an adaptive combination of information sources. The CNN provides the recognition of walking and gait periods. This information is used by the proposed PIG method to estimate the next most probable gait period along the gait cycle. The outputs from the CNN and PIG modules are combined by a proposed adaptive process, which relies on data from the source that shows to be more reliable. This adaptive combination ensures that the learning architecture provides accurate recognition and prediction of walking activity and gait periods over time. The learning architecture uses data from an array of three inertial measurement units attached to the lower limbs of individuals. The validation of this work is performed by the recognition of level-ground walking, ramp ascent and ramp descent, and the prediction of gait periods. The recognition of walking activity and gait period is 100% and 98.63%, respectively, when the CNN model is employed alone. The recognition of gait periods achieves a 99.9% accuracy, when the PIG method and adaptive combination are also used. These results demonstrate the benefit of having a system capable of predicting or anticipating the next information or event over time. Overall, the learning architecture offers an alternative approach for accurate activity recognition, which is essential for the development of wearable robots capable of reliably and safely assisting humans in activities of daily living.

Keywords: Activity recognition, deep learning, learning architectures, wearable sensors

1. Introduction

Walking is fundamental for humans to undertake activities of daily living (ADLs) independently such as translate from one place to another, socialise, do physical exercise, do shopping and interact with others and the surrounding environment [1]. The ability to walk can be degraded by different factors such as an injury or by the old age reached by the person, which affect the mobility, well-being and quality of life of the person [2]. Lower limb wearable robots have the potential to assist humans to perform walking activities and overcome mobility impairments [3]. This robot technology needs to be capable of recognising walking activities, gait periods and phases accurately, which is crucial to ensure a reliable, efficient and safe assistance [4]. Otherwise, the user might face the risk of stumbling, falling and suffering an injury. Advances in computational intelligence [5, 6] and wearable sensor technology [7, 8, 9] have shown to be a promising platform for the recognition of human activities. However, the development of robust methods capable of both recognising walking activities and predicting gait periods and phases still remains a challenge.

The recognition of walking activity and prediction of gait period are investigated in this work, which proposes a novel

learning architecture built with a Convolutional Neural Network (CNN), a Predicted Information Gain (PIG) and an adaptive weighted combination method. First, three walking activities (level-ground walking (LGW), ramp ascent (RA) and ramp descent (RD)) and eight gait periods (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing) are recognised using a CNN, which has shown its potential for recognition and control using different stimuli [10, 11]. Second, the output from the recognition process is used by the PIG approach [12], to predict the next gait period along the gait cycle. This prediction process is important to allow assistive robots to respond fast and accurately to anticipated events. Third, the proposed learning architecture combines the output from both processes, the recognition and prediction, using a novel adaptive weighted method. This proposed combination approach, ensures that the learning architecture uses more information from the source that is more reliable, and thus, making an accurate decision about the gait period been performed by the subject along the gait cycle [13, 14].

The recognition and prediction accuracy of the learning architecture is evaluated with participants performing multiple walking activities (LGW, RA and RD) and wearing three inertial measurement units (IMU) on the lower limbs. Systematic sensor data collection from walking activities is performed for

---

*Corresponding author

each participant. These datasets are used to train and test the capability for recognition and prediction of the proposed learning architecture. First, the accuracy for recognition of the walking activity and current gait period, being performed by the subject, is evaluated. Second, the prediction method is employed to observe the effects on the accuracy for the identification of gait periods. A third experiment analyses the recognition accuracy when noise is added to the original data. The experiments show that the recognition process is improved by adaptively combining it with information from the prediction process. Furthermore, the results show that the learning architecture is robust to noisy data. Overall, this work demonstrates the benefits in accuracy using systems capable of adapting based on observed and predicted sensory data.

This work is organised in six sections as follows: Section 2 presents the related works on walking recognition methods using different sensors. The modules that compose the proposed learning architecture are presented in Section 3. The experiments and results are described in detail in Section 4. The discussion and comparison of results are shown in Sections 5. The conclusions of this work are presented in Section 6.

2. Related work

The recognition of human movements and activities is an important process for human assistance. A large number of methods, from predefined rules to complex methods, have been developed for the recognition of activities of daily living.

Finite state machines (FSM), together with myoelectric and electromyography (EMG) signals, have been employed for the recognition of LGW, RA and RD activities [15, 16]. Data from floor reaction force, hip and knee joint angles were used together with an FSM for the identification of sitting, standing and LGW [17]. Commonly, these methods employed fixed and predefined set of parameters, which makes the recognition prone to fail even for slight changes in the sensor data.

Machine learning (ML) algorithms offer a robust alternative for intelligent, reliable and adaptive recognition systems. Techniques such as entropy distance, computer vision and image processing, together with wearable sensors, have been employed for detection of human activity [18, 19]. Adaptive decision trees with multiple wearable sensors were implemented for identification of LGW, standing and sitting with a mean recognition of 99% [20]. Linear discriminant analysis (LDA) and artificial neural networks (ANNs) and twelve EMG sensors were employed for the identification of locomotion modes [21]. Time-domain and frequency-domain features have been employed by LDA and ANN, together with nine EMG sensors, for intent recognition [22, 23]. Alternative approaches such as ANN with heuristic methods have been implemented for the identification of locomotion modes. Commonly, these works employ large arrays of multimodal sensors, such as accelerometers and foot ground contact data from LGW, running, stair ascent and descent [24, 25, 26]. All the works mentioned previously are capable of recognising human activities, while achieving accuracies ranging from 90% to 99%. However, these works

require a large number of sensors, making complex the processes for sensor synchronisation and data collection. Additionally, the use of large number of sensors, impacts on the energy consumption, computational cost and the complexity for the implementation of the algorithms.

The recognition of ADLs in real-time has been investigated using Fuzzy Logic (FL) methods, and data from joint angles and pressure sensors [27]. Ensemble of methods tends to provide enhanced recognition results, and thus, the ensemble of FL and ANN methods with EMG signals, was used for recognition of human intent with 95% accuracy [28, 29]. Although not portable, vision sensors and EMS signals have been used for training and testing support vector machines (SVMs) for human activity recognition. This method was capable of achieving accuracies from 77.3% to 99%. Unfortunately, a large number of sensors is required by this method, which limits its usage to indoor and well-controlled environments [30, 31]. SVMs and k-nearest neighbour (KNN) methods, together with angular velocity signals from sensors on the whole body, have been employed for activity recognition with accuracies ranging from 94% to 99.0% [32, 33]. Multi-class SVMs using data from an array of plantar pressure sensors were capable of recognising walking on flat surfaces and stairs with mean accuracies from 91.9% to 95.2% [34].

Probabilistic methods offer an alternative approach that includes the uncertainty of the sensor observations for the decision-making process. This method that has been successfully used for the development of robotic systems capable of perceiving, learning and decision-making processes [35]. Bayesian approaches have been employed, together with a variety of sensors, for the study of perception and decision-making for robot control [36, 37]. Gaussian mixture models (GMM) showed to be capable of characterising the probabilities for the accurate recognition of activities of daily living [38]. Similarly, dynamic Bayesian networks (DBN) showed to be capable of identifying walking activities on different terrains, using IMU and EMG sensors [39, 40]. Deep Learning (DL) techniques, based on Convolution Neural Networks (CNN), have gained popularity for the identification and classification of human activities. CNNs, trained with 3D data sequence from vision and IMU sensors, were able to detect a large number of activities with mean accuracy between 98% and 99.78% [41]. Ensemble of CNNs, with vision data, showed an improved activity recognition task achieving a mean accuracy of 99.68% [42]. Inertial measurement units, over the full body, were employed for recognition of ADLs using CNNs alone, and combined with Recurrent Neural Networks [5, 43].

CNNs are becoming popular for activity recognition, however, their use has been focused on recognition processes only. In this work, CNNs together with forward models and adaptive methods are investigated to perform recognition and prediction processes. These methods compose the proposed learning architecture for the recognition and prediction of walking activities and gait periods, respectively, during the gait cycle. Multiple IMUs, attached to the lower limbs of subjects, are employed to train and test the proposed learning architecture. Having a system capable of observing and anticipating infor-
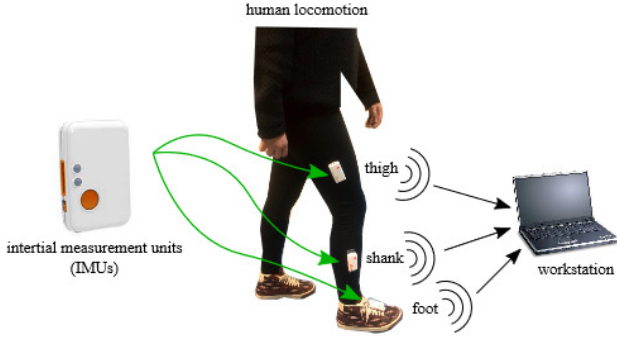
(A) Sensor attachment for data collection

(B) Level-ground walking

(C) Ramp ascent/descent

Figure 1: Walking activities for collection of data. (A) Diagram with three IMUs attached to the lower limbs of subjects. The data is sent to a computer for the subsequent analysis with the proposed methods. (B) Level-ground walking activity (LGW) on a flat surface. (C) Ramp ascent (RA) and ramp descent (RD) activities. Participants repeated ten times each walking activity.

mation or events, is also capable of improving its performance over time. Next sections describe in detail all the modules that composed the proposed learning architecture.

3. Methods

3.1. Experimental protocol and data preparation

Twelve male subjects, without gait abnormalities, were recruited from the Institute of Design, Robotics and Optimisation (iDRO), the University of Leeds. The subjects' ages, heights and weights were from 24 to 34 years old, 1.74 m to 1.79 m, and 77.6 kg to 85 kg, respectively.

Data from three IMU sensors, attached to the thigh, shank and foot of participants, were collected for this research. These IMU sensors, from Shimmer Inc., have 9 DoF each and provide data from accelerometer, gyroscope and magnetometer. Data from all sensors were systematically collected and sent to a computer for their posterior processing and analysis by the proposed learning architecture. The detection of the start of the gait cycle, during the data collection process, was performed using a foot pressure insole [44]. The attachment of sensors and data collection process are depicted in Figure 1A.

All subjects were asked to perform ten repetitions of LGW, RA and RD activities. For this purpose, a flat cement surface was used for LGW, and a ramp with an inclination of 8.5 deg was used for RA and RD, as shown in Figures 1B,C. Angular

velocity, accelerometer and magnetometer signals, in *x*- *y*- and -*z* axes, were collected from each sensor at a sampling rate of 100 Hz. The signals collected were grouped into 12 datasets, where each dataset was composed of 27 sensor signals (3 signals × 3 axes × 3 sensors) and 200 sensor samples, from each gait cycle and walking activity. This number of sensor samples was obtained from the walking speed that was similar and consistent between all participants. The datasets were divided into training (8 datasets) and testing (4 datasets) for validation of the proposed recognition and prediction strategy. An example of these signals from a walking activity is shown in Figure 2A. In this work, the data collected was first segmented into stance (60% of gait cycle) and swing (40% of gait cycle) phases. Then, the stance phase was segmented into five gait periods of same length (initial contact, loading response, mid stance, terminal stance). Similarly, the swing phase was segmented into three gait periods of same length (initial swing, mid swing, terminal swing). This segmentation of gait phases and periods is shown in Figure 2B. This segmentation strategy is used to analyse the potential for recognition of walking activity and prediction of gait periods with the proposed learning architecture composed of CNN and PIG methods.

3.2. CNN for the recognition of walking mode and gait period

The proposed recognition and prediction system is composed of a CNN module, a Predicted Information Gain (PIG) module and an adaptive weighted combination process.

3.2.1. Recognition of activity and gait period

A CNN is employed for the recognition of the walking and gait periods. The CNN recognises whether the human is performing LGW, RA or RD activities using data from wearable sensors. The architecture of the CNN, which is composed of two feature learning layers and one classification layer, is shown in Figure 3. The first feature learning layer is composed of 32 5×5 kernels for convolution and 32 2×2 kernels for max-pooling. The second feature learning layer uses 16 3×3 kernels for convolution and 16 2×2 kernels for max-pooling. The classification layer flattens the learning features, which are fully connected to a softmax layer, which is responsible for the estimation of the probability of the current walking activity. The data used by the CNN is received as a matrix of 27 signals × 25 samples, based on the segmentation of eight gait periods of the complete activity matrix (27 × 200). This data segmentation and arrangement allows the CNN to estimate the gait period during the walking activity performed by the human.

This computational intelligence approach allows the identification of the current walking activity and gait period performed by participants, e.g., LGW and pre-swing (gait period 5). With this information we can also determine whether the human is on the stance (gait period 1 to 5) or swing phase (gait period 6 to 8). The convolution and max-pooling layers used in the feature learning process are implemented as follows:

$$x_{ij}^{l} = b_j + \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} k_{ab} * y_{(i+a)(j+b)}^{l-1}, \qquad (1)$$
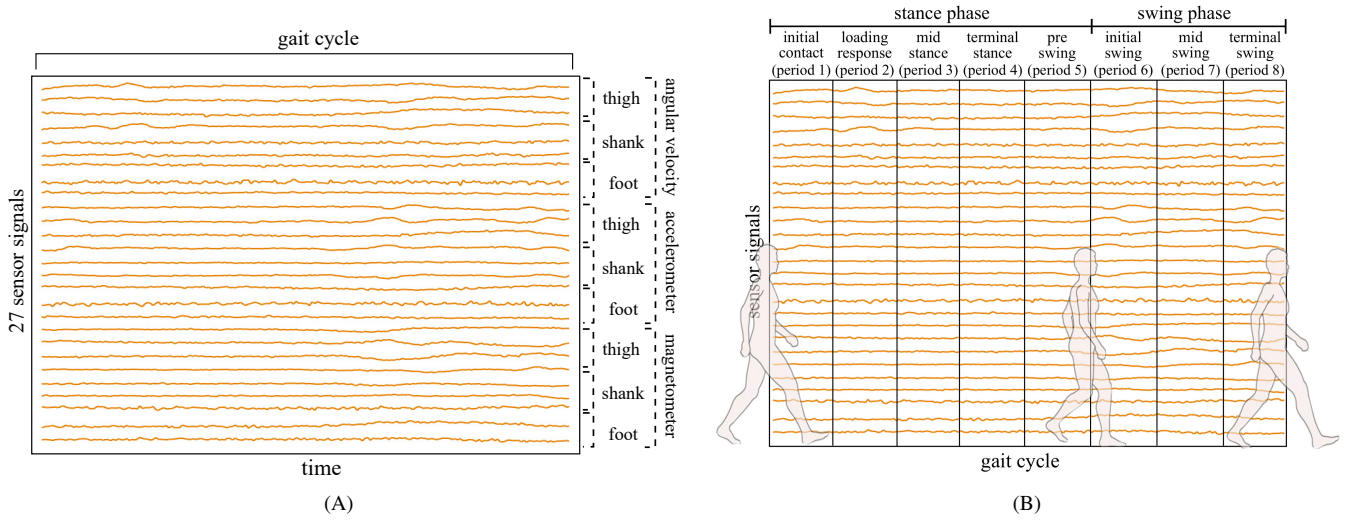
Figure 2: Sensor signals used for the recognition and prediction processes. (A) Example of concatenated signals from the gyroscope (*x,y,z*), accelerometer (*x,y,z*) and magnetometer (*x,y,z*) from the walking activity. These signals were collected from the sensors mounted on the thigh, shank and foot of participants. (B) Dataset segmented into periods, for the recognition and prediction of gait periods and phases.

where x_{ij}^l is the output from the *l*-th layer of the *j*-th feature map on the *i*-th unit, b_j is the bias, and the convolution process is denoted by the operator $*$. The convolution is performed between the $m \times m$ k_{ab} kernel and the nonlinear output $y_{(i+a)(j+b)}^{l-1}$ from layer $l-1$. The output from Equation (1) is used as input for the nonlinear function σ as follows:

$$y_{ij}^l = \sigma(x_{ij}^l), \qquad (2)$$

where the nonlinear output from the *l* convolutional layer is represented by y_{ij}^l. The nonlinear function σ defines the hyperbolic tangent function tanh. The implementation of each convolution is proceeded by a max-pooling layer, which performs a downsampling process that takes as input a $u \times u$ region and returns its maximum value. The proposed CNN model uses 2×2 input

region. This downsampling process is performed as follows:

$$y_{ij}^l = \max_{u \times u}(y_{ij}^{l-1}), \qquad (3)$$

where maximum values from y_{ij}^{l-1} are assigned to y_{ij}^l. The output from the feature learning layer, composed of convolution and max-pooling processes, are fully connected to a softmax layer. The latter process provides the probability for recognition of walking and gait periods, as follows:

$$P(c|y) = \frac{e^{y^T w_c}}{\sum_{n=1}^{N} e^{y^T w_n}}, \qquad (4)$$

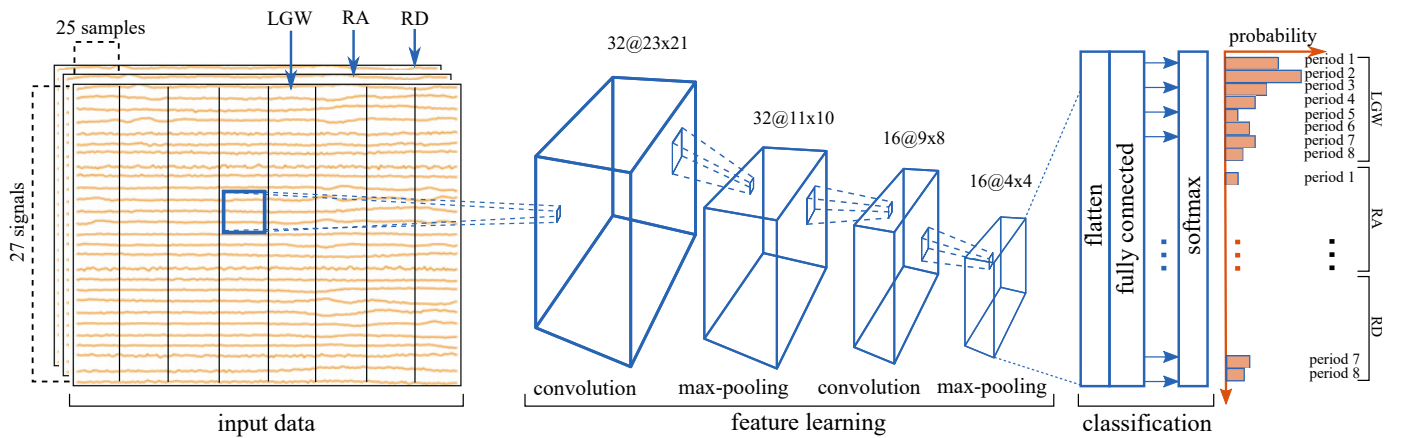$$\hat{c} = \arg\max_c P(c|y), \qquad (5)$$

Figure 3: Convolutional neural network architecture for recognition of walking activities and gait periods. The input data for the CNN, received from the three wearable sensors, are grouped into matrices of 27 signals × 25 samples. The feature learning process from the CNN is composed of two feature layers. The first layer is composed of 32 5×5 kernels for convolution and 32 2×2 kernels for max-pooling. The second layer uses 16 3×3 kernels for convolution and 16 2×2 kernels for max-pooling. The features extracted are used by a fully connected layer and softmax function for classification processes. The output from the softmax layer shows the probability for recognition, at current time *t*, of each gait period for each walking activity.
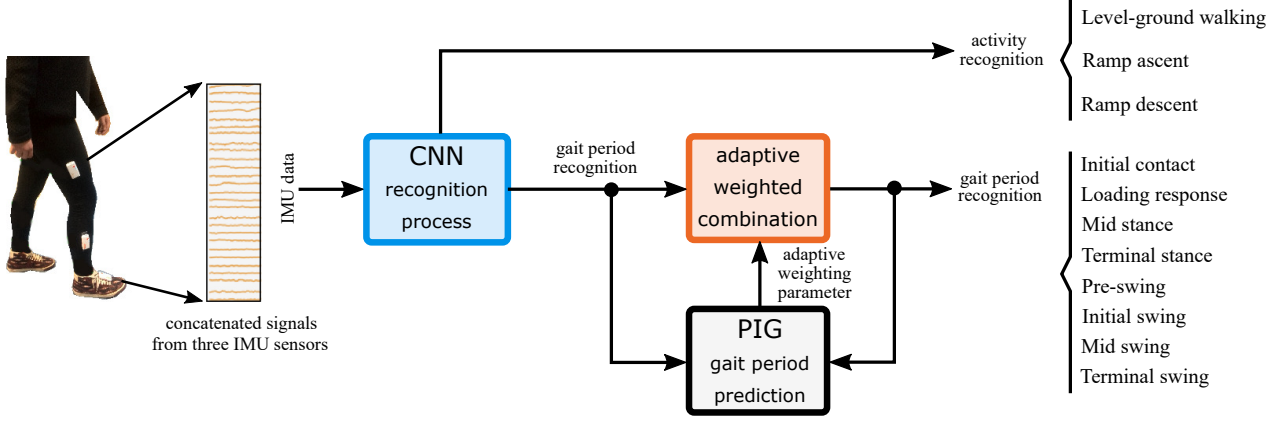
4

Figure 4: Proposed architecture employed for interconnection of the modules for recognition (CNN) and prediction (PIG method) processes, and adaptive weighted combination of information sources. The CNN performs the recognition of walking activity and gait periods. The PIG method predicts the current gait period based on the observation of events over time. The recognition of gait periods from the CNN and the prediction performed by the PIG method, are combined using a weighting parameter, which adapts its value based on the accuracy of predictions made by the PIG method. Thus, the adaptive weighted combination method will rely or assign more weight to the information source, CNN module or PIG method, that shows to be more accurate over time.

where the class c indicates the (c_{activity}, c_{period}) pair, and $P(c|y)$ is the recognition probability given the current sensor data denoted by y. The weight vector and total number of classes are represented by the parameters w and N, with $N = 24$ (3 walking activities $\times$ 8 gait periods). The most probable walking activity ($\hat{c}_{\text{activity}}$) and gait period ($\hat{c}_{\text{period}}$), defined by $\hat{c}$, are obtained with the *maximum a posteriori* (MAP) estimate as shown in Equation (5). The output from the CNN model is depicted in Figure 3, with LGW, RA and RD indicated by the first, second and third group of eight classes, respectively. Each group of eight classes also corresponds to the eight gait periods of each walking activity. Thus, the CNN approach outputs the simultaneous estimation of walking and gait period.

Identification by the CNN of both, the current walking activity and gait period, is important for assistive robotics. The development of intelligent robots, capable of reliably and safely assisting humans in ADLs, also need modules for the prediction of human movements. Section 3.2.2 describes a method, based on a forward model and an adaptive combination of information sources, for the prediction of gait periods.

3.2.2. Prediction of gait periods

A forward model based on a novel Predicted Information Gain (PIG) method is used for the prediction of gait periods during walking. This approach observes what decision, made by the CNN at time $t - 1$, would have provided the largest information gain at time t. For the case of gait periods, the proposed PIG approach observes the information gained from transitions between gait periods performed at previous times along the walking activity. This process outputs the parameter Δ, which is used for estimation of the next probable gait period. The predicted information gain approach is defined as follows:

$$\text{PIG} = \gamma \sum_{s^*} \hat{\Theta}_{\text{a,s,s}^*} D_{\text{KL}}(\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} \| \hat{\Theta}_{\text{a,s}}). \qquad (6)$$

The parameter $\hat{\Theta}$ denotes the estimated recognition output made by the CNN. The gait periods that compose the gait cy-

cle are $s = \{s_1, s_2, \ldots, s_N\}$ with $N = 8$ and transitions between these gait periods are represented by $a = \{a_1, a_2, \ldots, a_N\}$ with $N = 8$. The estimated recognition for the current gait period s given a transition a is denoted by $\hat{\Theta}_{a,s}$. The parameter $\hat{\Theta}_{a,s}$ shifts the output from the CNN by the transition value defined by a, which estimates what would have been the current gait period if a different transition a would have been performed at the previous gait period. The hypothetical next gait periods s^* for each transition a performed at previous gait period s are represented by $\hat{\Theta}_{a,s}^{a,s,s^*}$. The hypothetical outcomes s^* by a transition a in the current gait period s are denoted by $\hat{\Theta}_{a,s,s^*}$. Equation (6) is normalised by the parameter γ. The Kullback-Leibler Divergence (D_{KL}) provides the information that would have been lost for each simulated transition and hypothetical next gait period, at the previous decision times, as follows:

$$D_{\text{KL}}(\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} \| \hat{\Theta}_{\text{a,s}}) = \sum_{s^*}^{N} \hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} \log\left(\frac{\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*}}{\hat{\Theta}_{\text{a,s}}}\right). \qquad (7)$$

The PIG value from Equation (6) is employed to update the transition matrix Γ_t, which keeps track of the transitions along the gait cycle, to obtain the parameter Δ that indicates the position of the next most probable transition when the use is at specific gait period. This parameter shifts the probability of current gait periods, $P(c_{\text{period}}|y)$ with y being the sensor data collected at time t, for prediction of the next most probable gait periods, as follows:

$$\Gamma_t = \left(\frac{t-1}{t}\right)\Gamma_{t-1} + \left(\frac{1}{t}\right)\text{PIG}, \qquad (8)$$

$$\Delta = \arg\max(\Gamma_t), \qquad (9)$$

where the transition matrix at decision times t and $t - 1$ are Γ_t and Γ_{t-1}, respectively. The PIG value is employed as a reward that adapts based on the decisions and actions made over time by the recognition system. Then, the position of the largest

5

probability from the transition matrix, in Equation (9), is assigned to Δ to shift $P(c_{\text{period}}|y)$ for prediction of the gait periods for next time $t + 1$, as follows:

$$P_{\text{period}_{t+1}} = P(c_{\text{period}} + \Delta|y), \qquad (10)$$

where $P_{\text{period}_{t+1}}$ represents the predicted gait periods. This prediction is autonomously combined with the estimation of current gait periods, P_{period_t}, using the adaptive weighting parameter described in the following section.

3.2.3. Adaptive combination of information sources

Humans make use of multiple sources of information, combining them to improve the accuracy of decision-making processes. A novel strategy is proposed to perform the weighted combination of current and predicted information, where the weight, α, parameterise the reliability of each information source. This proposed strategy for the combination of sources of information is as follows:

$$\hat{P}_{\text{period}_t} = \alpha_t P_{\text{period}_t} + (1 - \alpha_t) P_{\text{period}_{t+1}}, \qquad (11)$$

where $\hat{P}_{\text{period}_t}$ is the updated gait period probability, obtained from the adaptive and weighted combination of current and predicted gait periods. This weighting parameter, α, autonomously adapts over time based on the reliability of each source of information. The adaptive procedure evaluates the error between the prediction from $P_{\text{period}_{t+1}}$, and the actual gait period $P_{\text{period}_t} = P(c_{\text{period}})$ as follows:

$$\xi_t = |P_{\text{period}_t} - P_{\text{period}_{t+1}}|, \qquad (12)$$

$$\alpha_t = \left(\frac{t-1}{t}\right)\alpha_{t-1} + \left(\frac{1}{t}\right)\xi_t. \qquad (13)$$

The error between the probability of the predicted gait period and the actual recognised gait period is represented by ξ_t. This error value is used as reward to update the weighting parameter α. Thus, Equation (12) establishes that if the distance between the prediction and actual recognition is small, then the error ξ will be small. Then, the weighted parameter α will be also small, relying more on the predictions from the forward model. In contrasts, if the distance is large, then the error ξ and weighted parameter α will be large, making the recognition system to rely more on current recognised gait periods. The proposed learning architecture and the interconnection of modules is presented by the flowchart in Figure 4.

4. Results

4.1. Recognition of walking activity and gait period

The recognition accuracy of walking activity and gait periods was validated with three walking activities (LGW, RA and RD). Three wearable sensors, attached on the lower limbs of subjects, were used for collection of angular velocity, accelerometer and magnetometer signals for the validation process. Figure 2A shows an example of these signals from a complete walking cycle. The signals from the walking cycle are
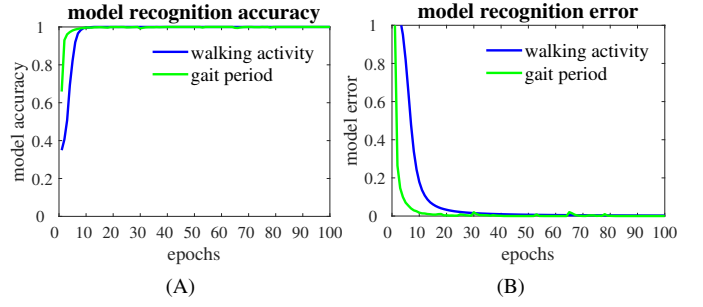

Figure 5: CNN model training for the recognition of the walking activity (blue curve) and gait period (green curve). (A) Accuracy and (B) error against the number of epochs for recognition processes perform by the CNN model.

segmented into eight gait periods (Figure 2B) for recognition of initial contact, loading response, mid-stance, terminal stance, pre-swing, initial swing, mid-swing and terminal swing. Sensor signals from 12 participants were split into two groups of eight and four datasets to train and test the learning architecture, respectively.

The performance in accuracy and error of the CNN model, was evaluated by drawing random samples from the training datasets (Figures 5A,B). The validation of the CNN shows that the recognition of both, walking (blue curve) and gait period (green curve) achieved the mean accuracy of 100% within 100 epochs. The results also show that the CNN also achieved 0% error for the recognition process. The CNN was also evaluated using sensor samples from the test datasets. Figure 6A shows the results from the recognition of individual walking modes, with a mean accuracy of 100%. The recognition of gait periods, with mean accuracy of 98.63%, is presented in Figure 6B. These results demonstrate that stance and swing phases are recognised with accuracies of 97.88% and 99.90%, respectively. This analysis is performed by averaging the accuracies from gait periods 1 to 5, for stance phase, and gait periods 6 to 8 for swing phase. This information, from walking and gait periods, is important to know the state of the human body during walking, e.g., heel contact and toe-off. The accuracy for recognition of gait periods for each walking activity is shown in Figure 7, with mean accuracies of 99.82%, 97.93% and 98.10% for LGW, RA and RD, respectively.

4.2. Prediction of gait periods

Prediction of gait periods allows the identification of the next most probable gait period during the gait cycle of a walking activity. This predictive capability is important to achieve better control of assistive robots, given that robots can anticipate and adapt their actions to expected events. The results for recognition of gait periods, for each walking activity, using the proposed prediction approach are shown in the confusion matrices of Figure 8. The recognition accuracy of gait periods was improved for all walking activities, which demonstrates the benefits of performing the prediction of gait periods. For level-ground walking, ramp ascent and descent, mean recognition accuracies of 100%, 99.97% and 100% were achieved,

CNN method activity recognition

	LGW	RA	RD
LGW	100		
RA		100	
RD			100

(A)

CNN method mean gait period recognition

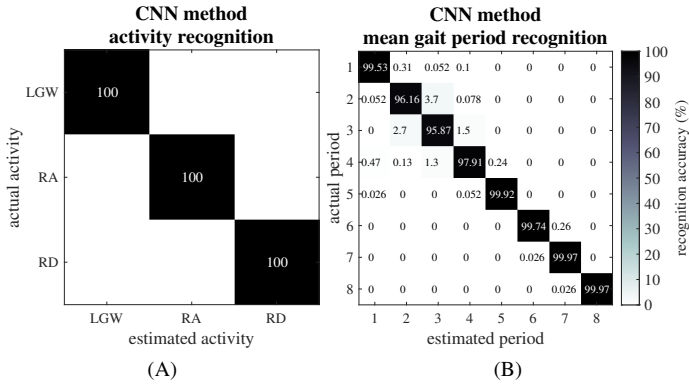|	1	2	3	4	5	6	7	8
1	99.53	0.31	0.052	0.1	0	0	0	0
2	0.052	96.16	3.7	0.078	0	0	0	0
3	0	2.7	95.87	1.5	0	0	0	0
4	0.47	0.13	1.3	97.91	0.24	0	0	0
5	0.026	0	0	0.052	99.92	0	0	0
6	0	0	0	0	0	99.74	0.26	0
7	0	0	0	0	0	0.026	99.97	0
8	0	0	0	0	0	0	0.026	99.97

(B)

Figure 6: Accuracy achieved by the CNN model for the recognition of walking activities and gait periods using new data. (A) Recognition of LGW, RA and RD activities. (B) Mean recognition accuracy of gait periods; 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, over all walking activities.

respectively. It is clearly observed that there is improvement over the results achieved when no predictive information was used for the decision-making process.

This experiment was performed using the prediction from the PIG model and the adaptive weighted combination approach. The combination of current and predicted gait periods is adaptively weighted, relying more on the information source that shows to be more accurate. The behaviour of the adaptive weighting parameter, for the three walking activities, is shown in the plots of Figure 9. Original and noisy data were employed to evaluate the accuracy and robustness of the adaptive weighted combination of information. In the case of original data (solid lines), random samples were selected from the 4 testing datasets to calculate α. A gradual increment in the adaptive parameter, from $\alpha = 0$ to $\alpha = 1$, is observed for the three walking activities. This shows that initially, with $\alpha = 0$, the recognition of gait periods relies on the CNN model only, and does not use the information from the PIG model. Then, the adaptive parameter modifies its value according to the predictions made by the PIG model. For LGW (Figure 9A) and RD (Figure 9C), predictions were accurate, and then, the value of the adaptive parameter showed a smooth increasing behaviour. For RA (Figure 9B), the adaptive parameter showed a small increasing and decreasing behaviour at the beginning of the experiment. This means that predictions were not accurate initially, and therefore, the weighting parameter had to rely more on the CNN model than on the predictions. However, after a few more samples, the adaptive parameter showed an increasing behaviour, given that predictions from the PIG model started to be accurate after the observation of more sensor samples.

For the evaluation of the proposed methods with noisy data, white noise with a signal-to-noise ratio of 70% was added to the original data. The behaviour of the adaptive weighting parameter for the three walking activities is represented by the dashed-lines in Figure 9. For level-ground walking (Figure 9A), the weighting parameter showed a similar behaviour to the original data (without added noise). For ramp ascent and ramp descent

(Figures 9B,C), the adaptive parameter showed an increasing and decreasing behaviour during the first samples drawn from the noisy dataset. Once more samples were observed, predictions from the PIG model achieved a larger accuracy, making the adaptive parameter to increase its value and rely more on the prediction process. These results show that the proposed PIG model and adaptive weighting parameter are robust and capable of autonomously adapting the data fusion process in order to improve the accuracy for recognition of gait periods while walking.

5. Discussion

Wearable assisitve robots and technology have shown great advances in recent decades. Especially, sensor and material technology have promoted the development of multisensory, lightweight and compliant robots that fit better to the human body. A variety of computational methods have been used for recognition of human movements. However, methods that include the capability of learning and adaptation, based on human movements, still remain a challenge. Therefore, this work presented a novel approach capable of learning and adapting using machine intelligence and inertial measurement units attached on the lower limbs of participants.

The proposed learning architecture uses a convolutional neural network (CNN), a novel predicted information gain (PIG) and adaptive combination of information approach. The CNN model is responsible for recognition of both, walking activities and gait periods. This CNN model receives input data from three IMU sensor attached to the lower limbs of participants. LGW, RA and RD activities were recognised with accuracy of 100% each. The proposed approach also provided the recognition of the eight gait periods in which the gait cycle was divided. These gait periods which are initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing, were recognised with mean accuracies of 99.5%, 96.2%, 95.9%, 97.9%, 99.9%, 99.7%, 100% and 100%, respectively. Normally, computational intelligence methods are capable of recognising walking activities with high accuracy, because of the large amount of data being available along the walking cycle. It is not the same case for recognition of gait periods due to small data contained in each gait period. For this reason, normally, the recognition process focuses on walking activity only, and heuristic methods, together with potentiometers or goniometers, are employed for recognition of gait periods. Our CNN model was able to recognise all the gait periods successfully, however, this process needs to be improved in order to achieve safe assistance to humans in real-time.

To improve the recognition of gait periods, the learning architecture needs to be capable of predicting the next event along the walking cycling. For this purpose, a forward model, implemented with a PIG approach, was used for prediction of gait periods. This forward model observes the transition between gait periods. Then, it analyses the amount of information that would have been gained for each possible gait period transition made at previous decision time. The transition that provides the largest information gain is used to estimate what would be the

CNN method gait period recognition - LGW (A)

CNN method gait period recognition - RA (B)

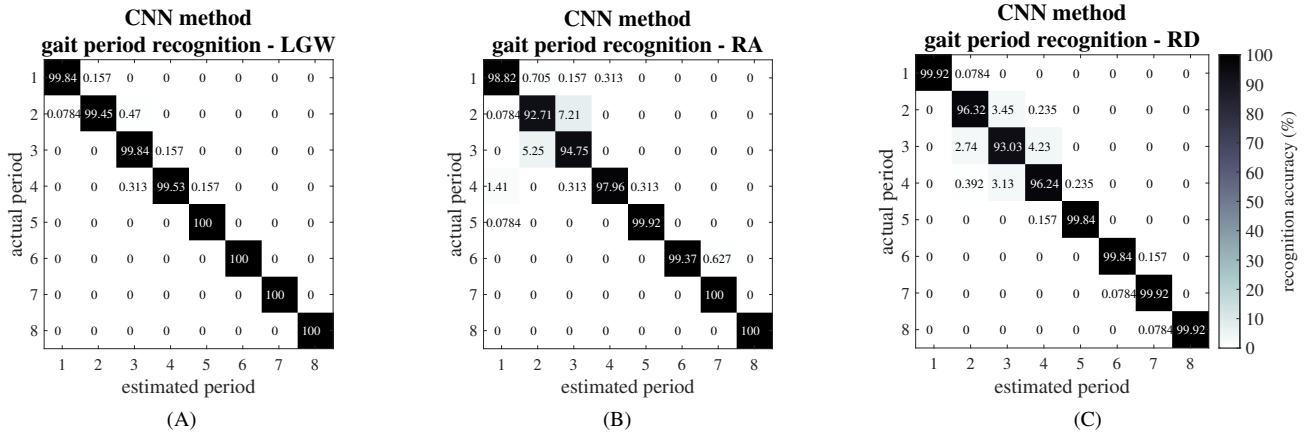**CNN method gait period recognition - RD** (C)

Figure 7: Recognition of gait periods for each walking activity using the CNN model and wearable sensor data. (A) Gait period recognition for level-ground walking (LGW) with mean accuracy of 99.82%. (B) Gait period recognition for ramp ascent (RA) with mean accuracy of 97.93%. (C) Gait period recognition for ramp descent (RD) with mean accuracy of 98.10%. On the one hand, level-ground walking provides the highest accuracy with low confusion between gait periods. On the other hand, ramp ascent creates more confusion between gait periods, making the CNN model to achieve the lowest accuracy.

PIG + adaptive weighted method gait period recognition - LGW (A)

PIG + adaptive weighted method gait period recognition - RA (B)

PIG + adaptive weighted method gait period recognition - RD (C)
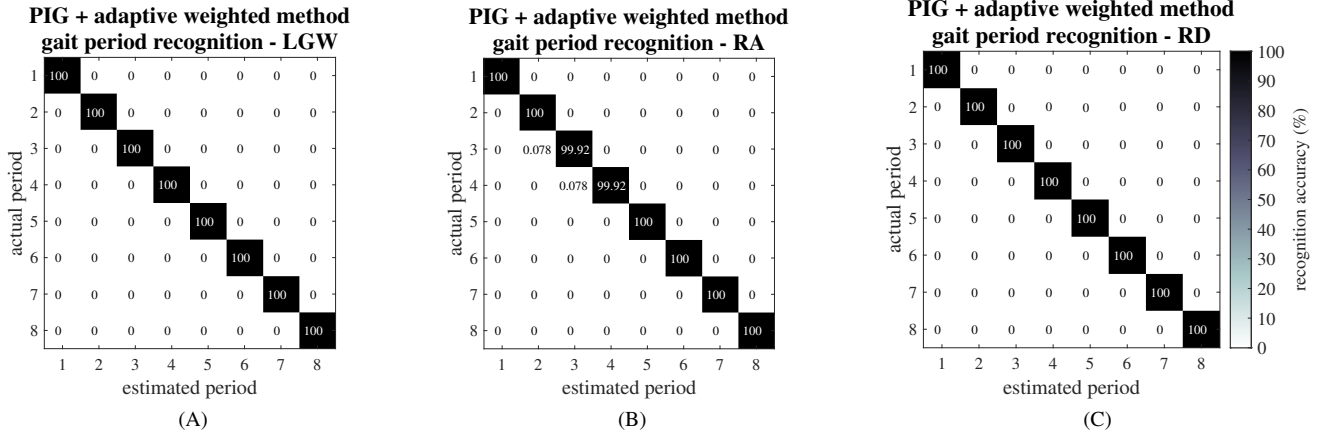
Figure 8: Recognition of gait periods using the PIG method and the adaptive weighted combination approach. (A) Gait period recognition for level-ground walking (LGW), with mean accuracy of 100%. (B) Gait period recognition for ramp ascent (RA), with mean accuracy of 99.97%. (C) Gait period recognition for ramp descent (RD), with mean accuracy of 100%. The results of this experiment show that the recognition accuracy of gait periods for all walking activities, has been improved by the use of the weighted information obtained from the predictive approach.

next most probable gait period for the current walking activity. This process predicts the most probable gait period, that will be observed the next time step by the learning architecture during the walking activity. Then, the predicted information is used together with the output from the CNN to improve the recognition process. This task requires the combination of two information sources, the prediction and the recognition outputs. Previous works have used a fixed and predefined weighted parameter for this combination process. In this work, the weighted parameter was adaptive based on the accuracy observed by both, the prediction and recognition outputs. This approach overcomes the need to pre-programmed methods, and instead, it allows the development of systems that intelligently adapt over time, according to the observation of their own performance and the changing environment.

The adaptive combination allowed the learning architecture to rely or give more importance to the information source that

showed to be more accurate. This means that the weighting parameter, responsible for the combination process, changed its value autonomously to ensure accurate recognition process. The results from the recognition of gait periods using the CNN only are shown in Figure 7. These results show that recognition of gait periods for the ramp activities is not as accurate as for the walking activity. In contrast, the confusion matrices in Figure 8, clearly show the improvement of the recognition process using the PIG and adaptive combination methods. The adaptation of the weighting parameter, for each of the walking activities, over time is shown in Figure 9. These experiments were also undertaken by adding noise for the analysis and evaluation of the adaptation process. The results show that the learning architecture was able to adapt and achieve accurate recognition using the original data (solid lines) and noisy data (dashed-lines). A comparison of the proposed architecture with state-of-the-art methods for recognition and prediction of walking activity and
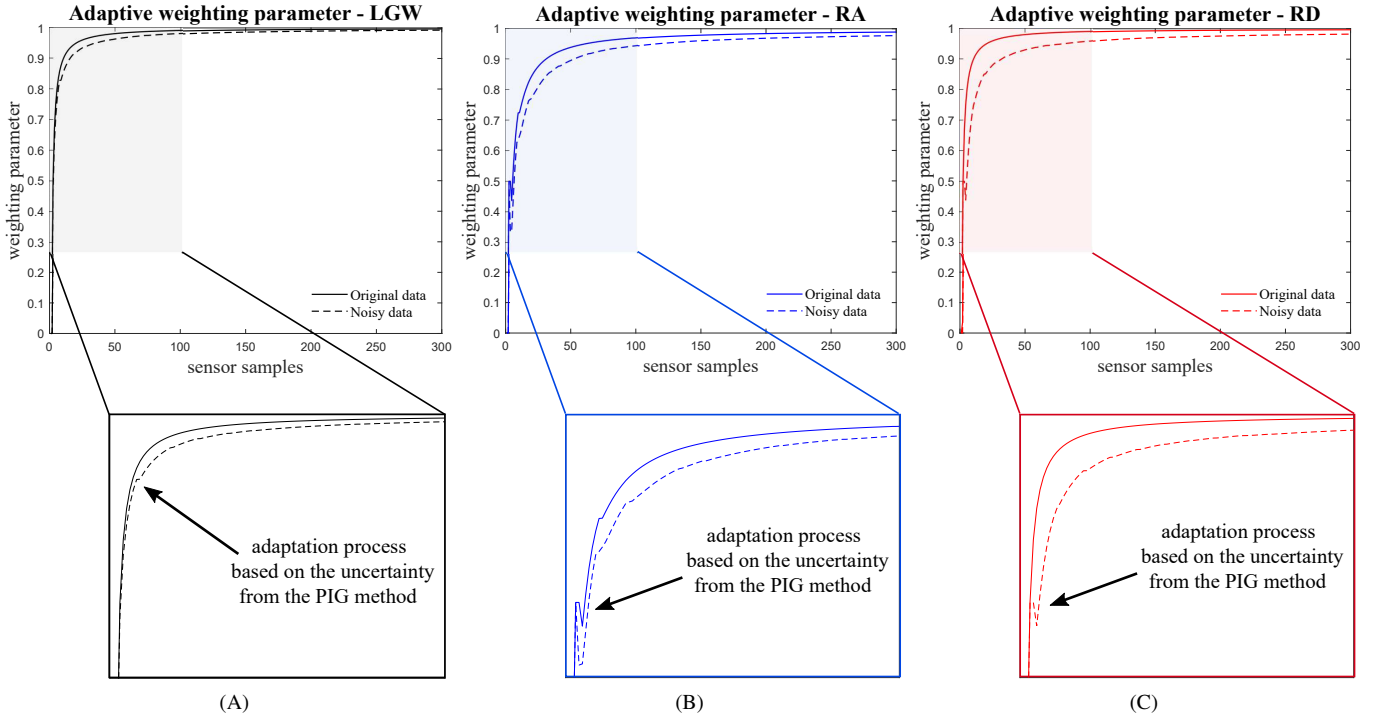
Figure 9: Adaptation of the weighting parameter for the combination of information from the CNN model and PIG method. The capability of adapting of the weighting parameter was evaluated using original (solid lines) and noisy (dashed lines) data. The increasing value of the weighting parameter is related to the confidence on the predictions made by the PIG module. For ramp ascent and descent, there is a perturbation, based on the low accuracy observed by predictions, which makes the weighting parameter to adapt and reducing the weight assigned to the information provided by the predictive module. Then, after more data is observed over time, predictions become more accurate, and thus, the value of the weighting parameter starts increasing.

gait periods is presented in Table 1. The accuracy achieved for recognition of activities depend on the method but also can be related to the data employed by these works. Independently of the data, only few methods have included the functionality for recognition of gait periods, and only our method has proposed an initial approach for prediction of gait periods. In this work, for the purpose of evaluating the potential of the proposed learning architecture, we used datasets that contain consistent number of sensor samples per gait cycle across all participants. We also made the assumption of gait periods of same length. However, both walking at different speeds and using gait periods with different lengths will be analyse in future works to be able to implement the propose methods in assistive devices. Thus, having methods with capabilities for recognition and prediction using wearable sensors still remains a challenge for the development of safe and reliable assistive systems.

The recognition and prediction processes, performed by the learning architecture, benefit the development of wearable assistive robots. The proposed method have the potential to be implemented in a portable computer (e.g., Raspberry Pi computer) with wearable inertial measurement units for integration and control of wearable assistive robots. The proposed work has also some limitations; for instance, 1) this method does not recognise activities such as sit-to-stand and climbing stairs, 2) the experiments have been undertaken in a laboratory and they need to be prepared for outdoor environments, 3) an external computer is employed for processing the sensor data. These

Table 1: State-of-the-art methods for recognition of walking activity and prediction of gait periods

Method	Activity	# Sensors	Activity recognition	Gait period recognition	Gait period prediction
Log-sum distance [45]	walking, ramps sitting	9	99.9%	–	–
Ensemble of classifiers [32]	walking, ramps stairs	9	97.60%	–	–
GMM [38]	walking, standing sitting	4	100%	–	–
SVM [31]	walking, ramps stairs	9	99%	97%	–
DBN [40]	walking, ramps stairs	13	98%	95.25%	–
Our approach	walking, ramps	3	100%	98.63%	99.9%

limitations can be addressed in the future work on recognition methods for assistive robots in outdoor environments.

Overall, the results from all experiments showed that the proposed learning architecture, successfully recognised walking activities and predicted gait periods with high accuracy. Thus, this research offers an approach that can be integrated into wearable robots, in order to deliver safe and reliable assistance to humans in their activities of daily living.

6. Conclusion

This research work describes the novel learning architecture for walking activity recognition and prediction of gait periods. This work uses data from three wearable sensors, attached to

the lower limbs of participants, while performing walking activities. This novel learning architecture is composed of a convolutional neural network, a predicted information gain method and a module for adaptive combination of information sources. Multiple experiments were undertaken for validation of the recognition and prediction methods. First, the convolutional neural network showed to be able to recognise, with high accuracy, all the walking activities performed by participants. Second, the predicted information gain method was able to predict the most probable event for the next time step during walking. Third, the adaptive combination method allowed the proposed learning architecture to autonomously adapt its performance, and thus, improve the accuracy of the recognition and prediction processes. The results from the experiments also showed that by allowing the learning architecture to react to anticipated events, based on the prediction process, its performance in terms of accuracy and potentially in terms of the speed can be improved. All these aspects offered by the proposed learning architecture, make it a potential approach for the development of intelligent wearable robots capable of recognising human movements and providing safe assistance in activities of daily living.

7. Acknowledgements

References

[1] C. Kirtley, Clinical gait analysis: theory and practice, Elsevier Health Sciences, 2006.

[2] D. A. Winter, Biomechanics and motor control of human gait: normal, elderly and pathological, University of Waterloo Press, 1991.

[3] B. Chen, H. Ma, L.-Y. Qin, F. Gao, K.-M. Chan, S.-W. Law, L. Qin, W.-H. Liao, Recent developments and challenges of lower extremity exoskeletons, Journal of Orthopaedic Translation 5 (2016) 26–37.

[4] M. Grimmer, K. Schmidt, J. E. Duarte, L. Neuner, G. Koginov, R. Riener, Stance and swing detection based on the angular velocity of lower limb segments during walking, Frontiers in neurorobotics 13 (2019) 57.

[5] A. Ignatov, Real-time human activity recognition from accelerometer data using convolutional neural networks, Applied Soft Computing 62 (2018) 915–922.

[6] H. F. Nweke, Y. W. Teh, M. A. Al-Garadi, U. R. Alo, Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges, Expert Systems with Applications 105 (2018) 233–261.

[7] I. H. López-Nava, A. Muñoz-Meléndez, Wearable inertial sensors for human motion analysis: A review, IEEE Sensors Journal 16 (22) (2016) 7821–7834.

[8] A. T. Asbeck, S. M. M. De Rossi, I. Galiana, Y. Ding, C. J. Walsh, Stronger, smarter, softer: Next-generation wearable robots, Robotics & Automation Magazine, IEEE 21 (4) (2014) 22–33.

[9] U. Martinez-Hernandez, L. W. Boorman, T. J. Prescott, Multisensory wearable interface for immersion and telepresence in robotics, IEEE Sensors Journal 17 (8) (2017) 2534–2541.

[10] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, nature 521 (7553) (2015) 436.

[11] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al., Human-level control through deep reinforcement learning, Nature 518 (7540) (2015) 529.

[12] D. Y.-J. Little, F. T. Sommer, Learning and exploration in action-perception loops, Frontiers in neural circuits 7 (2013) 37.

[13] R. Shadmehr, M. A. Smith, J. W. Krakauer, Error correction, sensory prediction, and adaptation in motor control, Annual review of neuroscience 33 (2010) 89–108.

[14] G. Maffei, I. Herreros, M. Sanchez-Fibla, K. J. Friston, P. F. Verschure, The perceptual shaping of anticipatory actions, Proceedings of the Royal Society B: Biological Sciences 284 (1869) (2017) 20171780.

[15] L. Peeraer, B. Aeyels, G. Van der Perre, Development of emg-based mode and intent recognition algorithms for a computer-controlled above-knee prosthesis, Journal of biomedical engineering 12 (3) (1990) 178–182.

[16] Q. Wang, X. Chen, R. Chen, Y. Chen, X. Zhang, Electromyography-based locomotion pattern recognition and personal positioning toward improved context-awareness applications, IEEE Transactions on Systems, Man, and Cybernetics: Systems 43 (5) (2013) 1216–1227.

[17] H. Kawamoto, Y. Sankai, Comfortable power assist control method for walking aid by hal-3, in: Systems, Man and Cybernetics, 2002 IEEE International Conference on, Vol. 4, IEEE, 2002, pp. 6–pp.

[18] K. Ozcan, S. Velipasalar, P. K. Varshney, Autonomous fall detection with wearable cameras by using relative entropy distance measure, IEEE Transactions on Human-Machine Systems 47 (1) (2016) 31–39.

[19] C. Chen, R. Jafari, N. Kehtarnavaz, Improving human action recognition using fusion of depth camera and inertial sensors, IEEE Transactions on Human-Machine Systems 45 (1) (2015) 51–61.

[20] H. Rezaie, M. Ghassemian, An adaptive algorithm to improve energy efficiency in wearable activity recognition systems, IEEE Sensors Journal 17 (16) (2017) 5315–5323.

[21] H. Huang, T. A. Kuiken, R. D. Lipschutz, A strategy for identifying locomotion modes using surface electromyography, Biomedical Engineering, IEEE Transactions on 56 (1) (2009) 65–73.

[22] L. J. Hargrove, A. M. Simon, R. Lipschutz, S. B. Finucane, T. A. Kuiken, Non-weight-bearing neural control of a powered transfemoral prosthesis, Journal of neuroengineering and rehabilitation 10 (1) (2013) 1.

[23] D. Peleg, E. Braiman, E. Yom-Tov, G. F. Inbar, Classification of finger activation for use in a robotic prosthesis arm, Neural Systems and Rehabilitation Engineering, IEEE Transactions on 10 (4) (2002) 290–293.

[24] K. Zhang, M. Sun, D. K. Lester, F. X. Pi-Sunyer, C. N. Boozer, R. W. Longman, Assessment of human locomotion by using an insole measurement system and artificial neural networks, Journal of Biomechanics 38 (11) (2005) 2276–2287.

[25] J. Staudenmayer, D. Pober, S. Crouter, D. Bassett, P. Freedson, An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer, Journal of Applied Physiology 107 (4) (2009) 1300–1307.

[26] A. M. Khan, Y.-K. Lee, T.-S. Kim, Accelerometer signal-based human activity recognition using augmented autoregressive model coefficients and artificial neural nets, in: Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE, IEEE, 2008, pp. 5172–5175.

[27] K. Yuan, A. Parri, T. Yan, L. Wang, M. Munih, N. Vitiello, Q. Wang, Fuzzy-logic-based hybrid locomotion mode classification for an active pelvis orthosis: Preliminary results, in: Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE, IEEE, 2015, pp. 3893–3896.

[28] S. E. Hussein, M. H. Granat, Intention detection using a neuro-fuzzy emg classifier, Engineering in Medicine and Biology Magazine, IEEE 21 (6) (2002) 123–129.

[29] F. H. Chan, Y.-S. Yang, F. Lam, Y.-T. Zhang, P. A. Parker, Fuzzy emg classification for prosthesis control, Rehabilitation Engineering, IEEE Transactions on 8 (3) (2000) 305–311.

[30] S. Gaglio, G. L. Re, M. Morana, Human activity recognition process using 3-d posture data, IEEE Transactions on Human-Machine Systems 45 (5) (2015) 586–597.

[31] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, K. B. Englehart, Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion, Biomedical Engineering, IEEE Transactions on 58 (10) (2011) 2867–2875.

[32] E. Fullerton, B. Heller, M. Munoz-Organero, Recognising human activity in free-living using multiple body-worn accelerometers, IEEE Sensors

Journal 17 (16) (2017) 5290–5297.

[33] J. Wannenburg, R. Malekian, Physical activity recognition from smartphone accelerometer data for user context awareness sensing, IEEE Transactions on Systems, Man, and Cybernetics: Systems 47 (12) (2016) 3142–3149.

[34] G.-M. Jeong, P. H. Truong, S.-I. Choi, Classification of three types of walking activities regarding stairs using plantar pressure sensors, IEEE Sensors Journal 17 (9) (2017) 2638–2639.

[35] S. Thrun, W. Burgard, D. Fox, Probabilistic robotics, MIT press, 2005.

[36] U. Martinez-Hernandez, A. A. Dehghani-Sanij, Adaptive bayesian inference system for recognition of walking activities and prediction of gait events using wearable sensors, Neural Networks 102 (2018) 107–119.

[37] U. Martinez-Hernandez, T. J. Dodd, M. H. Evans, T. J. Prescott, N. F. Lepora, Active sensorimotor control for tactile exploration, Robotics and Autonomous Systems 87 (2017) 15–27.

[38] H. A. Varol, F. Sup, M. Goldfarb, Multiclass real-time intent recognition of a powered lower limb prosthesis, Biomedical Engineering, IEEE Transactions on 57 (3) (2010) 542–551.

[39] M. T. Farrell, Pattern classification of terrain during amputee walking, Ph.D. thesis, Massachusetts Institute of Technology (2013).

[40] A. J. Young, A. M. Simon, N. P. Fey, L. J. Hargrove, Intent recognition in a powered lower limb prosthesis using time history information, Annals of biomedical engineering 42 (3) (2014) 631–641.

[41] J. C. Núñez, R. Cabido, J. J. Pantrigo, A. S. Montemayor, J. F. Vélez, Convolutional neural networks and long short-term memory for skeleton-based human activity and hand gesture recognition, Pattern Recognition 76 (2018) 80–94.

[42] E. P. Ijjina, C. K. Mohan, Hybrid deep neural network model for human action recognition, Applied Soft Computing 46 (2016) 936–952.

[43] F. J. Ordóñez, D. Roggen, Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition, Sensors 16 (1) (2016) 115.

[44] H. F. Maqbool, M. A. B. Husman, M. I. Awad, A. Abouhossein, N. Iqbal, A. A. Dehghani-Sanij, A real-time gait event detection for lower limb prosthesis control and evaluation, IEEE transactions on neural systems and rehabilitation engineering 25 (9) (2017) 1500–1509.

[45] F. Sikder, D. Sarkar, Log-sum distance measures and its application to human-activity monitoring and recognition using data from motion sensors, IEEE Sensors Journal 17 (14) (2017) 4520–4533.