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Towards an intelligent wearable ankle robot for assistance to foot drop

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***Abstract*— A wearable ankle robot prototype for assistance to foot drop is presented in this work. This device is built with soft and hard materials and employs one inertial sensor. First, the ankle robot uses a high-level method, developed with a Bayesian formulation, for recognition of walking activities and gait periods. Second, a low-level method, with a PID, controls the wearable device to operate in assistive and transparent modes. In assistive mode, activated by the toe-off detection, the wearable device assists the human foot in dorsiflexion orientation to reduce the effect of foot drop abnormality. In transparent mode, activated by the heel-contact detection, the robot device follows the movements performed by the human foot. The wearable prototype is validated with experiments, in simulation and real-time modes, for recognition of walking activity and control of assistive and transparent modes during walking. Experiments achieved 99.87% and 99.20% accuracies for recognition of walking activity and gait periods. Results also show the ability of the wearable robot to operate according to the gait period recognised during walking. Overall, this work offers a wearable robot prototype with the potential to assist the human foot during walking, which is important to allow subjects to recover their confidence and quality of life.**

I. INTRODUCTION

Wearable robots have shown a rapid progress in recent decades, mainly due to advances in sensor technology with lightweight, soft and portable measurement units [1], [2]. Special attention has been put to the use of wearable devices for healthcare, teleoperation, industry and gaming [3], [4]. Healthcare is a key area where wearable robots play a crucial role, assisting humans in activities of daily living (ADLs), but also allowing them to recover their quality of life.

For decades, wearable devices have been developed to assist humans with foot drop, which affects the capability and confidence to walk naturally [5]. Rigid wearable orthoses were used to generate rhythmic assistance during walking with constant speed [6], [7]. Detection of gait phases and control of wearable robots was performed with foot switches and pneumatic actuators [8], [9]. However, these devices, relied on foot switches and slow response actuators. Also, they did not employ computational intelligence methods for reliable recognition of walking. These aspects limit the potential of wearable devices, making them susceptible to fail in the presence of uncertainty from sensor measurements.

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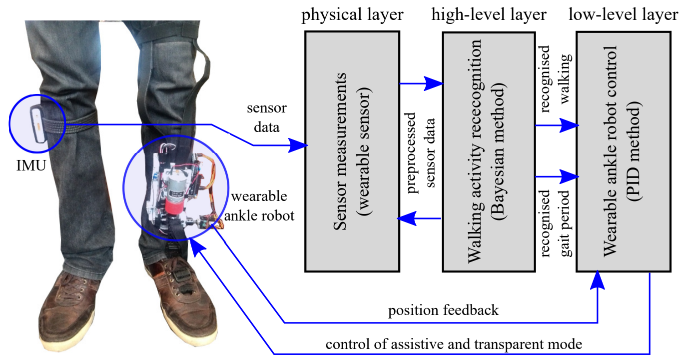


Fig. 1. Wearable ankle robot for assistance during walking. Data from an IMU are used by a Bayesian method for walking activity recognition. A PID controls the wearable robot in assistive and transparent modes.

In this work, an intelligent wearable ankle robot prototype to assist the human foot during walking is proposed (Figure 1). This ankle robot, built with rigid and soft materials, does not constrain the natural foot movements. The wearable device performs two main processes: 1) recognition of walking activities, gait periods and phases and 2) control of the robot to operate in assistive and transparent mode. The recognition process uses a probabilistic approach, with a Bayesian method, which have shown to be accurate, fast and robust to uncertainty in measurements with multiple sensors and robotic applications [10], [11], [12], [13], [14]. This probabilistic process allows the wearable robot to know when to activate and deactivate for assistance to the human body [15]. Control of assistive and transparent operation modes uses a proportional-integral-derivative (PID) method [16], [17]. In the assistive mode, the human foot is lifted up in dorsiflexion when the toe-off is predicted by the recognition process. The transparent mode, activated when the heel-contact is predicted, allows the human to perform natural foot movements in all directions.

A multilayer architecture, composed of high- and low-level layers, is used to implement the recognition and control processes [18], [19]. The wearable ankle robot is validated with multiple experiments in offline and real-time modes. Results from experiments show that fast and high accuracy are achieved by the ankle robot for recognition of level-ground walking, ramp ascent/descent, gait periods and phases. Furthermore, results show the ability of the wearable device to operate in the appropriate mode, during walking, according to the recognised gait period and phase.

Overall, the wearable ankle prototype demonstrates, based on experiments, to be a suitable robotic platform for the study and development of intelligent devices, capable to safely interact and assistance humans during walking activities.

II. METHODS

A. Experimental protocol and data collection

Sensor data were collected from 12 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. Participants were asked to walk at their self-selected speed while performing ten repetitions of level-ground walking, ramp ascent and ramp descent activities. Level-ground walking was performed on a flat cement surface, while a metallic ramp, with a slope of 8.5 deg, was used for ramp ascent and descent (Figures 2A,B,C). Angular velocity signals in x-y and -z axes were collected at a sampling rate of 100 Hz, from an IMU (Shimmer Inc.), attached to the shank of participants, and filtered with a cut-off frequency of 10 Hz. Two foot pressure-insole sensors were used, during the data collection only, to detect the beginning and end of the gait cycle.

Angular velocity signals measured from the shank of participants are shown in Figure 2D. Level-ground walking, ramp ascent and descent activities are represented by black, blue and red colour curves, respectively. Solid and dashed lines represent mean angular velocities and standard deviations, respectively. The data from the shank were prepared into column format to build training and testing datasets for the probabilistic recognition method. Angular velocity signals from each gait cycle were used to construct the histograms for recognition of walking activity. For recognition of stance and swing phases, the gait cycle was divided into eight periods as shown at the top of Figure 2D.

B. Robotic platform

A wearable ankle robot, composed of soft and rigid materials, was developed to provide assistance to foot drop during walking activities. The 3D design and components of the wearable device are shown in Figure 3A. This device is composed of a DC motor, motorised linear potentiometer, bearings, bevel gears, shaft and arduino board. The real wearable device and textile straps, for assistance to the human foot, are shown in Figure 3B. The weight of the wearable ankle robot is 1.2 kg and it can provide a maximum torque of 15 Nm, which is required for ankle assistance in dorsiflexion orientation during walking. This is a first prototype designed for a proof of concept, which allow the future development of optimised, lightweight and more ergonomic wearable assistive robots.

The motor shaft provides the assistance to the foot drop through the textile strap, which is attached to the shoe of the human. Also, the motor is able to react and follow the natural movements of the human foot without any restriction. Thus, the wearable device is capable to provide not only assistance when it is needed, but also to allow the human to naturally perform foot movements. In order to achieve accurate control of these human-robot interaction processes, a motorised linear potentiometer, integrated in the wearable ankle robot, detects and measures foot movements providing position feedback, at all times, during walking activities.

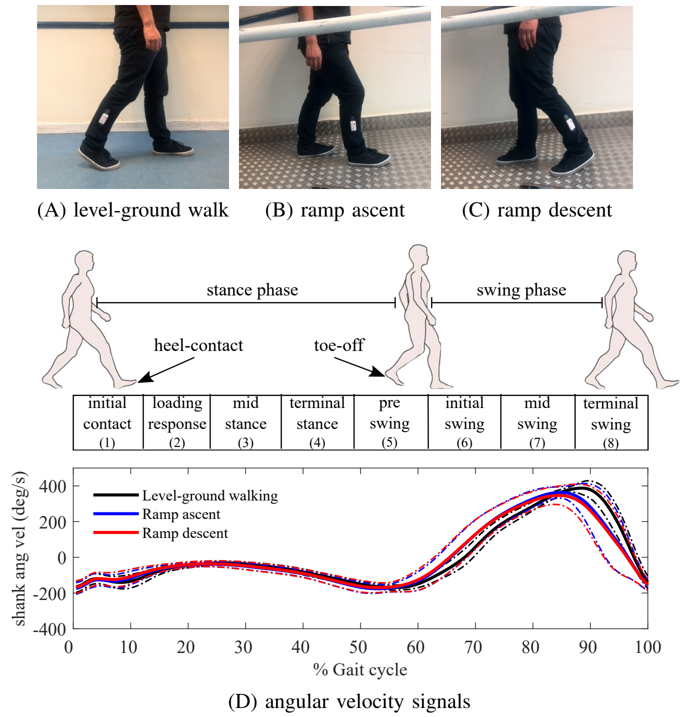


Fig. 2. (A)-(C) Level-ground walking, ramp ascent and ramp descent activities performed by participants using an IMU sensor. (D) Angular velocity signals collected from walking activities. Solid and dashed-lines are the mean and standard deviation, respectively. The gait cycle is segmented into 8 periods for recognition of gait periods and phases during walking.

The human wearing the ankle robot is shown in Figure 3C. This device uses a control architecture composed of high and low-level layers. First, the high-level layer is responsible for recognition of walking activities, gait periods and events. This is important to allow the wearable device to decide when to apply assistance to foot drop during the gait cycle. Second, the low-level layer is responsible for the actual control of the wearable device and assistance to the human. For that reason, proper interconnection and synchronisation of multi-level layers is crucial to achieve a robust and accurate performance with the assistive device. Figure 4 shows the interconnection of high and low-level layers.

C. High-level recognition of walking activity and gait period

A Bayesian formulation was used for recognition of walking activities and gait periods. Computational intelligence methods have shown to be reliable with multimodal sensor and applications [20], [21]. This method recursively updates the posterior probability from the product of prior probabilities and likelihood 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 class $c_n \in C$, $P(z_t|c_n)$ is the likelihood and z_t are the sensor measurements at time t. The process in Equation (1) is performed over all N classes c_n. Each class c_n corresponds to a (l_i, g_j) pair, where l_i and g_j are walking activity and gait period, respectively. For time $t = 0$, uniform prior probabilities,

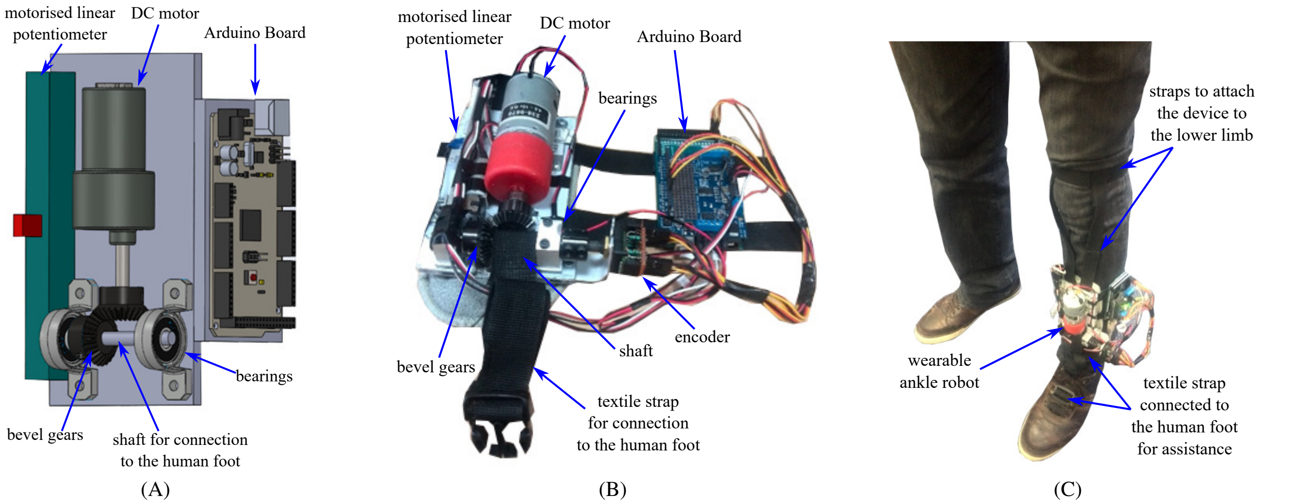


Fig. 3. Design and development of the wearable ankle robot. (A) Design and mounting of mechanical and electronic components of the wearable robot in 3D with SolidWorks. (B) Real wearable ankle robot integrated with mechanical, electronic (rigid materials) and textiles (soft materials) components. (C) Wearable ankle robot attached to the shank of a participant for data collection, recognition of walking activities and control while walking.

$P(c_n) = P(c_n|z_0) = \frac{1}{N}$, are assumed for all classes. The prior and number of classes are represented by $P(c_n|z_0)$ and N. For time $t > 0$, the prior, $P(c_n) = P(c_n|z_{t-1})$, is updated by the posterior at time $t-1$.

Angular velocity signals are used to construct the measurement model of the Bayesian classifier. A nonparametric approach based on histograms is used for the measurement model. The histograms are used to evaluate an observation z_t, and estimate the likelihood of a class c_n as follows:

$$\log P(z_t|c_n) = \log P_s(w_s|c_n) \tag{2}$$

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

$$P(z_t|z_{t-1}) = \sum_{n=1}^{N} P(z_t|c_n)P(c_n|z_{t-1}) \tag{3}$$

The iterative Bayesian process, performed by Equations (1) to (3), stops when the posterior, $P(c_n|z_t)$, exceeds a belief threshold, $\beta_{\text{threshold}}$, as follows:

$$\begin{gathered} \text{if any } P(c_n|z_t) > \beta_{\text{threshold}} \text{ then} \\ \hat{c} = \arg\max_{c_n} P(c_n|z_t) \end{gathered} \tag{4}$$

where $\hat{c}$ is the estimated class composed by the predicted walking activity and gait period pair, $(\hat{l}, \hat{g})$. This prediction, from the high-level method, is used by the low-level method, shown in Section II-D, for control of the wearable ankle robot. Figure 4 shows the flowchart of the high-level method for recognition of walking activity and gait period.

D. Low-level control of the wearable ankle robot

The output from the high-level recognition method can be used by a low-level controller, which is responsible to provide the assistance to foot drop during walking using the wearable ankle robot. In this work, a Proportional-Integral-Derivative (PID) method is employed as low-level controller to assist humans to foot drop during walking. The interconnection of high and low-level methods used by the wearable ankle robot is shown in Figure 4.

The low-level controller, activated by the output from the high-level recognition method, allows the wearable device to operate in two modes: 1) assistive and 2) transparent. The assistive mode is activated when the toe-off event is predicted, moving the foot of the subject in dorsiflexion orientation to a target position to avoid the foot drop. The transparent mode is activated when the heel-contact event is predicted, allowing natural movements of the human foot without any restriction from the wearable device. These operation modes make the wearable device capable to provide assistance and react to the natural movement of the human foot.

The diagram in Figure 5A shows the low-level controller, implemented with the PID method, for ankle assistance using the wearable robot during walking. The transfer function for the PID has the following form:

$$C(s) = \frac{K_d s^2 + K_p s + K_i}{s} \tag{5}$$

where K_d, K_p and K_i are the derivative, proportional and integral gains or parameters that need to be tuned. Here, the PID controller parameters were automatically tuned using the Control System Toolbox from MATLAB. Figure 5A shows the desired or target foot position, $x_d(t)$, which depends on the operation mode activated by the high-level layer, e.g., assistive or transparent. The output foot position, $x_o(t)$, is used as feedback to update the error signal, $e(t)$, and then, to adjust the PID control signal, $u(t)$.

In the assistive operation mode, the target position is defined as the maximum ankle angle obtained from a calibration process with the wearable device. This angle, measured from the motorised linear potentiometer integrated in the

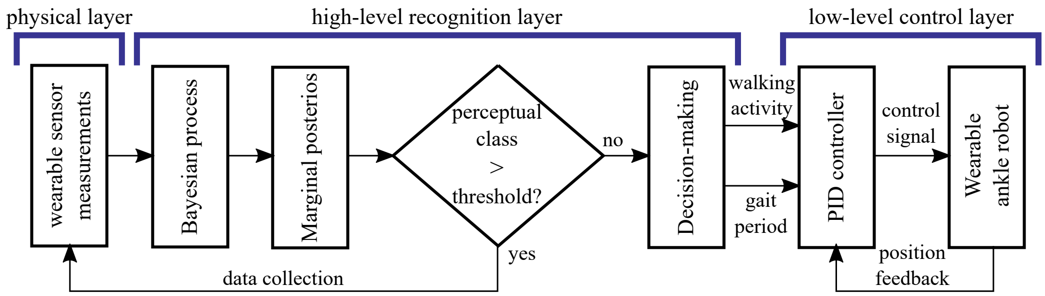
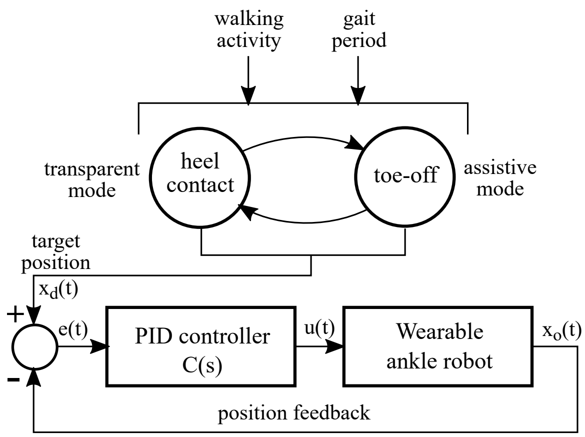
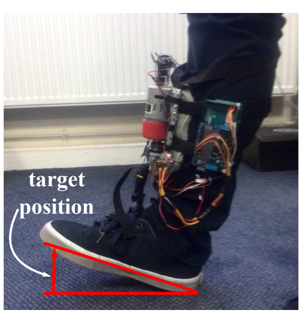


Fig. 4. Multilayer architecture implemented in the wearable ankle robot for data collection, recognition and control processes. The physical layer collects sensor measurements from the IMU attached to the shank of participants. The high-level layer, which implements the Bayesian method, is responsible for iterative data accumulation, perception and decision-making for recognition of walking activity, gait period and phase. The low-level layer, built with a PID, controls the wearable ankle robot to operate in assistive and transparent modes when toe-off and heel-contact are recognised, respectively, by the high-level layer. The low-level layer uses the position feedback, from the wearable device, to achieve an accurate and robust robot control while walking.



(A) Block diagram of the low-level controller



(B) Assistive mode

(C) Transparent mode

Fig. 5. Low-level control approach. (A) The target position, $x_d(t)$, and control in assistive and transparent mode depend on the toe-off and heel-contact recognition. The signal, $u(t)$, controls the wearable device over time. The PID control adapts according to the observed error, $e(t)$, given the position feedback, $x_o(t)$, from the wearable robot. (B) Target position, measured by the motorised linear actuator and digital encoder, for assistance to the human foot in dorsiflexion orientation. (C) Range of foot movements, in all orientations, allowed by the wearable ankle robot while operating in transparent mode.

wearable robot, is recorded by the low-level controller as the target position to move the human foot in dorsiflexion (Figure 5B). For the transparent operation mode, the wearable device follows the foot movements, based on the feedback from the motorised linear potentiometer, which continuously changes according to foot movements performed by the human (see Figure 5C).

III. Results

A. Recognition of walking activity and gait period

The accuracy of the high-level method for recognition of walking activities and gait periods was validated using real data from level-ground walking, ramp ascent and descent.

The high-level probabilistic method was configured with 24 classes c (3 walking activities $\times$ 8 gait periods). The recognition accuracy and decision time were evaluated using the belief threshold $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. This parameter permitted to control the confidence level and accuracy of the recognition system. Recognition results of walking activities are shown in Figure 6A. Recognition results showed a gradual improvement from a mean error of 21% (79% accuracy) to 0.13% (99.87% accuracy) for large belief thresholds. This shows that the Bayesian formulation improves the accuracy of the decision-making process through the accumulation of sensor measurements. Figure 6B shows the analysis of decision time, which is important to develop systems that respond in the appropriate time. A gradual increment in decision time was observed, requiring from 1 to 25 sensor samples for large belief thresholds. This behaviour was expected given that normally recognition methods need more evidence to achieve a better performance. Recognition accuracy for each walking activity is presented in Figure 6C. Black and white colours represent 0% and 100% accuracy, respectively. Level ground-walking, ramp ascent and descent activities were recognised with 100%, 99.84% and 99.78% accuracies, respectively.

An experiment for recognition of gait periods and phases was performed, which provides information about the state of the human body during the gait cycle. Here, the gait cycle was divided into eight gait periods, where stance is composed of gait periods 1 to 5 (initial contact, loading response, mid stance, terminal stance, pre-swing) and swing phase of gait periods 6 to 8 (initial swing, mid swing, terminal swing), respectively (Figure 2). Recognition results of gait periods are shown in Figure 6D. A gradual improvement in the accuracy was observed from a mean error of 7% (93% accuracy) to 0.8% (99.20% accuracy) for large belief thresholds. This means that high confidence levels allow to achieve accurate recognition of gait periods and phases

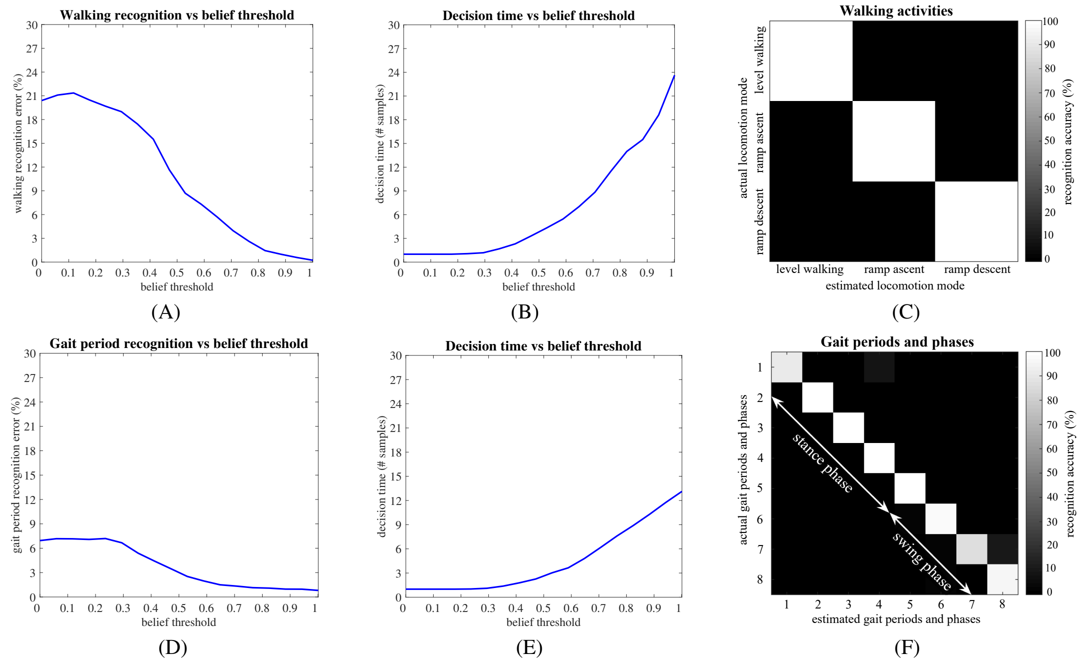


Fig. 6. Recognition results of walking activity, gait period and phase. (A) Mean recognition accuracy of level-ground walking, ramp ascent and descent activities against belief threshold. The accuracy is gradually improved for large belief thresholds. (B) Mean decision time or sensor samples needed to make a decision, which shows that the higher the recognition accuracy the larger the number of sensor samples required. (C) Recognition accuracy of individual walking activities. (D) Mean recognition accuracy of gait periods against belief threshold. The accuracy is improved for large belief thresholds. (E) Mean decision time for recognition of gait periods. This plot shows that the number of sensor samples increases for high accurate results. (F) Recognition accuracy of individual gait periods. This plot shows that gait periods 1 to 5 and 6 to 8 can be use for recognition of stance and gait phases, respectively.

Fig. 7. Participant walking while wearing the ankle robot and IMU sensor.

(stance and swing). Results from decision time analysis show an increment from 1 to 13 sensor samples needed to make a decision (Figure 6E). Thus, a mean of 13 sensor samples are required to identify the gait period with an accuracy of 99.20%. Recognition accuracy of each gait period is shown in Figure 6F. Black and white colours represent 0% and 100% accuracy. The gait periods were identified with accuracies of 92.83%, 100%, 99.60%, 100%, 99.98%, 97.94%, 87.66% and 97.50% for periods 1 to 8, respectively. This shows that the high-level recognition method recognises stance and swing phases with accuracies of 98.48% (gait periods 1 to 5) and 94.36% (periods 6 to 8).

B. Low-level control for assistance to foot drop

The capability of the wearable ankle robot to operate in assistive and transparent modes, during walking, was evaluated in real-time mode. For this experiment, participants were asked to wear the ankle robot, and an IMU sensor, while walking at their self-selected speed. Participants performed multiple repetitions of the experiment while sensor signals, detection of walking activity and gait periods were recorded.

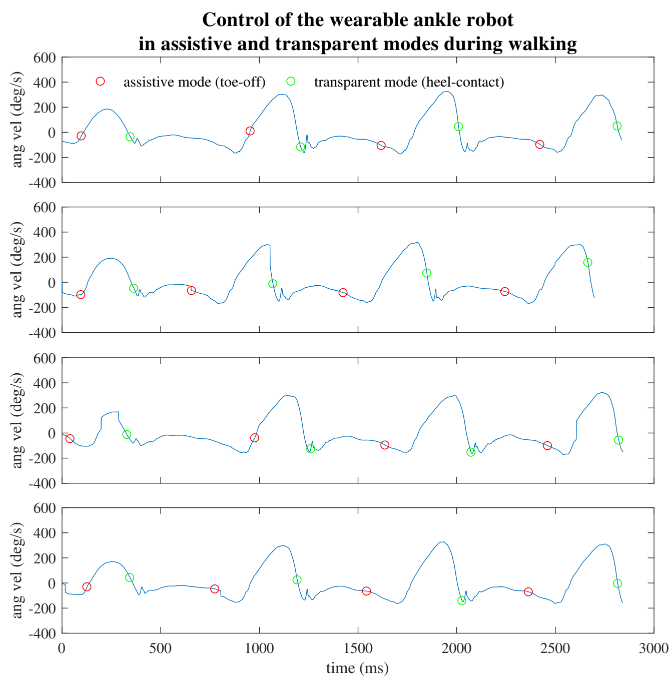


Fig. 8. Real-time control of the wearable ankle robot, in assistive (red circles) and transparent (green circles) modes during walking, with the multilayer architecture. The low-level robot control of operation modes used the walking activity and gait period recognition by the high-level method.

Figure 7 shows the wearable ankle robot, and IMU sensor, attached to the shank of a participant while walking.

The low-level controller, implemented with a PID method, was used to control the wearable robot based on the recognition output from the probabilistic high-level method. Figure 8 shows multiple results from the control of the wearable ankle robot in real-time. Angular velocity signals, from the IMU sensor attached to the shank of participants, are represented by blue colour lines. The activation of the wearable device to operate in assistive mode is triggered by the recognition of the toe-off during the gait cycle. Red colour circles in Figure 8 represent the wearable robot activated to work in assistive mode. Here is when the human foot is assisted and moved to the target position reducing the foot drop effect. The transparent mode is triggered when the heel-contact is recognised by the high-level method. In this operation mode, the wearable device allows the foot to move, freely and naturally, in all orientations. This contrasts with the limitation of natural movements imposed by rigid assistive devices. Activation of the robot in transparent mode, during the gait cycle, is represented by green colour circles shown in Figure 8.

It is worth mentioning that the activation of the wearable device, was not triggered at the same time step for all gait cycles. This behaviour was expected given that humans do not walk with a constant speed and trajectory. This means that the probabilistic high-level method tries to adapt to the changes observed during walking. Thus, the low-level control also adapts based on the behaviour of the high-level method. These results show the importance of hierarchical controllers in wearable robotics, but also, the need of adaptive methods that deal with uncertainty and changes from the environment.

Overall, results from all experiments, in offline and real-time mode, show that the proposed wearable ankle foot prototype is accurate and robust, giving it the potential to provide assistance to the human foot during walking.

IV. Conclusion

A wearable ankle robot prototype for foot assistance during walking was presented. This robot, composed of soft and hard materials, was capable to recognise walking activities, gait periods and events. This high-level recognition process used a Bayesian method and data from an IMU attached to the shank of participants. Recognition of toe-off and heel-contact were used by a low-level method, implemented with a PID, to control the robot in assistive and transparent modes. In assistive mode, the wearable robot provided foot assistance, in dorsiflexion orientation, during walking. In transparent mode, the robot allowed the human to perform natural foot movements. Validation experiments, in offline and real-time, showed that the wearable robot is fast and accurate for recognition of walking activities, gait periods and events. Results showed the capability of the wearable device to lift the human foot up when the toe-off was predicted. Similarly, the wearable robot followed the natural foot movement when the heel-contact was predicted. Overall, this work presented a prototype with the potential to assist the human foot during walking, which offers a platform for the development of the next generation of adaptive and intelligent wearable assistive robotic devices.

References

[1] A. T. Asbeck, S. M. M. De Rossi, I. Galiana, Y. Ding, and C. J. Walsh, "Stronger, smarter, softer: Next-generation wearable robots," *Robotics & Automation Magazine, IEEE*, vol. 21, no. 4, pp. 22–33, 2014.

[2] S. C. Mukhopadhyay, "Wearable sensors for human activity monitoring: A review," *IEEE sensors journal*, vol. 15, no. 3, pp. 1321–1330, 2015.

[3] J. L. Pons, *Wearable robots: biomechatronic exoskeletons*. John Wiley & Sons, 2008.

[4] U. Martinez-Hernandez, L. W. Boorman, and T. J. Prescott, "Multisensory wearable interface for immersion and telepresence in robotics," *IEEE Sensors Journal*, vol. 17, no. 8, pp. 2534–2541, 2017.

[5] J. D. Stewart, "Foot drop: where, why and what to do?" *Practical neurology*, vol. 8, no. 3, pp. 158–169, 2008.

[6] L.-F. Yeung, C. Ockenfeld, M.-K. Pang, H.-W. Wai, O.-Y. Soo, S.-W. Li, and K.-Y. Tong, "Design of an exoskeleton ankle robot for robot-assisted gait training of stroke patients," in *Rehabilitation Robotics (ICORR), 2017 International Conference on*. IEEE, 2017, pp. 211–215.

[7] M. Duvinage, R. Jiménez-Fabián, T. Castermans, O. Verlinden, and T. Dutoit, "An active foot lifter orthosis based on a pcpg algorithm," in *Rehabilitation Robotics (ICORR), 2011 IEEE International Conference on*. IEEE, 2011, pp. 1–7.

[8] Y.-L. Park, B.-r. Chen, D. Young, L. Stirling, R. J. Wood, E. C. Goldfield, R. Nagpal, *et al.*, "Design and control of a bio-inspired soft wearable robotic device for ankle-foot rehabilitation," *Bioinspiration & biomimetics*, vol. 9, no. 1, p. 016007, 2014.

[9] D. Y. Li, A. Becker, K. A. Shorter, T. Bretl, and E. T. Hsiao-Wecksler, "Estimating system state during human walking with a powered ankle-foot orthosis," *IEEE/ASME Transactions on Mechatronics*, vol. 16, no. 5, pp. 835–844, 2011.

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

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

[12] A. J. Young, A. M. Simon, N. P. Fey, and L. J. Hargrove, "Intent recognition in a powered lower limb prosthesis using time history information," *Annals of biomedical engineering*, vol. 42, no. 3, pp. 631–641, 2014.

[13] S. Thrun, W. Burgard, and D. Fox, *Probabilistic robotics*. MIT press, 2005.

[14] U. Martinez-Hernandez, T. J. Dodd, and T. J. Prescott, "Feeling the shape: Active exploration behaviors for object recognition with a robotic hand," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 12, pp. 2339–2348, Dec 2018.

[15] U. Martinez-Hernandez and A. A. Dehghani-Sanij, "Probabilistic identification of sit-to-stand and stand-to-sit with a wearable sensor," *Pattern Recognition Letters*, vol. 118, pp. 32–41, 2019.

[16] D. Erol and N. Sarkar, "Design and implementation of an assistive controller for rehabilitation robotic systems," *International Journal of Advanced Robotic Systems*, vol. 4, no. 3, p. 30, 2007.

[17] G. Aguirre-Ollinger, J. E. Colgate, M. A. Peshkin, and A. Goswami, "Active-impedance control of a lower-limb assistive exoskeleton," in *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*. IEEE, 2007, pp. 188–195.

[18] R. A. Brooks, "A robust layered control system for a mobile robot," *Robotics and Automation, IEEE Journal of*, vol. 2, no. 1, pp. 14–23, 1986.

[19] U. Martinez-Hernandez, I. Mahmood, and A. A. Dehghani-Sanij, "Simultaneous bayesian recognition of locomotion and gait phases with wearable sensors," *IEEE Sensors Journal*, vol. 18, no. 3, pp. 1282–1290, 2017.

[20] J. Ferreira, J. Lobo, P. Bessiere, M. Castelo-Branco, and J. Dias, "A bayesian framework for active artificial perception," *IEEE transactions on cybernetics*, vol. 43, no. 2, pp. 699–711, 2013.

[21] A. Rubio-Solis and G. Panoutsos, "Interval type-2 radial basis function neural network: a modeling framework," *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 2, pp. 457–473, 2015.