Towards a context-based Bayesian recognition of transitions in locomotion activities

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***Abstract*— This paper presents a context-based approach for the recognition of transition between activities of daily living (ADLs) using wearable sensor data. A Bayesian method is implemented for the recognition of 7 ADLs with data from two wearable sensors attached to the lower limbs of subjects. A second Bayesian method recognises 12 transitions between the ADLs. The second recognition module uses both, data from wearable sensors and the activity recognised from the first Bayesian module. This approach analyses the next most probable transitions based on wearable sensor data and the context or current activity being performed by the subject. This work was validated using the ENABL3S Database composed of data collected from 7 ADLs and 12 transitions performed by participants walking on two circuits composed of flat surfaces, ascending and descending ramps and stairs. The recognition of activities achieved an accuracy of 98.3%. The recognition of transitions between ADLs achieved an accuracy of 98.8%, which improved the 95.3% accuracy obtained when the context or current activity is not considered for the recognition process. Overall, this work proposes an approach capable of recognising transitions between ADLs, which is required for the development of reliable wearable assistive robots.**

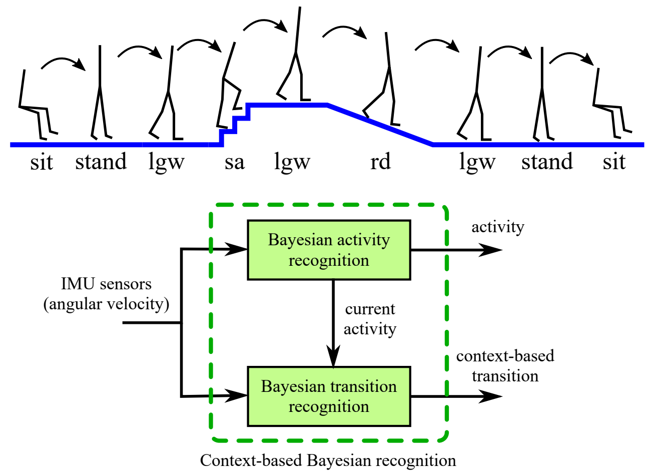

Fig. 1. Context-based approach for recognition of transitions between locomotion activities. This figure depicts one of the walking circuits used for data collection from wearable sensors attached to the shank of subjects.

I. INTRODUCTION

Wearable robots need to be able to recognise activities and transitions to reliably assist humans in activities of daily living (ADLs) [1], [2]. The rapid advances in sensor technology and machine learning have allowed the design of assistive robots capable of recognising locomotion activities [3], [4]. Recent works have shown that walking activities (e.g., level-ground walking and ramps) can be recognised accurately using array of sensors, e.g, inertial measurement units (IMUs), accelerometers and electromyography (EMG), together with Bayesian networks, Gaussian Mixture Models and Artificial Neural Networks [5], [6], [7], [8], [9].

Inertial sensors, Support Vector Machines (SVMs) and Linear Discriminant Analysis have been used for the recognition locomotion activities and *sit-to-stand* and *sit-to-lie* transitions [10], [11], [12], [13]. Body sensor networks, together with histograms, Dynamic Bayesian Networks and Time History Information can also recognise transitions between *walking*, *ramps*, *stairs* and *lying* activities [14], [15], [16]. Even though this progress, methods for accurate and fast recognition of transitions are still under research, given the important role they play in the development of robotic systems capable of assisting humans safe and reliably.

In this work, a context-based Bayesian approach for the recognition of transitions between locomotion activities is presented (Figure 1). First, a Bayesian formulation is implemented for recognition of 7 locomotion activities using data from wearable sensor attached to the lower limbs of subjects. A second module is implemented employing the same method for the recognition of 12 transitions extracted from the locomotion activities. Probabilistic approaches have shown their potential for perception, decision-making and control in a large variety of robotic applications [17], [18]. In this approach, the two recognition processes work independently. However, the set of transitions can be defined based on the current activity being performed by the subject. For instance, if the subject is sitting, then it is more likely to stand up and then walk, rather than start walking immediately from the sit state. For that reason, it is important to consider the context or current activity for the recognition of transitions.

This context-based approach initialises the prior probability of the Bayesian module responsible for the recognition of transitions. This initialisation process consists of adding a belief value to the next most probable transitions based on the current activity. This approach can be seen as a system that makes decisions based on history information [15], [19]. In this case, the recognition of activities and transitions are linked, where the Bayesian module for recognition of transitions uses input data from both, the signals from wearable sensors and the current estimated activity.

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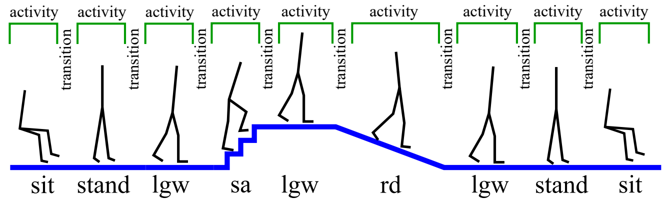
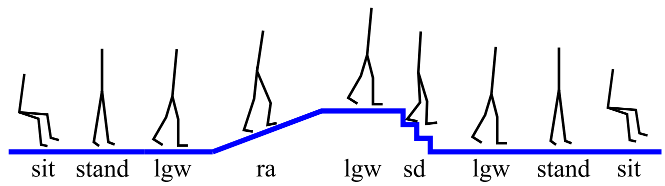
The proposed methods are validated using the ENABL3S Dataset [20] that contains a large number of samples from 7 locomotion activities (sit, stand, level-ground walking, stair ascent, stair descent, ramp ascent and ramp descent). This information has allowed the definition of 12 transitions between activities, as explained in next section. This dataset has been collected with multiple wearable sensors attached to the lower limbs of participants. The validation with this data has been performed in offline mode for the recognition of activities and transitions. The results show that the recognition accuracy from the context-based approach is improved over the accuracy obtained when the recognition of transitions does not consider the current activity being performed by the subject. The number of samples needed to make an accurate decision is also improved by the context-based recognition method, which means that the system is capable of performing both, accurate and fast decisions.

Overall, this work has proposed a method capable of recognising transitions between locomotion activities, which is an important aspect that needs to be considered for the development of safe and reliable wearable assistive robots.



(A) Walking circuit 1



(B) Walking circuit 2

Fig. 2. Circuits employed in the open source ENABL3S Dataset for data collection from activities of daily living. These activities are 1) *sit*, 2) *stand*, 3) *level-ground walking (lgw)*, 4) *stair ascent (sa)*, 5) *stair descent (sd)*, 6) *ramp ascent (ra)*, and 7) *ramp descent (rd)*. The following transitions are identified from these activities: 1) *sit-to-stand*, 2) *lgw-to-ra*, 3) *lgw-to-rd*, 4) *lgw-to-sa*, 5) *lgw-to-sd*, 6) *lgw-to-stand*, 7) *ra-to-lgw*, 8) *rd-to-lgw*, 9) *sa-to-lgw*, 10) *sd-to-lgw*, 11) *stand-to-sit*, and 12) *stand-to-lgw*. For this process, multiple wearable sensors were attached on the lower limbs of 10 healthy subjects, and each circuit was repeated 25 times by each subject.

II. Methods

A. Wearable sensor data from lower limbs

The training and testing of the proposed methods for recognition of locomotion activity and transitions, described in next sections, employ angular velocity signals from the left and right shank of subjects. These biomechanical signals are obtained from the Benchmark ENABL3S Dataset published in [20] and available to download from Figshare at https://doi.org/10.6084/m9.figshare.5362627. In this dataset, the angular velocity signals have been collected using two inertial measurement units (IMUs) attached to both shanks of 10 healthy able-bodied subjects; seven male and three female with 25.5±2 years, 174±12cm height and 70±14kg.

The ENABL3S Dataset employed two walking circuits for data collection from 7 activities as illustrated in Figure 2. These activities performed 25 times by each participant are 1) *sit*, 2) *stand*, 3) *level-ground walking* (*lgw*), 4) *stair ascent* (*sa*), 5) *stair descent* (*sd*), 6) *ramp ascent* (*ra*), and 7) *ramp descent* (*rd*). From these walking circuits and activities, the following 12 transitions are extracted: 1) *sit-to-stand*, 2) *lgw-to-ra*, 3) *lgw-to-rd*, 4) *lgw-to-sa*, 5) *lgw-to-sd*, 6) *lgw-to-stand*, 7) *ra-to-lgw*, 8) *rd-to-lgw*, 9) *sa-to-lgw*, 10) *sd-to-lgw*, 11) *stand-to-sit*, and 12) *stand-to-lgw*.

Each of the seven activities in the ENABL3S Dataset is labeled with an integer number from 0 to 6. The raw data from these activities and their corresponding labels are used for training and testing the proposed method. In our study, transitions are segmented by using a fixed number of samples (100 data samples) extracted from the end of the current activity to the beginning of the next activity performed by the subject. Here, we have employed 100 data samples for each transition between two activities, and each transition is labeled with an integer number from 0 to 11. Thus, all the raw data from these activities and transitions, extracted from all participants, has been used to create datasets for training and testing processes as described in the next sections.

B. Bayesian recognition approach

Two Bayesian modules are implemented for recognition of the locomotion activities and transitions depicted in Figure 3A and Figure 3B, respectively. Bayesian methods have shown to be powerful probabilistic machine learning techniques for decision-making and robotic applications [18], [21]. This probabilistic approach uses the following notation:

- C, a finite set of classes, e.g., locomotion activities, transitions between activities.
- z, measurements from the wearable sensors.
- n, denotes a specific class from the set $N = 7$ of locomotion activities.
- l, denotes a specific class from the set $L = 12$ of transitions between activities.

The Bayesian method updates the posterior probability by multiplying the prior probability 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. For $t = 0$, uniform prior probabilities, $P(c_n) = P(c_n|z_0) = \frac{1}{N}$, are assumed for all classes. For $t > 0$, the prior, $P(c_n) = P(c_n|z_{t-1})$, is updated by the posterior estimated at time $t-1$.

The measurement models for the Bayesian method use a nonparametric approach based on histograms, which are employed to evaluate an observation z_t, and estimate the likelihood of a class c_n as follows:

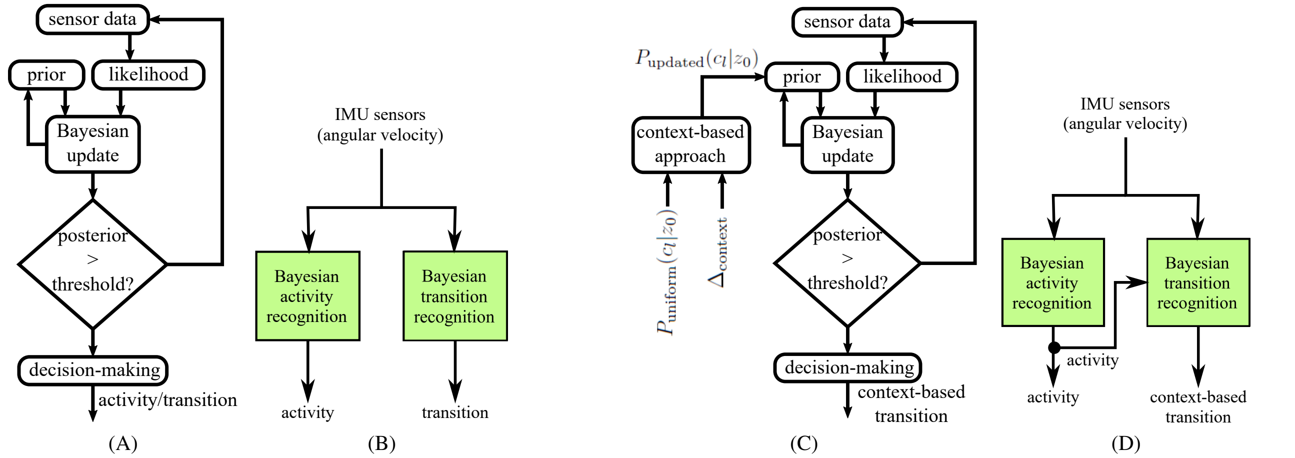


Fig. 3. Bayesian modules for the recognition of locomotion activities and transitions. (A) Bayesian approach that implements the method described in Section II-B for the recognition of activities and transitions. (B) Illustration of the two recognition processes implemented with the Bayesian recognition method, and where the transitions module does not consider the activity being performed by the subject. (C) Context-based Bayesian method for recognition of transitions between activities as described in Section II-C. (D) Illustration of the context-based approach, where the transition module uses information from both, the wearable sensors and the current recognised activity, to recognise the next most probable transition.

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

where w_s is the data from sensor s, and $P(z_t|c_n)$ is the likelihood of the observation z_t given a class c_n. Probability values in [0, 1] are ensured by the normaliser 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 process in Equation (1) iterates until the posterior, $P(c_n|z_t)$, exceeds a belief threshold, $\beta_{\text{threshold}}$ that can take values in [0, 0.05, ..., 0.99]. Then, the class at time t (e.g., activity, transition) is estimated as follows:

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

where $\hat{c}_{\text{activity}}$ is the estimated activity class from the activity recognition module. The process described from Equations (1) to (4) is similarly employed for the recognition of transitions but using $L = 12$ transitions classes. The process to estimate the transition class $\hat{c}_{\text{transition}}$ is as follows:

$$\begin{gathered}\text{if any } P(c_l|z_t) > \beta_{\text{threshold}} \text{ then} \\ \hat{c}_{\text{transition}} = \arg\max_{c_l} P(c_l|z_t)\end{gathered} \tag{5}$$

The steps and flowchart of the Bayesian approach are shown in Figure 3A, which is implemented in each block of Figure 3B for the recognition of the 7 activities and 12 transitions in Figure 2 and described in Section II-A. Angular velocity signals from the open source ENABL3S Dataset are employed for the construction of the measurement models and the analysis performed by the Bayesian method.

TABLE I

LIST OF VALID TRANSITIONS BETWEEN ACTIVITIES FOR THE CONTEXT-BASED BAYESIAN RECOGNITION APPROACH

activity	valid transitions
sit	stand
lgw	ra, rd, sa, sd, stand
ra, rd, sa, sd	lgw
stand	sit, lgw

C. Context-based transition recognition approach

The process described in Section II-B performs the recognition of activities and transitions independently. In this section, a context-based approach is proposed for the recognition of transitions based on the current data from the wearable sensors and the current estimated activity as shown in Figures 3C,D. Thus, the transition module makes a decision based on the context or state of the activity being performed by the subject. This approach allows the segmentation of valid transitions for each activity. For instance, the *sit* activity transits to the *stand* activity only, and the *stand* activity transits to *lgw* and *sit* only. Other transitions from these activities are invalid according to the walking circuits employed for data collection. The full list of valid transitions between activities is shown in Table I.

The context-based recognition method gives priority to the valid transitions for the estimated activity. For instance, when the activity module estimates that the current activity is *sit*, the Bayesian method in the transition module adds a belief value (Δ_{context}) to the next most probable transition *sit-to-stand*, but all the transitions are still analysed to reduce uncertainty. Similarly, when the estimated activity is *stand*, then a belief value is added to the next most probable transitions *stand-to-sit*, and *stand-to-lgw*.

The context parameter Δ_{context} is composed of the probability value of the estimated activity class $\hat{c}_{\text{activity}}$ from Equation (4), and the position of the next most probable transitions provided by the δ function as follows:

$$\Delta_{\text{context}} = (P(\hat{c}_{\text{activity}}), \delta(\hat{c}_{\text{activity}})) \tag{6}$$

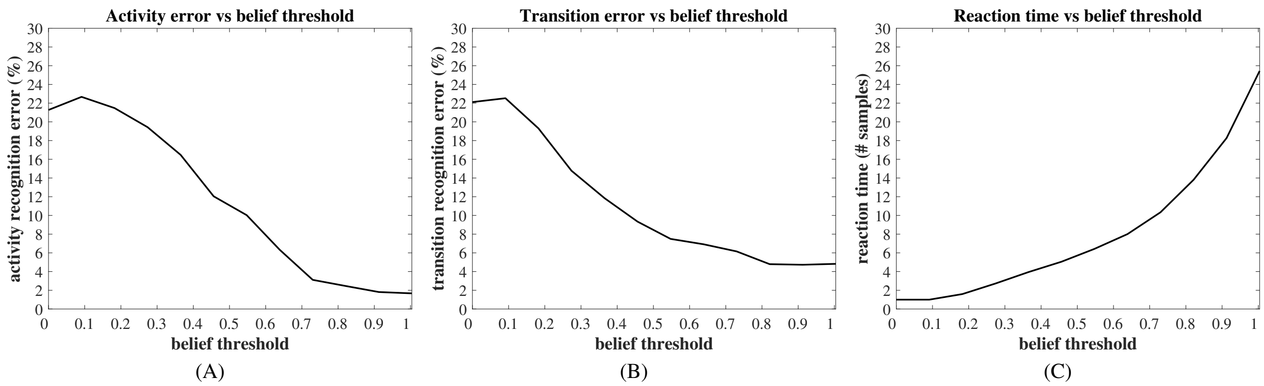


Fig. 4. Bayesian recognition of locomotion activities and transitions using the standard approach described in Section II-B and illustrated in Figure 3A,B. This process for recognition of transitions does not use information from the activity performed by the subject. (A) The Bayesian module for the recognition of activities was able to achieve the smallest error of 1.7% with a belief threshold of 0.99. (B), (C) The Bayesian module for the recognition of transitions was able to achieve the smallest error of 4.7% error with 18 data samples and belief threshold of 0.9.

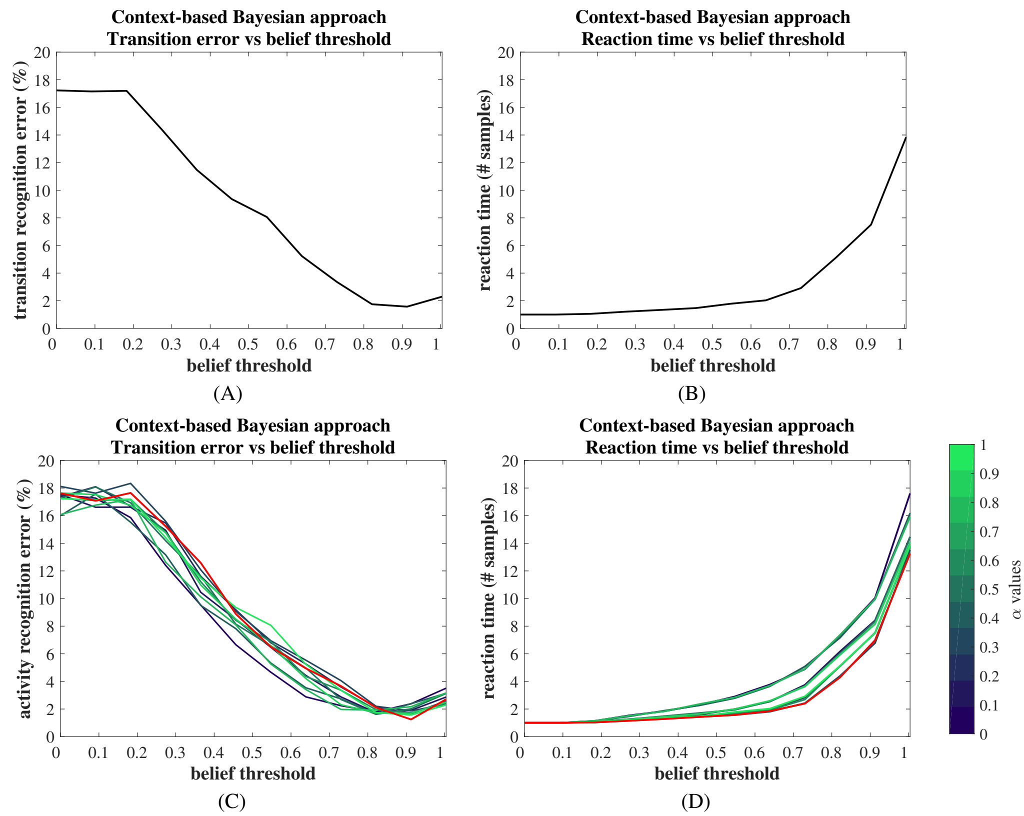


Fig. 5. Context-based Bayesian recognition of transitions between locomotion activities. This approach takes into consideration the activity being performed by the subject for the initialisation of the prior probability employed for the recognition of transitions, as explained in Section II-C and illustrated in Figure 3C,D. (A), (B) The recognition errors and number of samples required to make a decision, where the smallest error achieved by the context-based method is 1.5% and which required 8 data samples and belief threshold of 0.9. (C), (D) Curves with the results from the recognition errors and number of samples with different belief levels (α) used for the initialisation of the prior probability for the next most probable transitions. The best result was obtained with α=0.7 (red colour curve), which reduced the error to 1.2% and the number of samples to 7 with the belief threshold of 0.9.

The δ function returns the list of valid transitions for the current activity being performed by the subject estimated by the activity recognition module. Then, the context parameter is added to the uniform prior distribution using the weighting parameter α as follows:

$$\begin{gathered} P_{\text{uniform}} = P(c_l) = \frac{1}{L} \\ P_{\text{updated}}(c_l|z_0) = (1-\alpha)P_{\text{uniform}}(c_l|z_0) + \alpha\Delta_{\text{context}} \end{gathered} \tag{7}$$

where P_{uniform} is the uniform probability of the 12 transitions, $P_{\text{updated}}(c_l|z_0)$ is the prior probability of transition classes, which is updated increasing the prior belief of the next valid transitions by the context parameter. This updating process is controlled by the weighting parameter α = [0.0, 0.1, …, 1], in order to observe the effect of the amount of the prior information added to the prior distribution.

In the context-based approach for the recognition of transitions, the uniform prior probability is updated for each new decision to be made over time. The updating process of

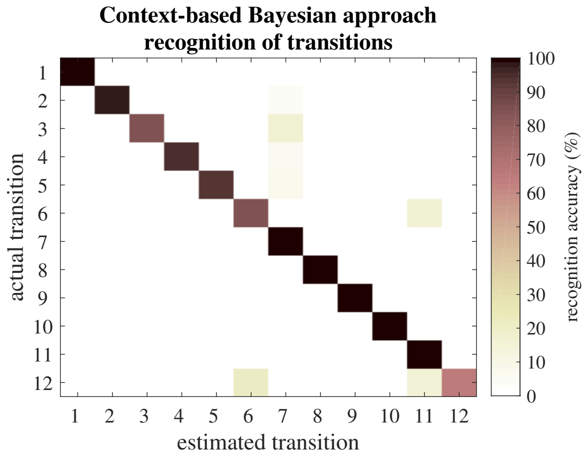


Fig. 6. Confusion matrix with the recognition of each individual transition. The transitions are organised as follows: 1) *sit-to-stand*, 2) *lgw-to-ra*, 3) *lgw-to-rd*, 4) *lgw-to-sa*, 5) *lgw-to-rd*, 6) *lgw-to-stand*, 7) *ra-to-lgw*, 8) *rd-to-lgw*, 9) *sa-to-lgw*, 10) *sd-to-lgw*, 11) *stand-to-sit*, 12) *stand-to-lgw*. White and black colours represent small and high accuracy results.

the uniform probability is made according to the estimated activity being performed by the subject.

III. Results

Multiple experiments on recognition of locomotion activities and transitions were performed to validate the proposed context-based recognition method. For the validation process, the open source ENABL3S Dataset was employed. Specifically, angular velocity datasets from the left and right shanks from the locomotion activities shown in Figure 2, were used for training and testing the proposed method.

The experiments were performed randomly selecting data samples from the testing datasets. The random selection of samples was repeated 10,000 times analysing the accuracy for recognition of transitions with belief thresholds $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$. Each belief threshold value was set automatically, one at a time, to observe the performance of the recognition of activities and transitions. All these experiments were performed in offline mode and the results are described in the following sections.

A. Recognition of activity and transition independently

The first experiment was the recognition of the 7 locomotion activities shown in the walking circuits in Figure 2. The results presented in Figure 4A were evaluated for the set of belief thresholds $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$, employed by the Bayesian approach to observe the accuracy of the recognition process. These results showed that the largest and smallest errors for recognition of locomotion activities are 23% and 1.7%, respectively, which were achieved with $\beta_{\text{threshold}} = 0.1$ and 0.99, respectively. This means that the approach in Figures 3A,B is capable of recognising, with an accuracy of 98.3%, whether the subject is performing the the activity *sit*, *stand*, *lgw*, *sa*, *sd*, *ra* and *rd*.

The second experiment was the recognition of the 12 transitions extracted from the walking circuits employed in the ENABL3S Database (Figure 2). Similarly to the first experiment, the Bayesian module for recognition of transitions was evaluated for the belief threshold $\beta_{\text{threshold}}$. The largest and smallest recognition errors achieved are 22.5% and 4.7%, respectively, which were obtained with $\beta_{\text{threshold}} = 0.1$ and 0.99, respectively (Figure 4B). The reaction time or number of data samples, needed by the recognition process to make a decision, are affected by the belief threshold as shown in Figure 4C. For instance, 1 and 18 data samples are required to obtain the largest and smallest transition recognition errors with $\beta_{\text{threshold}} = 0.1$ and $\beta_{\text{threshold}} = 0.9$, respectively. Thus, this approach is capable of improving the recognition accuracy but a large number of data is required. This trade-off between accuracy and number of data samples can be adjusted according to the specific application. In the case of robotic assistive devices, it is important that the recognition system is both, accurate and fast.

These experiments showed that the Bayesian module recognises locomotion activities with an accuracy of 98.3%, while the highest accuracy for recognition of transition is 95.3%. This performance can be improved when the context is considered for the recognition process, as shown by proposed context-based recognition method in the next section.

B. Context-based recognition of transitions

The experiments with the context-based approach use the estimated activity as input to the Bayesian module for the recognition of transitions (Figures 3C,D). It is important to recognise locomotion activities with high accuracy, otherwise, this information can negatively affect the performance of the context-based recognition approach.

The valid transitions between activities, shown in Table I, are used by the context-based approach, which adds an initial belief (Δ_{context}) to the next most probable transitions based on the current activity being performed by the subject (see Section II-C). The performance of this approach was evaluated for the set of belief thresholds $\beta_{\text{threshold}}$. The largest and smallest recognition errors achieved are 17.5% and 1.5%, which required 1 and 8 data samples, respectively (Figures 5A,B). The accuracy was improved when the recognition of transitions takes into account the current estimated activity. Similarly, the number of data samples for decision-making was reduced to 8, which means that the recognition approach is capable of performing accurate and faster decisions.

In this experiment it was also analysed the effect, on accuracy and reaction time, of different belief levels (Δ_{context}) added to the next transitions using the weighting parameter α = [0.0, 0.1, …, 1]. The accuracy and reaction time results are shown in Figure 5C,D, where the coloured curves represent different values of α. The results show that $\alpha =$ 0.7 (shown in red colour) achieved the best performance for the recognition of transitions with the smallest error of 1.2% and reaction time of 7 data samples. Figure 6 shows the recognition accuracy for each individual transition, where white and black colours represent small and high accuracy.

A comparison of the performance between the proposed method and previous works is presented in Table II. All methods achieve accuracies ranging from 98% to 100%

TABLE II

COMPARISON OF METHODS FOR RECOGNITION OF ACTIVITIES OF DAILY LIVING AND RECOGNITION OF TRANSITIONS BETWEEN ACTIVITIES

method	activities	transitions	sensors	recognition accuracy (activity)	recognition accuracy (transition)
Decision tree [12]	sit, stand, lying	2	3	98.26%	100%
SVM [16]	lying, sit	2	2	100%	98%
LDA [14]	level walk, stairs	6	1	99.4%	100%
DBN + Time history info [15]	level walk, ramps, stairs	5	13	98%	80%
our approach	level walk, ramps, stairs, sit, stand	12	2	98.3%	98.8%

and from 80% to 100% for recognition of activities and transitions, respectively. Decision trees and LDA methods can recognise transitions with 100% accuracy, however, these methods can recognised up to 6 transitions [12], [14]. Even though high accuracy is achieved for recognition of activities with DBN + Time History Information, only 80% accuracy is achieved for transitions [15]. Our proposed method achieved 98.3% and 98.8% accuracies for recognition of activities and 12 transitions using 2 sensors. This comparative analysis shows that our method, using context information, is capable of achieving accurate results for recognition of both, activities and transitions using a reduced number of sensors.

IV. CONCLUSION

This work presented a context-based method for the recognition of transitions between locomotion activities using wearable sensor data. This approach uses the current activity being performed by the subject an input for the recognition of the next most probable transition. The proposed method was implemented using two Bayesian modules for recognition of activities and transitions. The performance of these modules was validated using the open source ENABL3S Dataset. The validation process showed that the recognition of 7 activities achieved an accuracy of 98.3%. The 12 transitions were recognised with an accuracy of 1.2% (98.8% accuracy) using the context-based method. This result improved the recognition accuracy of 95.3% obtained when the transition was analysed without considering the locomotion activity being performed by the subject. Overall, this work shows that information from the context plays an important role in recognition process, which are essential to improve the reliability and safety of assistive robotic devices.

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