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Probabilistic locomotion mode recognition with wearable sensors

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***Abstract*— Recognition of locomotion mode is a crucial process for control of wearable soft robotic devices to assist humans in walking activities. We present a probabilistic Bayesian approach with a sequential analysis method for recognition of locomotion and phases of the gait cycle. Our approach uses recursive accumulation of evidence, as biological systems do, to reduce uncertainty present in the sensor measurements, and thus improving recognition accuracy. Data were collected from a wearable sensor, attached to the shank of healthy human participants, from three locomotion modes; level-ground walking, ramp ascent and ramp descent. We validated our probabilistic approach with recognition of locomotion in steady-state and gait phases in transitional states. Furthermore, we evaluated the effect, in recognition accuracy, of the accumulation of evidence controlled by increasing belief thresholds. High accuracy results achieved by our approach, demonstrate its potential for robust control of lower limb wearable soft robotic devices to provide natural and safe walking assistance to humans.**

I. INTRODUCTION

Wearable soft robotics has shown great technological advances in recent years, specially on soft actuators and low-level controllers to assist humans in walking activities [1]. However, recognition of locomotion mode for soft robots, a high-level process that plays a crucial role for control of walking assistive technologies, is still under development.

In this work, we present a probabilistic Bayesian approach, that together with a sequential analysis method, allows to perceive and recognise multiple locomotion modes (Figure 1). Probabilistic approaches have provided accurate recognition of locomotion from transfemoral amputees [2], [3]. Neuromuscular and mechanical sensor data from prosthetic legs have also been used to recognise locomotion by combination of classifiers [4]. Robust perception with soft sensors for robot control have also been benefited from probabilistic methods, dealing with the uncertainty present in the world, e.g., sensor noise and environment dynamics [5].

For training our method, we collected multiple sensor datasets from a wearable sensor worn by healthy human participants. For validation, experiments to recognise locomotion mode and gait cycle phases in steady-state and transitional state were performed. Overall, high recognition accuracy was achieved for all the experiments. This demonstrates the enormous potential of our probabilistic method for the development of robust wearable soft robotic devices, capable to safely assist humans in walking activities.

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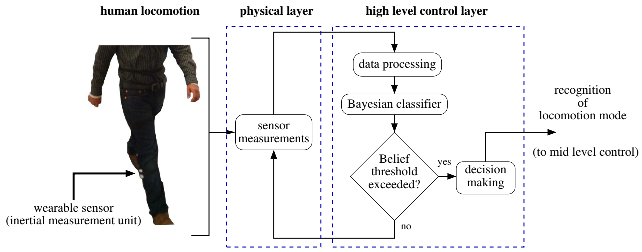

Fig. 1. High-level perceptual layer for recognition of locomotion modes and gait cycle phases, implemented with a Bayesian approach that reduces the uncertainty present in measurements from wearable sensors.

II. METHODS

A. Experimental protocol

Eight healthy male subjects, without any apparent gait abnormality, participated in this investigation. Subjects' ages ranged between 24 and 34, heights were between 1.74 m and 1.79 m, and weights were between 77.6 kg and 85 kg. Participants completed five repetitions of three locomotion modes; level-ground walking, ramp ascent and ramp descent.

B. Data collection and processing

Data were systematically collected from an inertial measurement unit (IMU), which composed of an accelerometer and gyroscope, was attached to the shank of human participants. IMUs have shown to be robust measurement devices for control of soft wearable robots for rehabilitation [6]. We also used a foot pressure insole, built with four piezoresistive sensors, to identify the gait cycle through the detection of heel contact and toe off [7]. Figure 2A shows the shank velocity data collected at a sampling rate of 100 Hz and processed using a second-order Butterworth filter with a cut-off frequency of 10 Hz.

C. Bayesian classifier

We used a probabilistic Bayesian approach, that together with a sequential analysis method, permitted to recognise both locomotion mode and gait cycle phases from multiple activities performed by humans. Our Bayesian formulation recursively updates the posterior probability from the product of the 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 $P(c_n|z_t)$ and $P(z_t|c_n)$ are the posterior probability and likelihood at time t. The prior probability at time $t-1$ is represented by $P(c_n|z_{t-1})$. For the initial time $t=0$ we assumed uniform prior probabilities $P(c_n|z_0) = \frac{1}{N}$. Properly normalised probabilities are obtained by $P(z_t|z_{t-1})$. The recursive process in Equation (1) is performed over all N

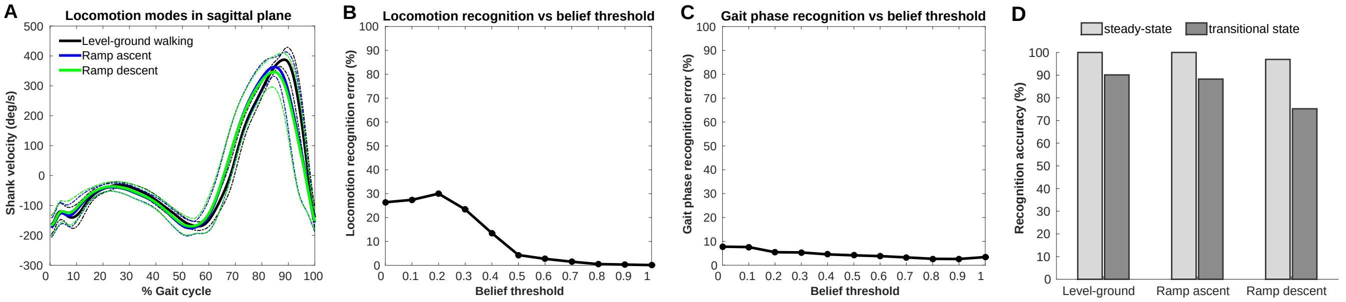

Fig. 2. (A) Shank angular velocity from level-ground walking (black colour), ramp ascent (blue colour) and ramp descent (green colour) locomotion modes. Dashed-lines show the standard deviation for each locomotion mode. (B),(C) Mean recognition error for locomotion and gait cycle phases for increasing belief thresholds. (D) Recognition of locomotion in steady-state mode and gait cycle phases (divided in eight phases) in transitional state mode.

classes $c_n \in C$. Each class c_n corresponds to a (l_i, g_j) pair, where l_i and g_j are the locomotion modes and gait cycle phases. The sensor observations at time t are defined by z_t. The posteriors are the joint distributions over the joint classes, then the beliefs over individual locomotion mode and gait cycle phase are given by the marginal posteriors:

$$P(l_i|z_t) = \sum_{j=1}^{J} P(l_i, g_j|z_t) \quad (2)$$

$$P(g_j|z_t) = \sum_{i=1}^{I} P(l_i, g_j|z_t) \quad (3)$$

with locomotion beliefs summed over all gait phases and gait phases beliefs summed over all locomotion classes. The likelihood is obtained by $P(z_t|c_n) = \sum_{s=1}^{S} \frac{P(m|c_n,s)}{S}$, where $P(m|c_n, s) = \frac{h(m,s)}{\sum_m h(m,s)}$ is a nonparametric approach based on histograms of sensor values from training data. The number of observed values m for sensor s is represented by $h(m, s)$ and normalised by $\sum_m h(m, s)$.

The accumulation of evidence, from the Bayesian process, is stopped once the belief threshold $\theta \in [0.0, 0.05, \ldots, 0.99]$ is exceeded. Then, the *maximum a posteriori* (MAP) is used to estimate and make a decision for the locomotion mode and gait cycle phase as follows:

$$\text{if any } P(c_n|z_t) > \theta \text{ then } \hat{c} = \arg\max_{c_n} P(c_n|z_t) \quad (4)$$

where $\hat{c}$ provides the estimated locomotion mode and gait cycle phase (l, g) pair. Thus, this output can be used for control at mid- and low-levels of wearable robotic devices.

III. Results

A. Recognition of locomotion mode and gait phases

First, we analysed the effects in accuracy for a set of belief thresholds $\theta = [0.0, 0.05, \ldots, 0.99]$ for all the locomotion modes and gait phases. A mean recognition error of 0.5% was achieved for all the locomotion modes (level-ground walking, ramp ascent and descent) as shown in Figure 2B. For recognition gait phases, we divided the gait cycle into eight phases of the same size, which also allows to know the progress of the gait cycle along time. Our probabilistic method was able to achieved a mean error of 2.2% for all the gait phases (see Figure 2C). These results with high accuracy were obtained with $\theta = 0.99$. We also observed the capability of our approach to gradually improve the recognition accuracy for increasing belief thresholds.

B. Recognition in steady-state and transitional states

Second, we analysed locomotion modes in steady-state and transitional state with belief thresholds $\theta = [0.0, 0.05, \ldots, 0.99]$. For the steady-state analysis, our method recognised level-ground walking, ramp ascent and descent locomotion modes with accuracies of 100%, 100% and 98.5% respectively for $\theta = 0.99$ (light grey bars in Figure 2D). For transitional state, we analysed the recognition accuracy for transitions between the eight phases of the gait cycle for each locomotion mode. Transitions for level-ground walking, ramp ascent and ramp descent were recognised with 92.5%, 89% and 75.5% accuracies (dark grey bars in Figure 2D). Results show the potential of our method for the development of intelligent wearable robotic devices to safely assist humans in thei walking activities.

IV. Conclusion

In this work, we presented a Bayesian approach with a sequential analysis method for recognition of human locomotion. Our approach demonstrated that recursive accumulation of evidence, as biological systems do, provides accurate recognition systems. Thus, interfacing our high-level perceptual layer method with mid- and low-level layers, offer a robust control approach for lower limb wearable soft robotic devices to safely assist humans in walking activities.

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