Human Motion Classification based on Multi-Modal Sensor Data for Lower Limb Exoskeletons

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***Abstract*— Intuitive exoskeleton control is fundamental since it contributes to improved user acceptance and wearability comfort. This requires the detection of user's motion intention and its incorporation into the exoskeleton control system. In this work, we propose a classification system based on Hidden Markov Models (HMMs), which facilitates the online classification of multi-modal sensor data acquired from a lower-limb exoskeleton based on previously defined motion patterns. For classification of these motion patterns at each time step, we consider the most recent sensor measurements by using a sliding window approach. We collected a training data set from a total number of 10 subjects performing 13 different motions with a passive exoskeleton equipped with 7 3D-force sensors and 3 inertial measurement units (IMUs). Our evaluation includes an analysis of the time needed for correct classification (latency), a validation for a training set containing all subjects and a leave-one-out validation to assess the generalization performance of the approach. The results indicate that our approach can classify motions of subjects included in the training set with an average accuracy of 92.80% and is able to achieve a generalization performance of 84.46%. With the selected parameters an average latency of 368.97 ms is achieved.**

Fig. 1: Sensorized passive exoskeleton for the left leg.

I. Introduction

In recent years, extensive research efforts have been dedicated to the area of exoskeletons for augmenting human performance, especially regarding the question how such devices can be efficiently controlled. For this purpose, classifying the current state of the user-exoskeleton system with machine learning methods has gained increasing importance. If the current state, especially the currently intended motion, is known, this knowledge can be used to enhance exoskeleton control or to predict future states, e.g. subsequent motions [1], [2]. Various machine learning approaches have been applied to classify motions with wearable devices. One possibility is to use time-invariant classifiers based on Hidden Markov Models (HMMs), support vector machines (SVM), linear discriminant analysis (LDA), artificial neural networks (ANN), Bayesian classifiers and neuro-fuzzy classifiers [3]. Those techniques can be applied to sensor signals from electromyography (EMG), electroencephalography (EEG) or mechanical sensors (e.g. joint angle encoders). Tsai et al. [4] use multi-channel EMG signals and SVMs to recognize upper arm motion patterns, aiming at advancements in the control of exoskeleton robots. Other approaches utilize Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN), see [5], or neuro-fuzzy classifiers [6] with EMG data. EEG-based human robot interfaces are applied to control lower limb exoskeletons [7], [8], [9] or hand orthoses [10]. Villa-Parra et al. identified patterns in EEG and sEMG signals via an ANN and SVM to control the exoskeleton H2 [11]. Since mechanical sensors such as angular encoders, inertial measurement units (IMUs) or torque sensors are already integrated in most powered prostheses or exoskeletons, these sensor modalities can also be used for motion classification. Varol et al. [12] use a combination of joint angles and ground contact forces for gait phase and motion classification of a lower limb prosthesis with LDA.

HMMs are commonly used to represent sequential time series data, such as human motions, since they have some degree of invariance to local warping [13]. The models can be trained with kinematic data [14], [15], [16], [17] or data of wearable sensors such as foot pressure soles [18] or accelerometers [19]. HMMs have also been used to classify motions performed with exoskeletons. Taborri et al. [20] detect the current gait phase of a lower limb orthosis by retrieving data of force and IMU sensors. Wang et al. [21] classify motions with an SVM based on IMU data and predict possible upcoming motions with HMMs for the Non-Binding Lower Extremity Exoskeleton (NBLEX). In contrast to rehabilitation devices, aspects such as versatile motion types, a minimal training procedure and a robust sensor setup are crucial requirements for exoskeletons to be able to reliably augment the user's motions.

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In this paper, we investigate and assess the quality of a motion classification approach based on multi-modal data of force sensors and IMUs, which are integrated in the physical human-robot interface (pHRI) of an exoskeleton. Key requirements for the acceptance and usability of such devices are a short setup time, no tedious calibration phase, intuitive control strategies as well as a sensor system that is robust against environmental effects and can be worn over clothing. For this purpose, we build a passive exoskeleton, which is based on our previous work [22] and is equipped with 7 3D-force sensors placed at given locations of the exoskeleton where interaction forces between the human body and the exoskeleton can be measured in a reliable way. Additionally, an IMU is attached on each of the 3 segments (shank, thigh, foot) of the exoskeleton. To classify the human motion we use continuous Hidden Markov Models (HMMs), which are trained with the motion recordings of 10 healthy subjects performing 13 different motion tasks.

The paper is organized as follows. In Section II, we describe the design and the sensor setup of the passive exoskeleton. Section III covers the modeling of multi-modal sensor data and our approach for HMM-based online motion pattern classification for these sensor modalities. The experimental setup as well as the evaluation of the classification accuracy and latency are presented in Section IV. Section V concludes the paper.

II. Exoskelton Design and Sensor System

As stated in Section I, only sensors which are permanently mounted on an exoskeleton are considered for motion classification in this work. Therefore, we constructed a device which should be easy to don and calibrate. It is equipped with force sensors and IMUs.

A. *Exoskeleton Design*

The passive exoskeleton for the left leg consists of three basic aluminum frame parts for the thigh, the shank and the foot which are connected by orthotic revolute joints[1] at the knee and ankle. Using soft aluminum (EN-AW 5083) allows slight frame adjustment to inter-subject leg characteristics when donning the exoskeleton and provides slight compensation of the missing degrees of freedom at the ankle and knee joint during operation.

The mechanical coupling between the exoskeleton and its wearer is achieved by orthotic Velcro straps on the anterior thigh and shank as well as a sports shoe at the foot. Since the force sensors should measure the interaction forces between exoskeleton and user, they are mounted on these Velcro straps via 3D-printed interfaces (see top zoomed image section in Fig. 3).

B. *Sensor System*

Forces in all spatial directions are acquired with seven 3D-force sensors[2] which are placed over relatively big muscles involved in locomotion, namely *m. rectus femoris* (Fig. 2 (a)), *m. biceps femoris* (Fig. 2 (b)), *m. gastrocnemius* (Fig. 2 (c)) and *m. tibialis anterior* (Fig. 2 (d)).

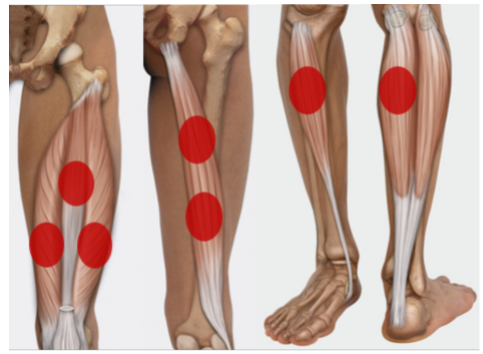

Fig. 2: Placement of the 3D-force sensors on the corresponding leg muscles (Figure adopted from [23]).

Due to the semi-spherical shape of the force sensors (colored red in Fig. 3), the maximum force, the resolution and the maximum dome deflection in compression direction ($100\,\mathrm{N}$, $6.25\,\mathrm{mN}$, $3\,\mathrm{mm}$) deviates from the aforementioned properties in shear direction ($25\,\mathrm{N}$, $7\,\mathrm{mN}$, $2.5\,\mathrm{mm}$). Data acquisition units sample the raw analogue data of up to 4 sensors with a maximum frequency of $100\,\mathrm{Hz}$.

The exoskeletons is furthermore equipped with three IMUs[3] which are placed on every segment of the exoskeleton (colored blue in Fig. 3), namely thigh, shank and foot. Orientations and linear accelerations of every IMU are processed by a micro-controller[4] with a frequency of $80\,\mathrm{Hz}$.

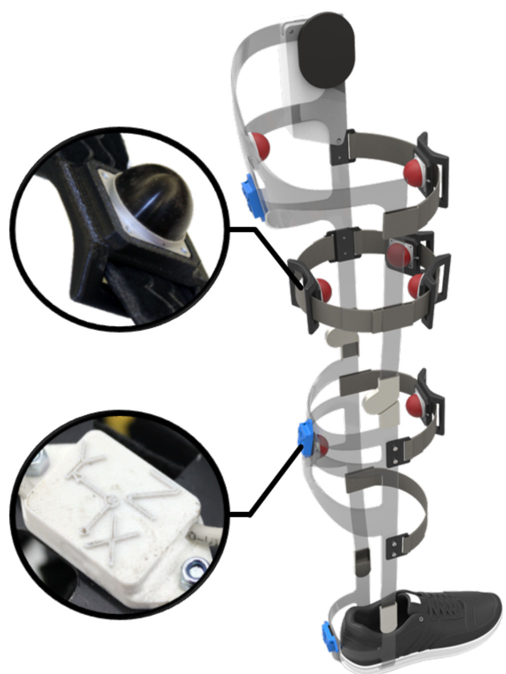

Fig. 3: Placement of IMUs (blue) and force sensors (red).

[1] Otto Bock HealthCare; 17B47=20 / 17B57=20
[2] Optoforce Ltd. OMD-30-SE-100N
[3] BNO055 IMU, Robert Bosch GmbH
[4] SAM3X8E ARM Cortex-M3, Microchip Technology Inc.

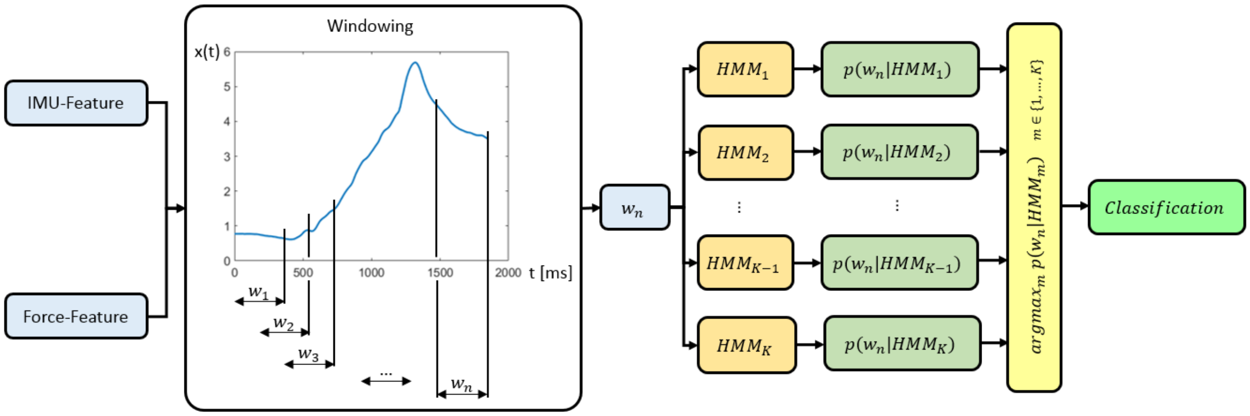

Fig. 4: Schematic scheme of the classification process.

III. Motion Modeling and Classification

In this work, we do not address the problem of finding a suitable low-dimensional multi-modal feature combination for classifying exoskeletons motions, and instead use a combination of pre-defined features for both the IMU and force sensors. In future work, we plan to explore the space of possible feature combinations with the goal of identifying low-dimensional combinations of these features to be able to possibly reduce the number of necessary sensors.

A. Modeling of Multi-Modal Motion Data

As stated in Section I, the ability to use the exoskeleton without a tedious calibration phase is crucial. Therefore, and due to inter-subject characteristics, e.g. different circumference of the thighs, an equal tightening of the Velcro straps cannot be guaranteed. This leads to different force values after every donning process for the same subject. Additionally, every subject has its own gait style causing different linear accelerations and orientations when two subjects perform the same motion type. To overcome this issue, the difference of two consecutive feature vectors $(F_t - F_{t-1})$ composed of IMU and force values is calculated and used as input for the HMMs.

The IMUs measure the linear acceleration in all spatial directions as well as the angular orientation which is represented by quaternions. Since quaternions are ambiguous (one angular configuration can be described by two quaternions), they are converted to Roll-Pitch-Yaw (RPY) angles. Therefore, the IMU feature (combination of all three IMUs) consists of 9 linear accelerations and 9 RPY values leading to a total dimensionality of 18.

As stated before, each of the seven force sensor measures the forces in all spatial direction. Combining the seven force sensors to the force feature leads to a dimensionality of 21. Hence, the feature vector used in this work, defined as a combination of IMU and force features, has a total dimensionality of 39. Since the IMU data (80 Hz) and the force data (100 Hz) are recorded with a different frequency, the IMU values are interpolated to 100 Hz and the timestamps are unified.

B. HMM-based Motion Classification

HMMs are used in the context of multi-class classification, referring to a classification problem where more than two classes are used. Each sample can only be assigned to one specific class since all classes are disjunct, meaning that an unknown observation has to be assigned to one specific motion class. One possible approach for this problem is to train one HMM per motion type and to use a classifier to determine the most probable motion class.

In our work, we trained HMMs using a fully connected topology and constrain covariance matrices to be diagonal. Observations are modeled with Gaussian distributions and the number of states is constant for all HMMs. In context of augmenting exoskeletons it is crucial that the used algorithm classifies the performed motion shortly after its beginning to ensure the support of the human during the motion execution in real-time (online). More details to HMMs and their application to time series data can be found in the existing literature [13], [24].

Fig. 4 presents our classification process for the sensor data. The feature vectors for every time step (10 ms) are concatenated. To realize an online application, we decided to use a sliding window approach. For this purpose, the acquired sensor data stream is split into windows (smaller slices of the data stream) with a constant window size (e.g. 300 ms). After a certain time (window step time), a new window is generated leading to an overlapping of the windows. Such overlap of the windows is necessary in order to be able to classify motions as fast as possible and to ensure that a window associated to a motion is not *missed*, e.g., due to unfavorable offset between the processed and the training data.

An unknown observation sequence, in our case a window, must be assigned to a finite set of classes HMM_k. Therefore, the log-likelihoods $p(w_n|\mathrm{HMM}_k)$ under each HMM are calculated and the window w_n is then assigned to the HMM (motion class) with the highest log-likelihood. For all evaluations, the number of states is set to 14 per HMM and a window step size of 10 ms is used. This step size corresponds to the sensor sample frequency and therefore is the lowest possible value.

IV. Evaluation and Results

A. Data Acquisition

Our data set consists of 10 healthy subjects (5 male, 5 female) which have been recorded with the passive exoskeleton described in Section II. Since the exoskeleton does not allow to adjust the segment lengths of its thigh and shank frame, only subjects with similar lower limb segment lengths have been selected for this study to avoid parasitic interaction forces caused by large kinematic misalignments. Table I provides an overview of the subject parameters.

TABLE I: Overview of subject parameters. UL denotes Upper Leg and LL denotes Lower Leg.

	Average	Std. Dev.
Age	25.10	3.86
Height [m]	1.73	0.03
Weight [kg]	66.00	5.85
BMI [$\mathrm{kg/m^2}$]	22.05	1.54
UL Circumference [cm]	55.20	3.20
LL Circumference [cm]	36.75	1.31
UL Length [cm]	42.80	2.63
LL Length [cm]	41.10	2.30

During one recording session, the corresponding subject was asked to perform a set of 13 different motion tasks with 10 repetitions each. The total size of the training data thus amounts up to 1300 trials. The motions have been chosen to represent basic motions associated with activities of daily living or working, namely: *walking forward (WF)*, *walking backward (WB)*, *turn left (TL)*, *turn right (TR)*, *sidesteps right (SR)*, *sidesteps left (SL)*, *going upstairs (GU)*, *going downstairs backwards (GB)*, *going downstairs (GD)*, *lift object (LO)*, *drop object (DO)*, *stand up (SU)* and *sit down (SD)*. The motion recordings *going upstairs*, *going downstairs backwards* and *going downstairs* were conducted on a 4 step staircase. For the lifting and dropping tasks, a 3 kg box was used.

Each subject was allowed to choose step length and motion speed arbitrarily but were asked to start locomotion with the exoskeleton leg (except for *TR, SR, LO, DO, SU, SD*). The order of motion tasks remaining unchanged in the order given above and the subject was standing or sitting still at the start and end of each recording. During the recording, only the actual motion task of the subject was captured while avoiding phases of no motion at the start and end, as far as practicable.

B. Evaluation

1) Window Sizes and Latency:

The goal of this paper is to perform online motion classification with HMMs, meaning that the system should classify motions as accurate and at the same time as early as possible. Therefore, the time (latency) until a motion is correctly classified is an important measure to judge the performance of such a system. This measure can be applied both for motions at the beginning of the classification process or for transitions between different motions. In both cases, latencies depend on the window size, with a small window size being advantageous for a fast classification. However, for a high classification accuracy longer windows are advantageous. Since these requirements represent a trade-off, we investigated the influence of the window size on the classification accuracy. In our evaluation, we consider a motion to be classified correctly if 10 consecutive windows of the data stream are correctly classified to avoid an erroneously classification.

To evaluate the window size and latency, HMMs were trained with window sizes in a range of 100-600 ms (steps of 100 ms) and tested with a stratified 5-fold cross validation over all subjects and motions. The 5-fold cross validation was stratified to accommodate the varying number of generated windows per subject caused by the self-selected motion speed of subjects influencing the recording lengths. The second column of Table II shows the accuracies of the evaluation for different window sizes.

TABLE II: Accuracies of stratified 5-fold cross validation and latencies for different window sizes over all subjects.

Window Size [ms]	Accuracy [%]	Latency [ms]
100	82.92	273.99
200	89.16	314.28
300	92.80	368.97
400	95.00	439.49
500	96.46	532.31
600	97.45	594.83

To determine the latency at the start of the classification process, the whole data set was padded with zero values for the first second of the motion. This technique was used because there is the possibility that a motion could be classified although the window is not completely filled with sensor data of the corresponding motion. The extended (padded) motion recordings were tested on the aforementioned models and their latencies are depicted in the third column of Table II. Fig. 5 presents the aforementioned accuracies and latencies for the different window sizes considered in our evaluation.

Given our results, as shown in Fig. 5, a window size of 300 ms provides a good trade-off between a high accuracy (92.80 %) combined with an acceptable latency (368.97 ms). For smaller window sizes, the accuracy drops under 90 %

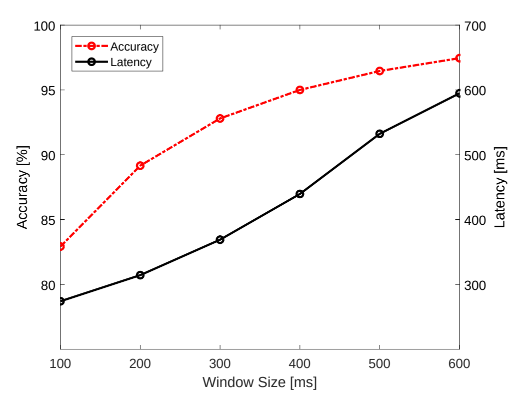

Fig. 5: Accuracies and latencies for different window sizes.

and window sizes over 400 ms could be disadvantageous for controlling exoskeleton devices.

2) Latency for Individual Motions:

After the window size was analyzed, we individually evaluated the latencies for all motions tasks at a window size of 300 ms. Fig. 6 shows the mean latency for each motion with the same zero padding as described above.

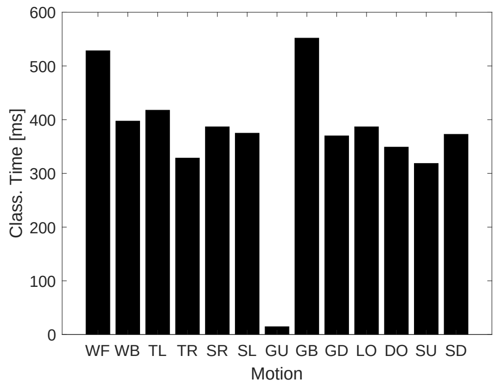

Fig. 6: Latencies of individual motion tasks.

For most motions (9/13) the latency is within the range of 300-400 ms. For *walking forward*, *turn left* and *going downstairs backwards* the latency increases to over 400 ms. *Going upstairs* has a value of 14.57 ms meaning that the motion is classified although the window is not fully filled with sensor data of a *going upstairs* motion. It could be observed that, as soon as sensor data of a motion and not only zeros (from zero padding) occur in a window, *going upstairs* is classified until there is enough data to classify the actual motion correctly, indicating that the HMM for *going upstairs* is learned to serve as some kind of ‘fall-back class’ in the underlying classification problem.

After evaluating the latency for motions at the beginning of the classification process, the same analysis was conducted for motion transitions. For this purpose, two motion recordings of one subject were randomly concatenated to simulate a motion transition. Only motion transitions with the same start and end position were concatenated, e.g. *stand up* with *walking forward*. Motion combinations such as *sit down* with *walking forward* were not considered. In total, 859 combined motions of all subjects were used to repeat the aforementioned evaluation with a window size of 300 ms. The results of this evaluation (red bars) are depicted in Fig. 7 in comparison with the results when using zero padded data (black bars). For the combined motions, the x-axis labels correspond to the second motion task which was appended when concatenating the data.

In general, there is no tendency towards a shorter classification latency for motion transitions compared to motions at the start of the classification process. The mean latency increases to 384.23 ms, however in contrast to the zero padded data there are 3 motions classified in less than 300 ms (*turn left, turn right, lift object*). This indicates that in the case of concatenated motion data a correct classification is

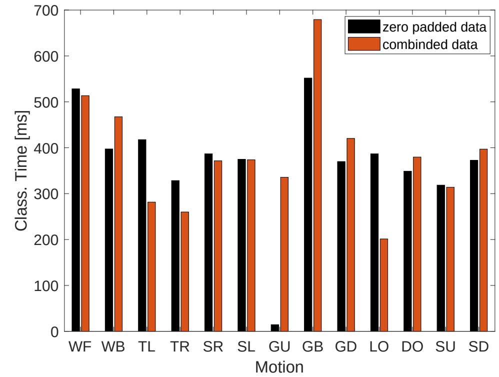

Fig. 7: Comparison of latencies for zero padded (black bars) and combined (red bars) motions.

possible although the window is not completely filled with sensor data and that the latency depends on the previously performed motion task.

3) Leave-One-Out Validation:

As stated before, short setup and calibration times are important if the device is to be used for augmenting applications. Therefore, we want to investigate how well the trained classification system generalizes to motion data observed from a subject not part of the training set. For that reason a leave-one-out analysis was conducted.

We trained our HMMs with 9 subjects with the same hyper-parameters mentioned before and tested the HMMs with the remaining subject of our data set. The results are shown in Table III. The first column lists the test subjects for the leave-one-out validation. The accuracy of the stratified 5-fold cross validation (CV accuracy) when testing with the 9 subjects used to train the model is depicted in the second column. The third column lists the accuracy when actually testing the data with the left out subject (LO accuracy).

The average accuracy when training and testing with stratified 5-fold cross validation is 93.15 % (±0.37). When testing with the left out subject, the average accuracy drops to 84.46 % and the standard deviation increases (±3.33). This analysis shows that our approach is able to achieve a comparable generalization performance when applied to subjects not contained in the training set.

TABLE III: Results of leave-one-out validation.

Test Subject	CV Acc. [%]	LO Acc. [%]
1	92.87	88.76
2	92.53	86.47
3	92.71	83.71
4	93.39	82.42
5	92.97	84.84
6	93.43	87.95
7	93.70	82.28
8	93.14	79.82
9	93.34	88.28
10	93.42	80.04
Average	∅93.15	∅84.46
Std. Dev.	0.37	3.33

V. Conclusion

In this paper, we investigated the quality of motion classification with Hidden Markov Models (HMMs) for a lower limb exoskeleton based on multi-modal sensor data, with the ultimate goal of improving intuitive control of such exoskeletons. In our approach, we use sliding windows to enable an online (during operation) classification. To acquire a data set for training and testing, experiments with 10 subjects performing 13 different motion tasks were conducted with a passive exoskeleton equipped with seven 3D-force sensors and three IMUs.

Our first evaluation focused on determining a window size which provides a reasonable trade-off between a high accuracy and a good latency. For this purpose, different window sizes were investigated with a stratified 5-fold cross validation. After comparing the resulting accuracies with the latencies, we determined a window size of $300\,\mathrm{ms}$ yielding to an average accuracy of $92.80\,\%$ and an average latency of $368.97\,\mathrm{ms}$.

In our second evaluation, we considered the latencies for each motion individually using a window size of $300\,\mathrm{ms}$. For this purpose, a zero padded data set (motions at the beginning of the classification process) and a data set consisting of randomly concatenated motions (motion transitions) have been tested. Comparing both data sets revealed no significant difference between motions at the beginning of the classification process and motion transitions.

These evaluations were followed by a leave-one-out validation to investigate the generalization of our approach, leading to an average accuracy of $84.46\,\%$ for observations from subjects not part of the training set.

Based on these results, we will conduct deeper analysis of the latencies for different motion transitions. Currently our approach assumes that the subject is always performing a motion, leading to incorrect classification results if the subject stands still. It might be possible to avoid this behavior by adding additional HMMs for standing still motions (idling). Furthermore, we will perform a systematic exploration of the feature space in order to identify which of the features are relevant, with the goal of simplifying the sensor setup.

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