A Wearable Real-time Human Activity Recognition System using Biosensors Integrated into a Knee Bandage

Hui Liu and Tanja Schultz
Cognitive Systems Lab, University of Bremen, Germany
{*hui.liu, tanja.schultz*}*@uni-bremen.de*

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Abstract: This work introduces an innovative wearable real-time Human Activity Recognition (HAR) system. The system processes and decodes various biosignals that are captured from biosensors integrated into a knee bandage. The presented work includes (1) the selection of an appropriate equipment in terms of devices and sensors to capture human activity-related biosignals in real time, (2) the experimental tuning of system parameters which balances recognition accuracy with real-time performance, (3) the intuitive visualization of biosignals as well as *n*-best recognition results in the graphical user interfaces, and (4) the on-the-air extensions for rapid prototyping of applications. The presented system recognizes seven daily activities: sit, stand, stand up, sit down, walk, turn left and turn right. The amount of activity classes to be recognized can be easily extended by the "plug-and-play" function. To the best of our knowledge, this is the first work which demonstrates a real-time HAR system using biosensors integrated into a knee bandage.

1 INTRODUCTION

Arthrosis is the most common joint disease and results in a perceptible reduction of life quality. Among all forms of arthroses, gonarthrosis is accounted for the largest proportion. Apart from the negative impact on the quality of life for many individuals worldwide, gonarthrosis leads to significant economic loss due to surgeries, invalidity, sick leave and early retirement. Recent studies demonstrate and evaluate the usage of sensors and technical systems for the purpose of knee rehabilitation, as for example after ligament injuries (Yepes et al., 2017) and surgery (Naeemabadi et al., 2018), to name a few. In an aging society, prevention and early treatment become an increasingly important part, since joint replacement surgeries carry secondary risks.

The mainstay of early treatment is an adequate amount of proper movement. It results in muscular stabilization and fosters functional maintenance of the joints. Moreover, movement is fundamental for the nutrition of both healthy and diseased cartilage. Nevertheless, the knee joint with lesions should not be overloaded by these movement to not re-activate or further exacerbate gonarthrosis due to an inflammation of the joint. This would lead to even more pain for the patient and worsens the overall conditions.

The overall goal of our work is to technically assist the early treatment of gonarthrosis by discovering the right dose of daily movement, which affects the functionality of the joint positively while preventing movement-caused overload of the diseased joint. First steps towards this goal were carried out by developing a technical system which continuously tracks the dose of everyday activity movements using biosensors integrated into a knee bandage. The results were documented in (Liu and Schultz, 2018), in which we proposed the framework *ASK* (***A****ctivity* ***S****ignals* ***Kit***) for biosignal data acquisition, processing and human activity recognition. The different features of this framework were introduced in a pilot study of person-dependent activity recognition based on a small dataset of human everyday activities.

1.1 Human Activity Recognition

Human activity recognition (HAR) is intensively studied and a large body of research shows results of recognizing all kinds of human daily activities, including running, sleeping or performing gestures.

For this purpose a large variety of biosignals are captured by various sensors, e.g. (Mathie et al., 2003) applied wearable triaxial accelerometers attached to the waist to distinguish between rest (sit) and active states (sit-to-stand; stand-to-sit and walk). Five biaxial accelerometers were used in (Bao and Intille,

2004) to recognize daily activities such as walking, riding escalator and folding laundry. In (Kwapisz et al., 2010) the authors placed an Android cell phone with a simple accelerometer into the subjects' pocket and discriminated activities like walking, climbing, sitting, standing and jogging. Furthermore, (Lukowicz et al., 2004) combined accelerometers with microphones to include a simple auditory scene analysis. (De Leonardis et al., 2018) compared the recognition performance of 5 classifiers based on machine learning (K-Nearest Neighbor, Feedforward Neural Network, Support Vector Machines, Naïve Bayes and Decision Tree) and analyzed advantages and disadvantages of their implementation onto a wearable and real-time HAR system.

Muscle activities captured by ElectroMyoGraphy (EMG) is another useful biosignal. It even provides the option to predict a person's motion intention prior to actually moving a joint, like investigated in (Fleischer and Reinicke, 2005) for the purpose of an actuated orthosis. Moreover, some researchers like (Rowe et al., 2000) and (Sutherland, 2002) applied electrogoniometers to study kinematics.

1.2 Goal of this Study

To achieve our overall goal of technical assisting the early treatment of gonarthrosis using biosensors integrated into a knee bandage, we envision the contributions to five research and development paths, i.e. (1) to recognize daily activities based on person-independent models, (2) to increase the amount of recognized daily activities, (3) to compare and select biosensors suitable for integration into a knee bandage and for wearable application, (4) to improve the activity recognition accuracy by further optimizing the activity models and system parameters, and (5) to implement a wearable real-time HAR system for field studies. This paper focus on our efforts toward the last item, i.e. the implementation of a wearable real-time HAR system.

In this study, we used the dataset introduced in (Liu and Schultz, 2018) as training set. It consists of biosignals from one male subject captured by two accelerometers, four EMG sensors and one electrogoniometer. The data are annotated, time-aligned and segmented on single-activity level based on a semi-automatic annotation mechanism using a push-button. Although, this single-subject dataset is rather small and by no means representative, we leverage these data as pilot dataset to showcase the development of an end-to-end wearable real-time human recognition system rapidly. To our knowledge, there are no published publicly available datasets yet which are suitable for real-time HAR using biosensors integrated into a knee bandage. However, we are quite aware of the limitations of this dataset, and are currently in the process of recording a larger dataset covering many activities from several subjects. First results of these data recording efforts are presented in section 3.2.

To model human activities we followed the approach as described in (Rebelo et al., 2013) using *Hidden-Markov-Models (HMM)*. *HMMs* are widely used to a variety of activity recognition tasks, such as in (Lukowicz et al., 2004) and (Amma et al., 2010). The former applies it to an assembly and maintenance task, the latter presents a wearable system that enables 3D handwriting recognition based on *HMMs*. In this so-called *Airwriting* system the users write text in the air as if they were using an imaginary blackboard, while the handwriting gestures are captured wirelessly by accelerometers and gyroscopes attached to the back of the hand.

Based on the training dataset and *HMM* modeling, we design and implement a wearable real-time HAR system using biosensors integrated into a knee bandage, which is connected to an intuitive PC graphical user interface.

2 EQUIPMENT AND SETUP

2.1 Knee Bandage

We use the Bauerfeind GenuTrain knee bandage[1] as the wearable carrier of the biosensors (see Figure 1). It consists of an anatomically contoured knit and an integral, ring-shaped, functional visco-elastic cushion, which offers active support for stabilization and relief of the knee.

2.2 Devices

We chose the *biosignalsplux* Research Kits[2] as recording device. One *PLUX* hub[3] records signals from 8 channels (each up to 16 bits) simultaneously. We used two hubs for recording the data and connected the hubs via a cable which synchronizes signals between the hubs at the beginning of each recording. This procedure ensures the synchronization of sensor data during the entire recording session.

[1] www.bauerfeind.de/en/products/supports-orthoses/knee-hip-thigh/genutrain.html

[2] biosignalsplux.com/researcher

[3] store.plux.info/components/263-8-channel-hub-820201701.html

Figure 1: Bauerfeind GenuTrain knee bandage.

2.3 Biosensors and Biosignals

Similar to (Mathie et al., 2003) and (Liu and Schultz, 2018), we used two triaxial accelerometers[4], four bipolar EMG sensors[5] and both channels of one biaxial electrogoniometer[6], as they were proved to be effective and efficient. The sensors were placed onto the bandage to capture muscles and positions most relevant to activity recognition, as summarized in Table 1. We used both channels of electrogoniometer to measure both the frontal and sagital plain since we intend to recognize rotational movements of the knee joint for example when walking a curve in the activities "curve-left" and "curve-right".

Table 1: Sensor placement and captured muscles.

Sensor	**Position / Muscle**
Accelerometer (upper)	Thigh, proximal ventral
Accelerometer (lower)	Shank, distal ventral
EMG1	Musculus vastus medialis
EMG2	Musculus tibialis anterior
EMG3	Musculus biceps femoris
EMG4	Musculus gastrocnemius
Electrogoniometer	Knee of the right leg, lateral

The signals of all biosensors were recorded wirelessly at different sampling rate. Table 2 shows the sampling rate of each sensor type.

From table 2 we can see, that accelerometer and electrogoniometer signal are both slow signals, while the nature of EMG signals require higher sampling rates. Low-sampled channels at 100Hz are upsampled to 1000Hz to be synchronized and aligned with high-sampled channels. Table 3 shows the arrangement of the sensors on Hub1 and Hub2, respectively.

Table 2: Sampling rates of biosensors.

Sensor	**Sampling rate**
Accelerometer	100Hz
Electrogoniometer	100Hz
Electromyography	1000Hz

Table 3: Channel layout of *PLUX* Hub1 (fast), Hub2 (slow).

	Channel	**Sensor**
PLUX Hub1 (fast)	1	Electromyography EMG 1
	2	Electromyography EMG 2
	3	Electromyography EMG 3
	4	Electromyography EMG 4
	5	-
	6	-
	7	-
	8	-
PLUX Hub2 (slow)	1	Accelerometer (upper) X-axis
	2	Accelerometer (upper) Y-axis
	3	Accelerometer (upper) Z-axis
	4	Electrogoniometer - sagital plain
	5	Accelerometer (lower) X-axis
	6	Accelerometer (lower) Y-axis
	7	Accelerometer (lower) Z-axis
	8	Electrogoniometer - frontal plain

2.4 ASK Framework

We continued to program under the framework of *ASK* introduced in (Liu and Schultz, 2018) with a graphical user interface. The *ASK* PC-software connects and synchronizes several *PLUX* hubs easily to subsequently collect data from all hubs simultaneously and continuously. In "Recorder" mode and semi-automatic "Annotator" mode, all recorded data are archived properly with date and time stamps for further processing. In real-time "Decoder" mode introduced in section 4, the recorded data are used for recognition in real-time.

3 EXPERIMENTAL STUDY

An experimental study was performed to compare two scenarios: the recognition of human activities in an offline scenario, aka without real-time limitations,

[4] biosignalsplux.com/acc-accelerometer
[5] biosignalsplux.com/emg-electromyography
[6] biosignalsplux.com/ang-goniometer

and the adaptation of the recognition system to an online scenario with limited processing time, for which we trade recognition accuracy for decoding speed. For this purpose we apply one seven-activities dataset and one eighteen-activities dataset.

3.1 Seven-activities Dataset

We used the seven-activities dataset from (Liu and Schultz, 2018) that contains four recording sessions from one male subject as online dataset currently for the real-time HAR system. In these recordings, seven activities are organized in two categories, i.e. ”stay-in-place” and ”move-around”, which results in two activity lists for the data acquisition prompting protocol as follows:

- **Activity List 1** *”Stay-in-place”* (40 repetitions): sit → sit-to-stand → stand → stand-to-sit.
- **Activity List 2** *”Move-around”* (25 Repetitions): walk → curve-left → walk ⇀ (turn around) ⇀ walk → curve-right → walk ⇀ (turn around).

Table 4 and Table 5 gives occurrences, total effective length, minimum length and maximum length of these seven activities.

Table 4: Occurrences and total length of the seven activities in seven-activities dataset.

Activity	Occurrences	Total length
sit	25	79.92s
stand	23	81.41s
sit-to-stand	24	47.31s
stand-to-sit	23	44.11s
walk	67	172.93s
curve-left	17	61.96s
curve-right	16	66.25s
Total	**195**	**553.87s**

Table 5: Minimum and maximum length of the seven activities in seven-activities dataset.

Activity	Min. length	Max. length
sit	1.64s	7.78s
stand	1.49s	17.82s
sit-to-stand	1.44s	2.57s
stand-to-sit	1.19s	2.84s
walk	1.35s	4.57s
curve-left	1.81s	13.00s
curve-right	1.56s	18.12s
Global	**1.19s**	**18.12s**

We are aware that this dataset is very small and is neither sufficiently nor necessarily large enough to establish reliable recognition accuracies for daily activities. However, the purpose here was to rapidly prototype an end-to-end wearable real-time human recognition system. The classification accuracy of this dataset resulted in 97% (Liu and Schultz, 2018). In Section 4.3 we introduce the ”plug-and-play” function, which allows for easy on-the-fly extensions to more activity classes and more training data. We collected a larger dataset of eighteen activities (see below), which will become online for real-time recognition after validation in further work.

3.2 Eighteen-activities Dataset

We continued to record a new larger dataset of eighteen activities from seven male subjects under the framework of (Liu and Schultz, 2018). Beside the increase of the number of activities, we also extended the types of sensors and biosignals: Four types of additional biosensors were included, i.e. one airborne microphone, one piezoelectric microphone, two gyroscope and one force sensor. The fusion of biosignals allows the study of sensor comparison and selection for the purpose of reliable activity recognition. This eighteen-activities dataset has not been used for real-time recognition system yet.

Table 6 and Table 7 gives occurrences, total effective length, minimum length and maximum length of these eighteen activities.

Table 6: Occurrence and total length of the eighteen activities in eighteen-activities dataset.

Activity	Occurrence	Total length
sit	47	123.75s
stand	46	127.70s
sit-to-stand	45	30.94s
stand-to-sit	53	72.90s
stair-up	55	190.45s
stair-down	57	181.96s
walk	220	554.07s
curve-left-step	57	143.09s
curve-left-spin	46	109.15s
curve-right-step	51	67.51s
curve-right-spin	48	41.50s
run	97	151.27s
v-cut-left	53	43.76
v-cut-right	55	61.75s
lateral-shuffle-left	53	97.54s
lateral-shuffle-right	52	90.42s
jump-one-leg	59	61.36s
jump-two-leg	63	63.40s
Total	**1157**	**2212.52s**

Most of the activities in this table are self-explanatory, a few may needs some explanation:

Table 7: Minimum and Maximum length of the eighteen activities in eighteen-activities dataset.

Activity	Min. Length	Max. length
sit	0.86s	4.69s
stand	1.36s	4.73s
sit-to-stand	0.15s	1.30s
stand-to-sit	0.56s	3.10s
stair-up	1.59s	4.93s
stair-down	1.37s	4.86s
walk	1.18s	4.78s
curve-left-step	1.10	3.87s
curve-left-spin	1.25s	3.39s
curve-right-step	0.54s	3.19s
curve-right-spin	0.28s	1.88s
run	0.64s	2.74s
v-cut-left	0.29s	2.08s
v-cut-right	0.35s	2.37s
lateral-scuffle-left	0.73s	4.11s
lateral-scuffle-right	0.75s	3.98s
jump-one-leg	0.33s	2.85s
jump-two-leg	0.51s	1.63s
Global	**0.15s**	**4.93s**

- **Curve-left/right-step vs. curve-left/right-spin:** "step" means that the subject makes a big 90° turn with several walking steps, while "spin" suggests a fast 90° turning of the body like the parade command "right turn" or "right face".
- **Lateral-shuffle-left/right:** these two activities are often used by tennis, soccer and basketball players. The subject starts with left/right foot moving left/right laterally and the other foot following, and continues shuffling in the same direction for the desired amount of time.
- **V-cut-left/right:** these two activities mean that the subject changes his/her direction by roughly 90° at jogging speed.

3.3 Feature Extraction and Modeling

For training and decoding the biosignals captured by the biosensors need to be preprocessed.

First, the biosignals are windowed using a rectangular window function with overlapping windows. Second, a mean normalization is applied to the acceleration and EMG signals to reduce the impact of Earth acceleration and to set the baseline of the EMG signals to zero. Then, the EMG signal is rectified, a widely adopted signal processing method for muscle activities.

Subsequently, features were extracted for each of the resulting windows. We denote the number of samples per window by N and the samples in the window by $(x_1,...,x_N)$. We adopted the features from (Rebelo et al., 2013) extracting for each window the *average* for the accelerometer and electrogoniometer signal, defined as:

$$avg = \frac{1}{N}\sum_{n=1}^{N} x_n, \quad (1)$$

We extracted also *average* for the four types of additional signal from the airborne microphone, the piezoelectric microphone, the gyroscopes and the force sensor.

For the EMG signal we extracted for each window the *Root Mean Square*:

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x_n^2} \quad (2)$$

Features of different biosignals can be combined by early or late fusion, i.e. the feature vectors of single biosignal streams are either concatenated to form one multi-biosignal feature vector (early fusion) or recognition is performed on single biosignal feature vectors and the combination is done on decision level (late fusion). Our framework allows for both fusion strategies, in this work we rely on early fusion which showed to outperform the late fusion strategy in the context of real-time HAR.

3.4 Parameter Tuning and Decoding

Similar to (Liu and Schultz, 2018) we applied our *HMM*-based in-house decoder *BioKIT* to modelling and recognizing the described activities. Among others *BioKIT* supports the training of *Gaussian-Mixture-Models (GMMs)* to model the *HMM* emission probabilities. Each activity consists of a fixed number of *HMM* states, where each state is modeled by a mixture of Gaussians.

Based on the eighteen-activities dataset and the automatically generated reference labels for each segment using the semi-automatic annotation function, we iteratively optimized the number of *HMM* states and Gaussian mixtures per each *HMM* state.

Figure 2 and Figure 3 demonstrate examples of tuning different parameters in cross validation experiments with the configuration of 10ms window length, 5ms overlap and 21-dimensional normalized feature vectors.

Due to the limited data quantity we stopped evaluating the number of gaussians at 10 in order to achieve reliable results. Similar experiments for tuning different parameters were executed thoroughly and we arrived at a conclusion that the application of eight *HMM* states and ten Gaussians offers the best recognition results.

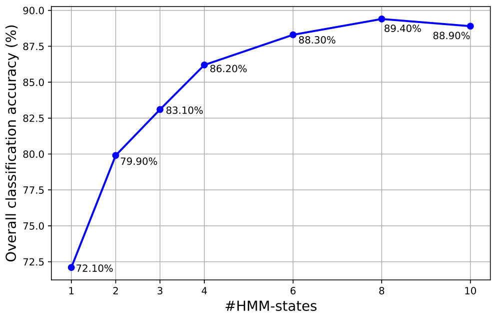

Figure 2: Parameter tuning: number of *HMM* states. Window length: 10ms; overlap: 5ms; dimension of normalized feature vectors: 21; number of Gaussians per each *HMM* state: 5.

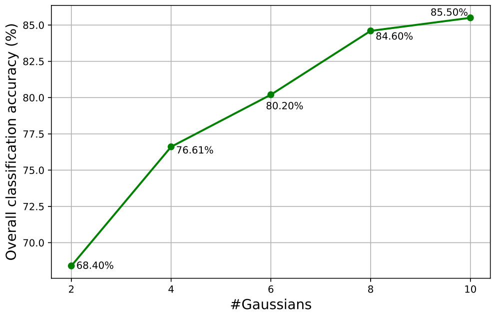

Figure 3: Parameter tuning: number of Gaussians per each *HMM* state. Window length: 10ms; overlap: 5ms; dimension of normalized feature vectors: 21; number of *HMM* states: 2.

Using these current best performing parameters, the overall person-dependent recognition accuracy achieves almost 90%. Figure 4 illustrates the recognition results in percentage from one cross validation experiment in confusion matrix. Table 8 gives the criteria *Precision*, *Recall* and *F-Score* in average of each activity in cross validation experiments.

As can be seen in Figure 4 and Table 8, activities ”jump-one-leg”, ”jump-two-leg”, ”lateral-shuffle-right” and ”stair-up” were correctly recognized in every experiment.

Recently we applied feature vector stacking followed by a linear discrimination analysis and further improved the results to roughly 95% recognition accuracy. In addition, a merge-split algorithm is planned to be applied for adaptive determination of the optimal number of gaussians per state. Additional work to further improve the performance is under way.

Table 8: Criteria *Precision*, *Recall* and *F-Score* in average of each activity from cross validation experiments.

Activity	Precision	Recall	F-Score
sit	0.85	0.78	0.81
stand	0.90	0.75	0.81
sit-to-stand	0.95	1.00	0.97
stand-to-sit	0.96	1	0.98
stair-up	1.00	1.00	1.00
stair-down	0.96	1.00	0.98
walk	0.92	0.88	0.90
curve-left-step	0.79	0.83	0.80
curve-left-spin	0.71	0.91	0.78
curve-right-step	0.95	0.88	0.91
curve-right-spin	0.80	1.00	0.89
run	0.90	0.86	0.87
v-cut-left	0.66	0.70	0.64
v-cut-right	0.5	0.56	0.50
lateral-shuffle-left	0.96	0.96	0.95
lateral-shuffle-right	1.00	1.00	1.00
jump-one-leg	1.00	1.00	1.00
jump-two-leg	1.00	1.00	1.00

4 WEARABLE REAL-TIME HAR SYSTEM

We developed a wearable real-time HAR system and used the above described seven-activities dataset (section 3.1) to investigate the end-to-end system performance.

4.1 Balance Accuracy versus Speed

From Table 5 we can see, that no activity in this dataset is shorter than 1.9 seconds. This a-priori information let us to decide the window length and window overlap length and these two lengths were optimized to balance recognition accuracy versus processing delay. The activities in the seven-activities dataset were modeled with one *HMM* state per activity and a longer window length was chosen. A shorter step-size results in a shorter delay of the recognition outcomes, but the interim recognition results may fluctuate due to temporary search errors. On the other hand, longer delay due to long step-sizes contradicts the characteristics of a real-time system, though it generates more accurate interim recognition results. Based on experiments we chose a balancing setting of 400ms window length with 200ms window overlap. These values gave satisfactory recognition results with a barely noticeable delay within 1 second.

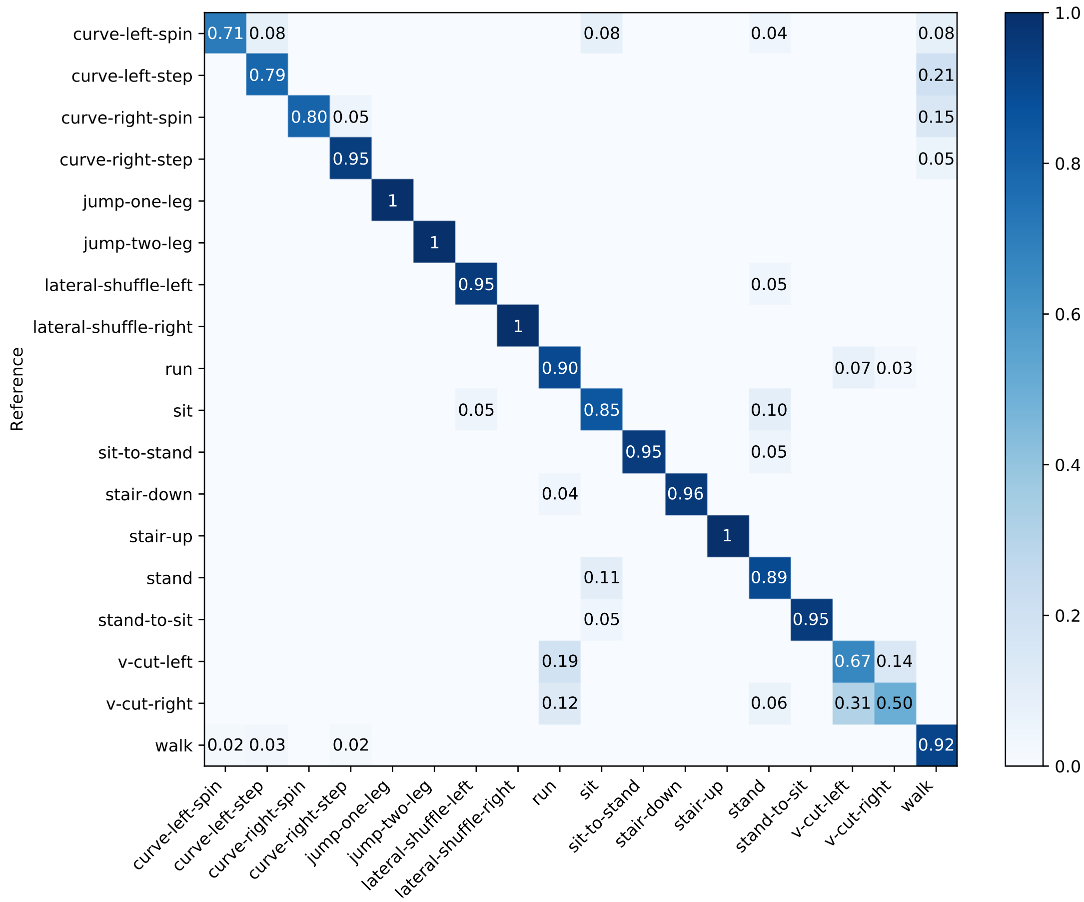

Figure 4: Confusion matrix of recognition results in percentage from one cross validation experiment.

4.2 Graphical User Interface (GUI) and Customization

After model training, the system starts recording data continuously from the biosensors integrated into the knee bandage. We implemented this new functionality with graphical user interface (GUI) in *ASK* PC-software (Liu and Schultz, 2018) to continuously output the recognition results as well as to visualize the biosignals. The latter feature enables the user to monitor the biosignal recording while the former feature may serve as input to post-processing steps and to inform down-stream applications. The recorded data are displayed serially on the left-hand side of the interface display, and the *n*-best (usually we set *n* as 3) recognition results in terms of activity classes associated with the calculated probabilities indicated by length of bars are shown on the right-hand side of the interface display (see Figure 5).

The GUI allows to switch biosignals and activities on and off for the real-time activity recognition. This way, it is very straight-forward to quickly test the sensors and system properties during system development and evaluation (see Figure 6).

4.3 On-the-Fly Extensions

After we successfully tested our real-time HAR system using the seven-activities dataset, we implemented a new function named ”plug-and-play”. This function can be understood literally: we can load new activity sensor data on-the-fly, retrain the activity models, and restart the recognition process automatically with the updated activity models. The ”plug-and-play” function has several benefits and the following three use cases:

Providing more Training Data for an existing Activity. In (Liu and Schultz, 2018) we presented a framework name *ASK* of data acquisition and semi-automatic annotation. The real-time HAR system is also an extension of this framework. Therefore, we could use the ”annotator mode” (See Figure 6) to record more data, such as ”stand-to-sit”, and at the same time generate annotation labels on them (See Figure 7). These new data will automatically be used next time for training the real-time HAR system, that

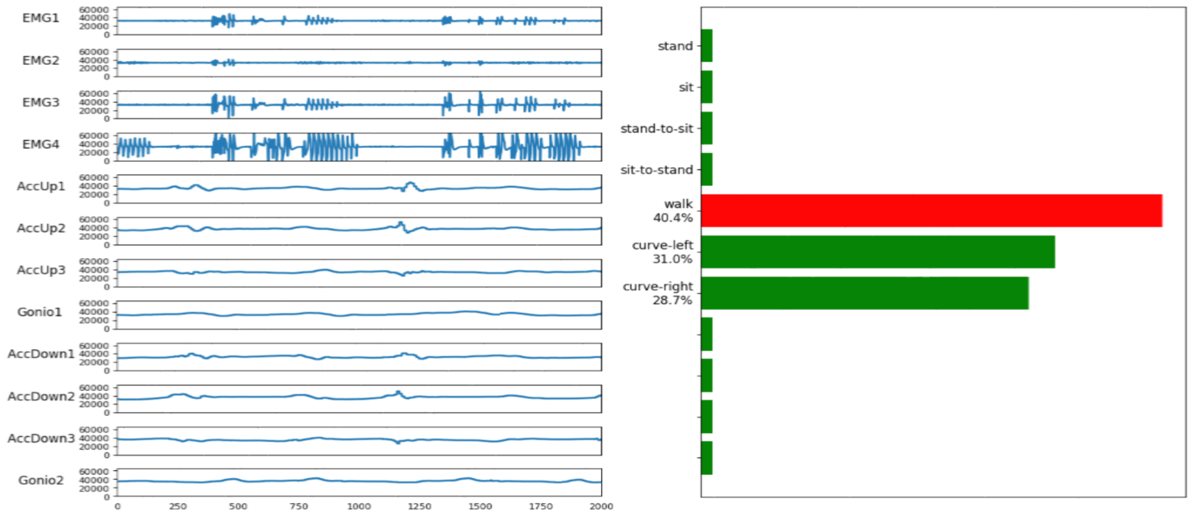

Figure 5: Screenshot: the performance of the real-time HAR system.

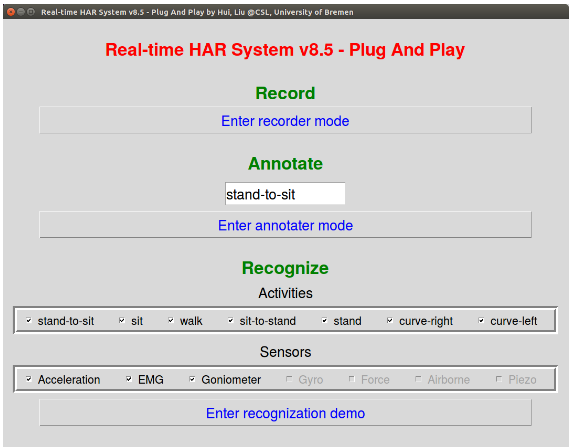

Figure 6: Screenshot: sensor and activity selection menu.

Figure 7: Screenshot: *ASK* software with annotation mode: the next activity to do is ”stand-to-sit”.

is to say, we ”plug” more data and ”play” with an improved recognition system.

Increase the Activity Classes to be recognized. Even the recognition of new activities are enabled most simply. We just need to type a new activity name, such as ”lie down”, in the text-box, re-run ”annotator mode”, record and label a minimum of 12 instances of ”lie down”. These steps take about five minutes, when finished the real-time HAR system is started with the new activity ”lie down” already prepared to be recognized.

Enable the Study of Person-independent Real-time HAR System. Similar to the first usage, we can record more data for existing activities from different subjects, the system will then serve automatically as a person-independent HAR system, provided that we continue to study proper model configuration and parameters for person-independent application.

5 CONCLUSIONS

In this paper we brought forward a wearable real-time Human Activity Recognition (HAR) system using biosensors integrated into a knee bandage that capture a variety of biosignals related to human everyday activities. This HAR system opens up new avenues for computer-aided assistive rehabilitation systems using wearable medical appliances. To the best of our knowledge, this is the first work which implements a real-time HAR system using biosensors integrated into a knee bandage.

The paper describes the biosensors and devices that capture biosignals related to human activities, the design and implementation of a software platform integrating methods for modeling, training, and recognition of human activities based on biosignals recognition and a graphical interface to interact with a user. The final HAR system recognizes human daily activities in real-time with performances above 90% accuracy and a barely noticeable delay. It further provides a "plug-and-play" function for on-the-fly extensions such as enabling the recognition of unseen activities. Further work will be devoted to improve the recognition performance in a person-independent setting on a larger set of activities, and to integrate the HAR output into an assistive rehabilitation system for people suffering gonarthrosis.

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