# Human Activity Recognition for an Intelligent Knee Orthosis

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Abstract: This paper investigates the possibility to classify isolated human activities from biosignal sensors integrated into a knee orthosis. An intelligent orthosis that is capable to recognize its wearers activity would be able to adapt itself to the users situation for enhanced comfort. We use a setup with three modalities: accelerometry, electromyography and goniometry to measure leg motion and muscle activity of the wearer. We segment signals in motion primitives and apply Hidden Markov Models to classify these isolated motion primitives. We discriminate between seven activities like for example walking stairs and ascend or descend a hill. In a small user study we reach an average person-dependent accuracy of 98% and a person-independent accuracy of 79%.

## 1 INTRODUCTION

Passive orthoses are widely used for conservative therapy of diseases like Gonarthrosis, which is Osteoarthritis in the knee joint. Depending on the type of arthrosis, these orthoses apply a constant force on the knee joint to correct a defective position. This is usually painful or at least unpleasant for the wearer after a certain amount of time. Future active orthoses could be able to vary this force depending on the current wearers activity and therefore only apply force if the knee joint is stressed, e.g. while walking stairs but not while the wearer is sitting. This will impose less strain on the wearer. In order to develop such a system, it will be necessary to recognize the wearers activity, which is the topic of this paper. The study presented in this paper is part of a larger effort to develop such active orthoses.

In this paper we evaluate the possibility to recognize human activities based on data from biosignal sensors solely placed on or under an existing passive knee orthosis to allow future integration of sensors. The contribution of this paper is the evaluation of the ability to recognize activities with these restrictions on sensor placement as well as providing a proof-of-concept for the development of an activity recognition system for an intelligent orthosis.

The focus of this work is the question how well we can discriminate already segmented isolated motion primitives. In case of periodic activities like walking, we define a primitive as one cycle, in case of non-periodic activities like sitting down, we define a primitive as the complete motion. Therefore, prior to classification, the continuous data recordings need to be segmented into isolated motion primitives. We use an automatic approach for the segmentation of all periodic activities and perform manual segmentation for non-periodic activities. We use Hidden-Markov-Models (HMM) as classifier and model each of the seven motion primitives with one HMM. In future work we want to rely on the implicit segmentation ability of HMMs to allow for realtime usage.

## 2 RELATED WORK

Gait and posture are often categorized as the standard human movement from which analysis allow clinical evaluation. In the past, some studies have proved the reliability of accelerometry on activity recognition on data collected from different areas of the body. For example, in (Mathie et al., 2003), the use of triaxial accelerometers successfully distinguished between activity (transitions sit-to-stand and stand-to-sit and walk) and rest. In the context of physical activity recognition, in (Welk and Differding, 2000), sedentary activities such as sitting or sleeping are discriminated from moderate intensity activities such as walk-


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ing through the analysis of acceleration data.
The use of EMG or electrogoniometers have been applied mostly on kinematics evaluation (Rowe et al., 2000) or on pattern comparisons for diagnosis (Suda, 2011).
However, these aforementioned researches use only accelerometers, goniometers or EMG sensors separately with less restrictions on sensor placement.

Hidden Markov Models (HMM) are widely used for activity recognition (Lukowicz et al., 2004). They are especially useful if motions can be modeled as a sequence of motion primitives like for example gestures from a gesture alphabet (Amma et al., 2012).

# 3 DATA ACQUISITION AND SIGNAL PROCESSING

## 3.1 Experimental Setup

We equipped a standard Ortema[1] ipomax passive orthosis with two triaxial accelerometers and one biaxial goniometer. Additionally, six EMG sensors to measure muscle activity were put on the skin under the orthosis. It is a requirement of our application scenario to place all sensors on or under the orthosis, since all sensors should be integrateable into the orthosis in the future. The orthosis itself consists of two rigid shells, one for the upper and one for the lower leg which are fixed to the leg with straps. The shells are connected by a joint on each side in order to allow flexion of the knee joint. The accelerometers were placed on the frontside of the orthosis, one on the lower part and one on the upper part to measure acceleration of tibia and femur respectively. The goniometer was placed on the joint so it can measure the angle of the orthosis joint which can be assumed equal to the angle of the knee joint. Although the goniometer is biaxial only the axis aligned to the rotation axis of the orthosis joint was used. EMG electrodes were placed on the knee's main extensor and flexor muscles: *semimembranosus*, *semitendinosus*, *gastrocnemius* (external and internal), *vastus lateralis* and *vastus medialis*. Figure 1 shows the EMG electrodes' locations (A, B) as well as the complete experimental setup (C).

The signals were recorded wirelessly with two synchronized bioPluxresearch[2] devices at a sampling rate of 1000 Hz.
We performed a study with 6 healthy male subjects in the age between 20 and 30. Although the orthosis was

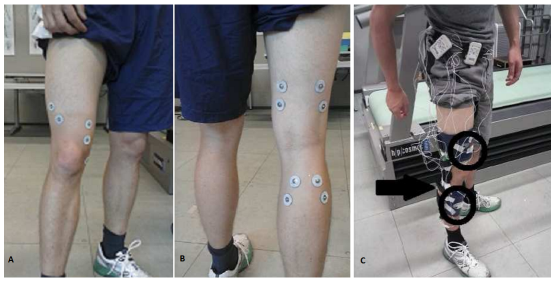

Figure 1: (A, B) Placement of electromyography surface electrodes (C) Complete experimental setup: two Bioplux research devices, two ACC (circles), six EMG and one goniometry sensors (arrow) placed on a regular Ortema right knee orthosis.

not adapted to the anatomy of the subjects, all participants were able to move their knee freely and didn't feel any pain. Additionally, we made video recordings of the experiments for reference.

## 3.2 Acquisition Protocol

The subjects performed the following 7 activities for the given number of repetitions:

- **Activity 1.** Sit and stand (20 repetitions);
- **Activity 2.** Sit, stand and walk a few steps (5 repetitions);
- **Activity 3.** Walk to a chair, turn, sit and stand (20 repetitions);
- **Activity 4.** Walk and stairs up (10 repetitions);
- **Activity 5.** Walk and stairs down (10 repetitions);
- **Activity 6.** Ascend a hill (2 repetitions of 2 minutes each, with 27% of inclination);
- **Activity 7.** Descend a hill (2 repetitions of 2 minutes each, with 27% of inclination);

Activities 6 and 7 were performed on a treadmill with an adjustable inclination at a walking speed of 2.5 km/h.
The combined activities were chosen to have more challenging data for future evaluation of continuous recognition of activities. Since this is not in the scope of this paper the recorded data was segmented into motion primitives. In total, we work with 7 movements: *walk* (W), *stand-to-sit* (St), *sit-to-stand* (Si), *stairs up* (Su), *stairs down* (Sd), *ascend* (A) and *descend* (D).

## 3.3 Data Segmentation

The purpose of the data segmentation step is to split the continuous sensor recordings into motion primi-

[1] www.ortema.de
[2] www.plux.info

tives. For the periodic motions *walk*, *stairs up*, *stairs down*, and *ascend* and *descend* a hill, we define a motion primitive as one complete gait cycle. For motions like *stand-to-sit* and *sit-to-stand*, we define a motion primitive as the movement that occurs between the two static postures "stand" and "sit". We segment each continuous periodic signals in its unique motion primitives. We segment the periodic activities according to the standard segmentation of gait cycles in (Sutherland, 2002). A gait cycle consists of a stance and a swing phase and starts and ends with the initial contact of the heel on the floor. At this point of the gait cycle the knee angle is minimal.

For cyclic motions we compute the minima of the goniometer signal and take these as segment borders. Figure 2 illustrates the resulting segmentation. The

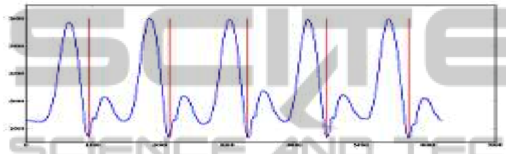

Figure 2: Example segmentation of the activity *walk* shown for the goniometer signal. The minima represent segment borders.

non-periodic movements *stand-to-sit* and *sit-to-stand* were segmented manually based on the goniometer signal. We visually checked the results of the automatic segmentation to verify the correctness of our data segmentation.

#### 3.3.1 Data Corpus

After acquisition and segmentation of all recorded data, the segments for the seven different activities form our data corpus. In order to get a balanced dataset for the evaluation we randomly chose 17 segments per person for each activity, which is the minimum number of samples we recorded over all activities. The resulting balanced data corpus therefore consists of 119 segments per person and 714 segments in total.

### 3.4 Classification and Feature Extraction

For feature extraction, the signal is windowed using a rectangular window function with 50 ms window length and no window overlap. All features are computed on the resulting windows. We denote the samples in one window by $(x_1, \ldots, x_N)$ where $N$ is the total number of samples per window. Along the experiments, for each window, we extract the *Average* $avg = \frac{1}{N}\sum_{k=0}^{N-1} x_k$ for the goniometer and accelerometer's output and the *Root Mean Square (RMS)* $RMS = \sqrt{\frac{1}{N}(x_1^2 + x_2^2 + \ldots + x_N^2)}$ for the EMG signals.

We use continuous density Hidden Markov Models (HMM) as classifier (Rabiner, 1989). Each motion primitive is modeled by one HMM with a left-to-right topology with 10 states and Gaussian-Mixture-Models with two components. In future work we want to evaluate the ability to concatenate the primitive models to recognize continuous activities without the need for explicit segmentation. We use the BioKit toolbox developed at the Cognitive Systems Lab for the HMM training and decoding.

## 4 EXPERIMENTS

We evaluate the classification accuracy for classifying isolated motion primitives for all modality combinations in a subject-dependent and a subject-independent context.

### 4.1 Experiment 1: Subject-dependent

To evaluate the subject-dependent accuracy of the classifier we performed a leave-one-out cross-validation for each subjects data. We reach accuracies between 65% and 98% depending on the signal modalities used. Table 1 shows the results from which we can state that the combination GON&ACC has the highest accuracy.

Table 3 shows the confusion matrix for the best performing signal combination GON&ACC.

Table 2 shows the classification accuracy per subject for the best set. High accuracies are reached for all subjects. For the subject-dependent case, we believe that a robust activity recognition is possible.

Table 1: Classification accuracy (mean and standard deviation) per combination of signals in subject's dependent and independent context.

| | **Classification Accuracy (%)** | |
|---|---|---|
| | **Subject dependent** | **Subject independent** |
| **EMG** | $65.41 \pm 0.17$ | $44.57 \pm 13.87$ |
| **GON** | $83.33 \pm 0.12$ | $61.46 \pm 11.67$ |
| **ACC** | $97.34 \pm 0.01$ | $75.05 \pm 22.65$ |
| **EMG&GON** | $72.13 \pm 0.17$ | $47.94 \pm 14.60$ |
| **GON&ACC** | $98.32 \pm 0.05$ | $78.70 \pm 21.64$ |
| **EMG&ACC** | $81.23 \pm 0.14$ | $55.52 \pm 14.46$ |
| **All** | $87.54 \pm 0.13$ | $63.66 \pm 17.14$ |

Table 2: Classification accuracy (mean and standard deviation) per subject for the GON&ACC set in a subject's dependent and independent context.

| | Classification Accuracy (%) | |
|---|---|---|
| **Subjects** | **Subject dependent** | **Subject independent** |
| **1** | $97.32 \pm 0.04$ | $36.13 \pm 21.43$ |
| **2** | $99.11 \pm 0.02$ | $83.19 \pm 10.11$ |
| **3** | $97.32 \pm 0.04$ | $89.08 \pm 4.56$ |
| **4** | $98.22 \pm 0.03$ | $78.15 \pm 8.17$ |
| **5** | $98.22 \pm 0.03$ | $94.12 \pm 0.15$ |
| **6** | $99.11 \pm 0.04$ | $91.52 \pm 0.87$ |

Table 3: Confusion matrix for GON&ACC in a subject-dependent and subject-independent (between brackets) context, in percentage.

| | **W** | **St** | **Si** | **Su** | **Sd** | **A** | **D** |
|---|---|---|---|---|---|---|---|
| **W** | **95(89)** | 0 | 0 | 0 | 3(4) | 1(0) | 1(7) |
| **St** | 0 | **100(83)** | 0 | 0 | 0(17) | 0 | 0 |
| **Si** | 0 | 1(0) | **99(83)** | 0(17) | 0 | 0 | 0 |
| **Su** | 0 | 0 | 0 | **98(92)** | 2(4) | 0(4) | 0 |
| **Sd** | 0(4) | 0(1) | 0(1) | 0(9) | **98(66)** | 0(1) | 2(18) |
| **A** | 0(1) | 0 | 0 | 1(32) | 0 | **99(67)** | 0 |
| **D** | 0(19) | 0 | 0 | 0 | 1(9) | 0 | **99(72)** |

### 4.2 Experiment 2: Subject-independent

We evaluate the subject-independent performance with a leave-one-out cross-validation on the subjects. That means we test on one subjects data and train on the data of the remaining subjects. We use all samples in our database, resulting in 595 samples for training and 119 samples for testing for each subject.

We reach accuracies between 49% and 79% for the different signal modalities. Table 1 shows the results and, analogously to the subject-dependent evaluation, we can state that the combination GON&ACC has the highest accuracy. Nevertheless, compared to the subject-dependent case, the accuracy is much lower which can be explained by the variations in human motion for different subjects.

Table 3 shows the confusion matrix for GON&ACC. We can see that the movements *stairs down* and *ascend* are easily confused with *descend* and *stairs up*, respectively. This is not surprising since the performed motions are very similar for these pairs of activities.

Table 2 shows the classification accuracy per subject for the GON&ACC set.

Concerning the evaluation per subject, the recognizer performed with an accuracy between 36% and 94% with an average of 79%. Due to the small number of subjects, the generalization ability of the classifier is relatively low and thus we can see a low performance for subject 1.

## 5 CONCLUSIONS

In this work we evaluated the possibility to recognize human activities from different biosignal sensors. We reach a person-dependent accuracy of 98% and a person-independent accuracy of 79%. The combination of GON&ACC signals gives the highest accuracy. Based on the dataset and the models for the motion primitives acquired in this work, we will investigate continuous recognition of activities in the future, which will be the next step towards an active intelligent knee orthosis.

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