Human Activity Pattern Recognition based on Continuous Data from a Body Worn Sensor placed on the Hand Wrist using Hidden Markov Models

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Abstract. The work concentrates on combining discrete and continuous data in an algorithm to detect complex activity patterns.With the InvenSense MotionFit^{TM} Software Development Kit (SDK) accelerometer and gyrometer data are recorded with the MPU-9150 sensor.[1] The raw data consisiting of processed daily acticities are preprocessed via a shifted window and different features are calculated. Afterwards activity recognition is done in MATLAB using the PMTK3 toolbox from Murphy *et al.* [2], where the classification algorithms are continuous Hidden Markov Models (cHMM).

Introduction

Activity pattern recognition analysis based on continuous sensor data using the MPU-9150 sensor is used to recognize daily activities in an everyday life environment. Activity recognition is currently a subject of intensive research, because of it's importance in many different fields. The motivation of this work lies in specific in the growing generation of older adults, and the need to provide them a secure and appropriate living standard. The continuous sensor data are used to recognize activities with a basic machine learning algorithm.

The demographic changes lead to more people suffering from Alzheimer's and Parkinson's disease. The challenge of the increasing number of dementia patients can be approached by Ambient Assisted Living Technologies like activity recognition, as some tasks of care givers can be eliminated or can be performed easier. This includes, among other things, sensors which control kitchen appliances like stoves, and guarantee the appropriate usage due to activity recognition. [3]

Human activity recognition based on accelerometer and gyrometer sensor data is an important task in the field of AAL technologies. The work focuses on the recognition of complex daily activities like tooth brushing, dinner preparation, changing clothes and others. The annotated data is recorded with the MPU-9150 sensor and the InvenSense MotionFit^{TM} Software Development Kit (SDK). Supervised classification algorithms, namely continuous Hidden Markov Models (cHMM), are used to detect different daily activities.

The current attempts to detect human behavior and activity can be classified by the type of the sensors used (1) body worn sensors, (2) video cameras and (3) domotic sensor networks. [4] This work concentrates on body worn sensors. The data gained from body worn sensors consist of accelerometer and gyrometer data.

1 Related Work

There are many research studies over human activity recognition in different settings.[5, 6, 7, 8, 9] Most of these works are based on acceleration data and tries to recognize daily activities like [5, 6, 7, 9]. The main difference between the works lies in the choice of parameters in the different steps of recognition, meaning preprocessing, feature extraction, and finally training and classification.

Each study uses different sample frequencies during preprocessing. Bao *et al.*[5] used a sample frequency of

76.25Hz, Ravi *et al.*[6] and Shoaib *et al.*[8] used 50Hz. To get a hint which frequency is accurate in daily activity recognition, but still doesn't need too much memory, Khusainov *et al.*[9] compared different sampling rates and inferred that most of the body movements are contained in frequency below 20Hz.

Shoaib *et al.*[8] record a combination of accelerometer, gyrometer and magnetometer data from a smartphone sensor and later six different activities with seven classifiers are analyzed. Shoaib *et al.*[8] show that the combination of accelerometer and gyrometer completes the system and gives better results during physical activity recognition. The feature calculation is kept as simple as possible with two time domain features. They handle four dimensions x, y, z and the magnitude $\sqrt{x^2+y^2+z^2}$ and compute mean and standard deviation. On top of the work from Shoaib *et al.*[8] the frequency domain features are included within this work and the aim is to find out the performance including more complex activities.

In [10] a feature dataset is provided. They recorded eight activities from a group of 30 persons with a sampling rate of 50Hz. All activities were performed twice with a smartphone on the waste recording the accelerometer and gyrometer data. They calculated a bundle of 561 features and experimented mainly with a multi-class support vector machine, showing an overall accuracy of 96% for test data consisting of 2947 patterns.[10]

This work is mainly based on Bulling *et al.* [11], where body-worn accelerometer and gyrometer sensors are recorded to detect hand gestures which where commonly used during daily activities. They recorded 12 activities and inbetween non-specific activities, so called 'NULL'-class, are performed. Data from two persons with three sensors placed on their arms in different heights are gathered. The sensor are placed on top of the right hand, outer side of the right lower and upper arm. The data comes from a three-axis accelerometer and a two-axis gyrometer, both recording annotated motion data at a sampling rate of 32Hz.[11]

2 Activity recognition

The activity recognition consists the following steps. First the sensor is placed and the raw data are recorded. Afterwards preprocessing is done, which means data segmentation and filters are applied. During feature extraction, features are calculated. Finally, the training and classification is done with a continuous Hidden Markov Model (cHMM).

2.1 Data

The InvenSense MotionFit^{TM} Software Development Kit (SDK) is used to record data. The MPU-9150 is a nine-axis MotionTracking device optimized to fulfill the purposes for wearable sensor applications.[1]

The MPU-9150 sensor is placed on the left hand wrist, with which the daily activities are mostly executed, because of sinistrality. The recording is done in different time units in a $59m^2$ flat. In table 1 common daily activities [12] are displayed, which are recorded in this study with a sampling frequency of 50Hz.

Table 1: List of recorded daily activities.

labels	activities	
1	NULL	
2	comb hair	
3	wash face	
4	wash hands	
5	brush teeth	electric/ non electric
6	make bed	
7	change clothes	
8	put blinds up/down	
9	prepare food	
10	eat with	folk/ spoon/ chopsticks
11	open/close window	
12	read newspaper/book	
13	putting shoes on	
14	drink from/with	straw/ mug/ cup

Each activity is saved with their 3-axis accelerometer and 3-axis gyrometer data. Inbetween all activities a 'NULL'-activity is performed, which consists of preparing the next activity and closing the preceding activity. The data gathering extends over days in many small sessions, which is the reason why the sessions are put together to one dataset later on.

Data segmentation is performed via annotation during recording, saving information over start and duration of the activity. The annotation is automated via an app, which allows the recording within specific time units, which are determined by the user and the annotation of the data accords to the user's purpose.

2.2 Preprocessing

Only data which are recorded more than once are used for analysis. This is done with one of two methods. The first method cuts out 'read newspaper/read book', 'putting shoes on' and 'drink from/with straw/mug/cup' from the whole dataset, but the 'NULL'-classes between the activities remain in the dataset. The second method redefines those classes labels to the 'NULL'-class label.

Some other activities are put together to one: 'Tooth brushing electric' and 'Tooth brushing non electric' get label 5 as well as 'Eat with folk', 'Eat with spoon' and 'Eat with chopsticks', which are assigned to label 10. Each sensor records data in three dimensions and a fourth dimension, describing the magnitude $\sqrt{x^2+y^2+z^2}$, is added for each sensor.

In the preprocessing step the artifacts and noises are reduced by filters and the signal is prepared for later feature extraction.[11] The noise and artifacts are disturbances which can corrupt the human activity recognition. During the study median filter and a 3rd order low-pass Butterworth filter are tested. These filters are also used among others in [10]. The 3rd order low-pass Butterworth filter has a cutoff frequency of 20Hz. This rate is sufficient, as the frequency of human body motions is 99% below 15Hz.[10]

The application of the median filter causes a smoothing of the data compare figure 1. Butterworth filters are used to cut high frequencies. The functionality of a third order low pass Butterworth filter with 20Hz cutoff frequency for a data segment of the original dataset can be seen in figure 2. The original data is displayed in blue and the filtered data is displayed in red.

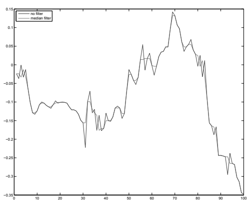

Figure 1: Median filter.

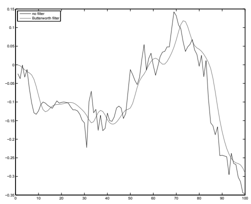

Figure 2: Butterworth filter.

2.3 Feature Mapping

In the feature extraction step the raw data are converted into features. This features are calculated for each annotated activity with a shifted window sized 50, containing 50 data vectors, and an overlap of 50%, which is the most significant value for overlap in past works.[13, 5] The mean, standard deviation, correlation [5, 6], energy [5, 6] and frequency domain entropy [5] are calculated for this data, as those are the most popular features for acceleration signals in activity recognition.[7]

The features can be divided into time domain features and frequency domain features. Time domain features are mean, standard deviation and correlation. Frequency domain features are energy and entropy. The energy and entropy calculation is much more expensive in comparison to the time domain features, because of the Fourier transformation (FFT).[8]

A periodic function in time is described with a direct current (DC) component. The DC component over the window is the mean value. Standard deviation is important for the reason of different range of values for different activities. Periodicity in the data is saved in the energy feature. Correlation between axes is useful to differentiate activities with translation in one dimension. As example, walking and stair climbing can be distinguished over correlation data.[5, 6]

In table 2 the calculation methods for the different features are depicted, where w is the window length and x_j are discrete FFT components. It is important to use a minimum number of features that allow good performance and at the same time minimize computational costs and memory.[11] Experimenting with the features get to the conclusion that entropy shows no improvement of the results. The best combination of features are mean, standard deviation and correlation.

2.4 Training

For activity recognition cHMMs are used. This is a supervised model which needs to get trained before operating.[11] Therefore the data has to be split into training and test data.

As some activities are not so common it is not possible to divide the data in usual 20% test data and 80% training data. Therefore one activity is cut out from each activity class, with the 'NULL'-class behind for the test data set. The remaining part is used as training data. An example for the structure of training and test data can be seen in figure 3 and 4.

Table 2: Features.

Features	calculation
mean	$\mu = \frac{1}{w}\sum_{j=1}^{w} x_j$ $x_j \ldots$ values
standard dev.	$\sigma = \sqrt{(\frac{1}{w}\sum_{j=1}^{w}(x_j-\mu)^2)}$
energy	energy$= \frac{1}{w}\sum_{j=1}^{w} \mid x_j \mid^2$
correlation	$cov(x,y) = \frac{1}{w}\sum_{j=1}^{w}(x_i-\mu_x)(y_i-\mu_y)$ $corr(x,y) = \frac{cov(x,y)}{\sigma_x\sigma_y}$
entropy	Frequency-domain entropy is calculated as the normalized information entropy of the discrete FFT component magnitudes of the signal.[5]

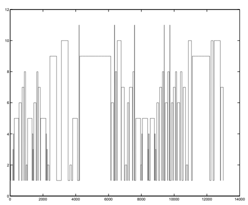

Figure 3: Training data.

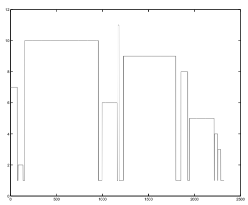

Figure 4: Test data.

The training needs a training set $\{(\mathbf{X}_i, y_i)\}_{i=1}^{N}$ consisting of N pairs of feature vectors $\mathbf{X}_i$ with corresponding labels y_i. In cHMMs the model parameters $\theta = (\pi, A, B)$ are learned by minimizing the classification error.[11] In this work the transition matrix A, can be calculated with the labeled training data as well as B, a list of pairs (μ, Σ) that define the distributions. Only π has to be guessed.

2.5 Classification

The classification consists of two steps. The first one maps a set of class labels to each feature vector of the test data with corresponding scores. In the second step the scores are used to calculate the maximum score and take the corresponding class label y_i as the classification output.[11]

2.6 Performance Evaluation

The classification of the activities can be either correct 'True Positive' and 'True Negative' or wrong 'False Negative' and 'False Positive'. The performance metric which is used for this model is a confusion matrix, with accuracy, sensitivity(=recall), specificity and precision.

The confusion matrix gives a breakdown of the misclassified activities by the model. The rows show the instances in each actual activity class and the columns show the instances for each predicted activity class. The values in one row are the results from the comparison of all ground truth instances, from the actual class, to the predicted class labels.[11] In table 3 a simple confusion matrix can be seen, where the last column describes the recall values, the last row the precision values and the last box describes the accuracy.

If the dataset is unbalanced, for example when the number of ground truth instances vary significantly, the overall accuracy is not representative for the whole classifier. A normalized confusion matrix inhibits this problem by using percentage of the total number of ground truth activity instances.[11] This problem occurs also in small scale during this study, that is the reason why all parameters are included in performance evaluation and no normalization is done.

Table 3: Simple confusion matrix.

	activity 1	activity 2	activity 3	recall
activity 1	11	2	0	84.62
activity 2	0	4	0	100
activity 3	1	0	5	83.33
precision	91.67	66.67	100	86.96

3 Validation

In the first attempt a validation with the provided data from Bulling *et al.* [11] and Anguita *et al.* [10] is accomplished to justify the use of continuous Hidden Markov Models (cHMM).

3.1 Bulling *et al.*[11]

In [11] data from 2 persons performing 12 activities are recorded: opening a window, closing a window, watering a plant, turning book pages, drinking from a bottle, cutting with a knife, chopping with a knife, stirring in a bowl, forehand, backhand and smash. Additionally, a non-specific activity was performed called 'NULL'-class.[11] The inertial measurement unit (IMU) is placed on 3 positions, the upper arm, the lower arm and the hand wrist on the right side.[11] For evaluation, the hand position is used.

Provided data with a 32Hz sampling rate are used to calculate the features: mean, standard deviation, correlation and energy for all 7 axes. This 7 axes come from the 3-axes accelerometer and 2-axes gyrometer gathered data, including one axis for each sensor, representing the magnitude. This features are further used to calculate the cHMM model.

The calculated results from the cHMM are compared with the results in the paper from Bulling *et al.* [11]. This circumstances are shown in figure 5, where precision and recall is compared to the applied cHMM in this thesis using the same dataset. The same characteristic, namely lower precision than recall, can be seen. The different values between results of Bulling *et al.* [11] and this thesis are mostly caused by the number of features and the model used in [11]. They only calculated two features, mean and standard deviation and the classification algorithm uses a folding step.[11] In comparison this thesis takes into account the mean, standard deviation, energy and correlation features.

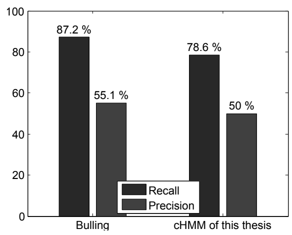

Figure 5: Precision and recall for sensor data from Bulling *et al.* [11] and this cHMM.

In [11] the precision lies by 87.2% using the sensor placed on the hand wrist. This relates to the results of an accuracy of 81.71% and good recall and precision values for each activity class in the confusion matrix. Therefore it follows, that the used cHMM is accurate.

3.2 Anguita *et al.*[10]

Anguita *et al.* gathered data from 30 volunteers, which followed a defined protocol of activities, consists of standing, sitting, laying down, walking, walking downstairs and upstairs. This data are collected via a Galaxy S II. smartphone on the waist, recording accelerometer and gyrometer data with a sampling rate of 50Hz and 5 seconds break between two activities.[10]

Only a part of the 561 features vector of the provided data is picked for evaluating the cHMM. The feature data is already noise reduced by median filter and 3rd order low-pass Butterworth filter with a 20Hz cut-off frequency and others.[10] In particular the data of mean, standard deviation and correlation is used for all three axes X, Y, Z.

The confusion matrix shows the precision in the last row, the recall in the last column and accuracy in the last box. In table 4 the confusion matrix of the cHMM is depicted. In table 5 the results of Anguita *et al.*[10] are reproduced. In contrast to the cHMM applied in this study, Anguita *et al.* used a multiclass Support Vector Machine (MC-SVM). The different accuracy can be attributed to the less used features, the usage of only one accelerometer and one gyrometer dataset, and the more complex MC-SVM model in [10].

Table 4: Confusion matrix of cHMM.

Walking	W.Upstairs	W.Downstairs	Sitting	Standing	Laying Down	
422	0	74	0	0	0	85.07
0	400	71	0	0	0	84.93
0	39	381	0	0	0	90.71
2	1	3	406	68	11	82.69
6	9	5	26	468	18	87.97
0	0	2	298	44	193	35.94
98.14	89.09	71.08	55.62	80.69	86.94	77.03

4 Experiments

In all experiments except 'Continuous/Discrete data', the activities which occur only once in the recording period are put in the 'NULL'-class activities. In 'Continuous/Discrete data' the once recorded classes are cut out of the whole dataset, leading to an one percent improvement. In real environmental applications this makes a small difference and therefore is not necessary.

Table 5: Confusion matrix of MC-SVM [10].

Walking	W.Upstairs	W.Downstairs	Sitting	Standing	Laying Down	
492	1	3	0	0	0	99.12
18	451	2	0	0	0	95.75
4	6	410	0	0	0	97.62
0	2	0	432	57	0	87.98
0	0	0	14	518	0	97.37
0	0	0	0	0	537	100
95.72	98.04	98.80	96.86	90.09	100	96

4.1 Training and test sets

Different sort of training and test data partitions are analyzed. For example, the test data includes the third repetition of each single activity class and takes either the 'NULL'-class behind or in front of each cut activity. Another approach uses the second repetitions, again with either the 'NULL'-class in front of the activities or behind. This results are compared to each other see figure 6, 7 and table 6. Out of the table, illustrating the changes in accuracy, specificity and sensitivity, the conclusion can be drawn, that the 3rd activities with 'NULL'-class behind, implies the best result.

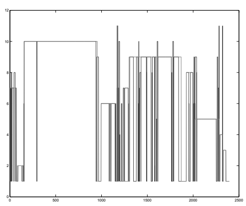

Figure 6: 3rd activities with 'NULL'-class behind.

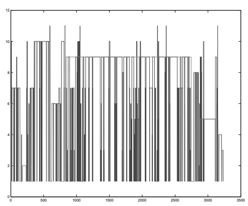

Figure 7: 2nd activities with 'NULL'-class in front.

Also different feature combinations are constructed and the accuracies are compared, leading to the most appropriate combination of mean, variance, correlation without the magnitude for the 3rd back data set.

4.2 Filters

In this section a median filter and a 3rd order low pass Butterworth filter with a corner frequency of 20Hz is used to remove noise, based on Anguita *et al.* [10].

Table 6: Accuracy, specificity and sensitivity for different sets.

Experiment	accuracy	specificity	sensitivity
3rd back	80.24	89.08	63.81
3rd front	79.84	88.35	61.25
2nd back	63.99	82.66	67.91
2nd front	64.67	85.48	56.18

For the best combination of features experimented above accuracy, specificity and sensitivity of filtered and non-filtered data are represented in table 7. If filters are applied, the sensitivity gets better, but the accuracy and specificity gets worse. Therefore filters seem unnecessary for this dataset.

Table 7: Accuracy, specificity and sensitivity for filtered and non filtered data.

Experiment	accuracy	specificity	sensitivity
no filter	80.24	89.08	63.81
filter	79.53	88.26	67.62

4.3 Accelerometer/Gyrometer

This experiment deals with analysis of accelerometer and gyrometer data on their own and combined. The outcomes of the accelerometer and gyrometer data on their own are further compared with the results of Bulling *et al.* [11].

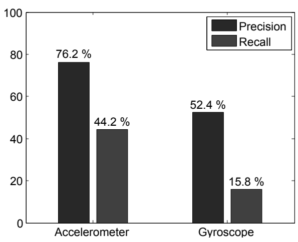

Figure 8: Precision and Recall by Bulling *et al.* [11].

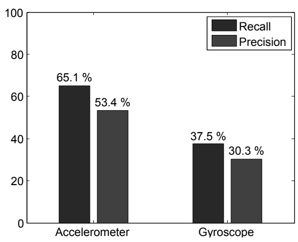

Figure 9: Precision and Recall of this study.

The single accelerometer dataset is more accurate than the single gyrometer dataset. This results coincide with those of Bulling *et al.* [11]. In [11] the gyrometer data on their own is also worse than the accelerometer data on their own. These circumstances are illustrated in figures 8 and 9, where precision and recall are symbolized as blue and red bars. It can be noticed, that the results in the study of Bulling *et al.* [11] reach higher level of precision and lower level of recall than the results in this study. This is mostly caused by the greater dataset in [11]. The results in this study are not worse, but differ in activities as well as range and sort of recording.

The combination of accelerometer and gyrometer data is less accurate, combining accuracy, specificity, recall and precision therefore the conclusion can be drawn that gyrometer data is unnecessary in this case.

4.4 Extra cHMM

Activities are now divided in sub-activities with an extra cHMM. In specific, for each often misclassified activity-class, a cHMM is applied to divide the activities in sub-activities. The number of sub-activities depends on the number of states in the cHMM. Hence an iteration is done, constructing a 2-5-state cHMM, choosing the cHMM with highest accuracy.

For example the improvement by using the divided 'Tooth brushing' class comes from the case that electric tooth-brushing has a higher frequency.

The extra cHMM model is very sensitive. During the experiments only the parameter, for 'k'-fold cross-validation and the parameter, number of activity classes divided, are considered. But also a change in tolerance and of maximal iterations within the cHMM effects the outcome. The tolerance is always set to $1e^{-5}$ and the maximal iteration is set to 10.

In figures 10 the basic cHMM is shown, in contrast to figure 11, where the results for including sub-activities for tooth brushing, putting blinds up/down and prepare food are displayed, symbolized as Viterbi path (blue) correlating with the original labeled path (red). The results with sub-activities show a better fit to the original path. The experiments show that accuracy and specificity gets better, but do not justify higher runtime.

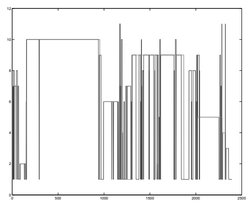

Figure 10: Basic cHMM.

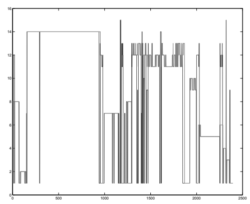

Figure 11: Extra cHMM.

4.5 Continuous/Discrete data

The combination of continuous and discrete data is analyzed in this section. Test and training data get an additional column, consisting of the room number, describing the room where the activities are performed. The 'NULL'-class activities become half the room label from the previous activity and half the room label from the following activity. The process represents the usage of smart home sensors in combination with wearable sensors. An improvement of the results can be recognized. The outcomes in table 8 show that accuracy improves about 9% and sensitivity about 10%, while specificity stays nearly the same. This justifies the effort of collecting both data, continuous and discrete.

Table 8: Accuracy, specificity and sensitivity for continuous and continuous & discrete data.

Experiment	accuracy	specificity	sensitivity
continuous	81.21	99.66	79.03
continuous & discrete	88.75	100	91.39

A great improvement can also be seen in the comparison of the Viterbi path (blue) and the original labeled path (red) in figure 12 and 13. Figure 12 shows results with continuous data and figure 13 with the combined dataset.

Overall the classes are not so likely misclassified as 'NULL'-class anymore, but one drawback is that the 'NULL'-class is much more likely misclassified as other activities.

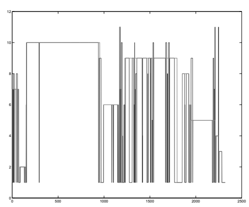

Figure 12: Continuous data.

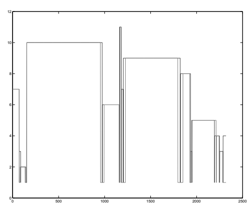

Figure 13: Con. & disc. data.

5 Conclusion and Outlook

Human activity recognition in Ambient Assisted Living (AAL) using a 3-axis gyrometer and a 3-axis accelerometer is performed. This raw data are preprocessed and split into test and training data sets. Later on features are extracted. Based on these features a continuous Hidden Markov model (cHMM) is constructed.

The cHMM model is validated with provided data and results from Bulling *et al.* [11] and Anguita *et al.* [10]. Afterwards different experiments were accomplished. The outcome shows, that using only accelerometer data with mean, variance and correlation leads to the best results. The conclusion is that gyrometer data are not necessary for good results and filters do not really contribute to significant improvement. The most important outcome is, that the combination of discrete and continuous data considerably improves the results.

The experiments have to be treated with caution, as the dataset is not big enough to get general statements and is only recorded from one person. Another drawback of the data is the recording sessions. It is recorded in different sessions with breaks inbetween, but still is applicable to real environments.

Research should focus on the combination of discrete data from binary sensors and continuous data from wearable sensors. This will lead to more robust and trustable models. A broader consideration, meaning a bigger dataset with more activities and people included, would lead to results which allow to imply more general statements.

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