Improving Human Activity Recognition by Smart Windowing and Spatio-Temporal Feature Analysis

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ABSTRACT
This paper presents a promising approach to enhance multi-sensor based activity recognition in smart homes. The research is originated in the domain of Active and Assisted Living which mainly is about supporting older people to master their daily life activities. The paper proposes (a) a windowing technique which can be used for online sensor streaming and (b) a set of different statistical spatio-temporal features to recognize activities in real time. In order to check the overall performance, this approach was tested using the CASAS dataset. The results proved a high performance based on different evaluation metrics despite a large number of classes.

CCS Concepts
I.5 [Design Methodology]: Classifier design and evaluation - Pattern Recognition

Keywords
Active and Assisted Living (AAL), Windowing, Activity Recognition, Healthcare

1. INTRODUCTION
Recent advances in computer science and engineering, electronics and sensor technologies have resulted in a significant progress in the field of Human Activity Recognition (HAR) systems [1]. Active and Assisted Living (AAL) [2] is one of the HAR application domains where activities of (mainly older) persons or patients are monitored using modern, unobtrusive technologies to detect situations, in which assistance is needed. By determining and providing the right support, AAL systems will allow their users to live autonomously within their familiar home environment.

PETRA '16, June 29-July 01, 2016, Corfu Island, Greece
© 2016 ACM. ISBN 978-1-4503-4337-4/16/06…$15.00
DOI: http://dx.doi.org/10.1145/2910674.2910697

Activity recognition can be described as the process of combining simple actions that are identified using sensory observations to determine activities. Therefore, such environments rely on sensors that are localized inside a person's home.

In HAR systems, an activity is a sequence of simple events (e.g., walking, opening, closing) performed by a human [3]. Most of the existing HAR approaches combine such simple events to recognize human activities.

In general, the activity recognition process consists of several steps. Initially, raw sensor data is collected and passed through the *pre-processing phase* to remove the noise and the redundant data from the raw sensor stream. Then, the pre-processed data passes through the *windowing phase* to identify the most significant segments of the data. These segments are used in the *feature extraction phase* which is to determine (by classification) a specific activity. To increase accuracy, dimensionality reduction might be applied; this also may reduce the computational effort needed for feature classification [4].

Designing such activity recognition system is challenging due to the spontaneous nature of human activities.

Within this paper, we present a specific technique for the windowing phase and discuss a robust activity recognition approach using spatio-temporal features. The research is a part of the Human Behavior Monitoring and Support (HBMS)[1] project, which aims at a comprehensive AAL-System for supporting any kind of basic and daily live activities [5,6,7].

The paper is organized as follows: Section 2 gives an overview of the state-of-the-art approaches. Section 3 discusses the overall architecture of our activity recognition approach. Section 4 presents the obtained results and the overall performance evaluation. The paper ends in Section 5 with a conclusion.

2. RELATED WORK
During the last decade, different approaches for human activity recognition under uncertainty have been reported. They can be classified into three major categories along their underlying model types: logic-based context models, graphical models, and syntactic models.

Logic-based context models use expressions and rules to describe context properties such as entities, their properties, and the relationships in between. To recognize complex human activities,

[1] HBMS is funded by the Klaus Tschira Stiftung gGmbH, Heidelberg.

for example, the Ontology Web Language (OWL[2]) [8] and Answer Set Programming (ASP) [9,10] are used for ontology representation and Knowledge Base (KB) creation, respectively.

Graphical models are used to describe complex activities in a higher level representation, e.g., Bayesian Dynamic Networks [11], Hidden Markov Models [12], Dempster-Shafer [13], Conditional Random Fields (CRFs) [14], Gaussian Mixture Models (GMM) [15], and extended naive Bayes classifier to incorporate low order temporal relationships [16].

Syntactic models describe the real world events by structuring them using a set of production rules, e.g., rough set theory [17] and fuzzy logic [18].

Activity recognition based on inferencing OWL 2 (Ontology Web Language) models is still a major research area [8]; an advantage here is, that OWL 2 ontologies are supported by a fuzzy logic-based reasoner to handle uncertainty. The fuzzy logic fusion method provides an effective means to meet the requirements of recognizing human daily-life activities [19]. However, it defines membership functions and production rules that are extremely domain- and problem-specific. The Bayesian inference suffers from the difficulty in defining a priori probabilities and the inability to consider general uncertainty [20].

Hidden Markov Models (HMM) showed promising results in the field of activity recognition, but they do not perform perfectly for our purpose since human behavior is not Markovian [21].

To overcome the limitations of the Bayesian inference method, the Dempster-Shafer method generalizes the Bayesian theory to allow for probability distribution support, not only to a single hypothesis but also to the union of hypotheses [22]. The Dempster-Shafer and Bayesian methods produce identical results when all the hypotheses are singletons and mutually exclusive [23]. Additionally, the combination rule of the classical Dempster-Shafer theory can be implemented to fuse data from sensors, but it can lead to illogical results in the presence of highly conflicting evidence. Therefore, we aim at a technique which (a) avoids the previous limitations (b) provides a high recognition rate, and (c) performs in real time.

3. PROCESS STRUCTURE

The process structure of our approach consists of two major phases: (1) an *offline phase* for analyzing and windowing the streaming data and (2) an *online phase* to recognize activities by using the same windowing technique.

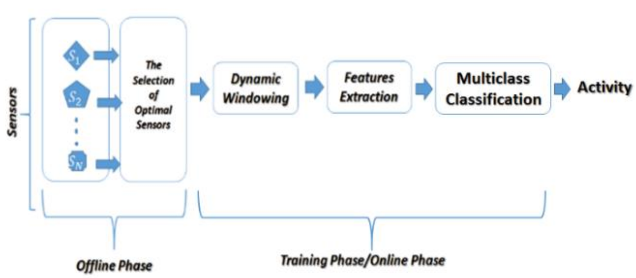

Figure 1: Process Structure

[2] www.w3.org

3.1 Dynamic Windowing

In literature, three major approaches have been reported that deal with the windowing of streaming data.

***Segmentation with fix window size*:** Sensor data streams are divided into chunks that consist of,

a) a constant number of sensor events, or
b) sensor events occurring in a predefined constant time interval.

Note, that this strategy may lead to situations where (the data indicating) an activity is spread over several different chunks [24,25,26].

***Segmentation along specific sensor events*:** This approach comes with a varying window duration, and thus has the advantage that activities with longer duration can be determined. However, then there might be periods in which not enough sensors are activated [27].

Probabilistic dynamic Windowing: This approach uses a probabilistic approach which maximizes the probability of the most likely window size for a specific activity. The idea is to incorporate the time decay and mutual information by using weightings of sensor events within a window [28].

Our approach proposes such dynamic windowing based on the number of activated sensors (out of a number of usually discussed features[3]) for a particular activity, and a subsequent analysis of spatio-temporal features.

Thus, the basic concept is to analyze, in the training phase, a given sensor dataset w.r.t. enumerated features in order to determine the number of sensors whose activations together best fit for the recognition of a certain activity: "*best fitting sensor set*".

The analysis can, e.g., be performed by using Information Gain (IG) attribute evaluation [29]. In our experiments, using the CASAS dataset (see section 4.1), this analysis came with the result that the number of activations for each sensor is the most relevant attribute.

Thus, we recommend to sort the sensors along their activation times, and to iteratively check the quality (IG rank) of the windows containing the first *2, 3,..., n* sensors. The window size delivering the highest IG rank will contain the best fitting sensor set, i.e., the optimal number of sensors for a particular activity.

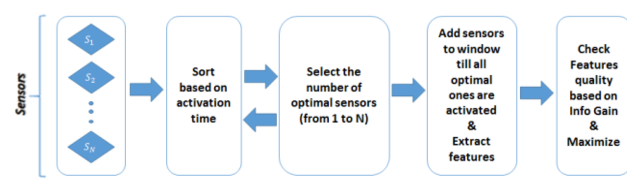

Figure 2: windowing for activity recognition

Consequently, in the online phase, sensor data will have to be collected in a window until the best fitting sensor set of an activity is activated (see Figure 2).

This approach allows to establish an "*occurrence vector*" (representing a window-related histogram) which is the number of activations for each sensor as shown in figure 3. This vector is used subsequently for feature extraction.

[3] Number of activations of each sensor, activation duration of each sensor, number of activated sensors for each activity, and the location of the sensor.

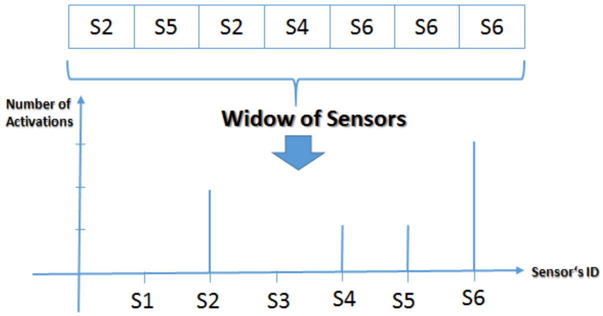

Figure 3: occurrences histogram

3.2 Feature Selection

In this section, we shortly introduce the set of specific spatio-temporal features that we are using in our approach for calculation, evaluation and the final feature vector composition.

3.2.1 Temporal Features

Human activity recognition systems consider, two types of temporal features [30]:

(a) absolute temporal features which are independent of other activities, and

(b) relative temporal features that relate to other activities .

In our approach we adopt both types.

absolute Time (absTime):

absTime is defined to be the sum of the durations of all activities observed (supposing that activities are not performed in parallel), where N is the total number of activities.

$$absTime(a_i) = \sum_{i=1}^{N} startTime(a_i) - endTime(a_i) \tag{1}$$

Relative Time (relTime):

Relative temporal features are supposed to represent some useful information for classification [22]. In other words, they can be used for identifying relation patterns between activities using reasoning mechanisms. For example, a person might not have a routine time for taking a shower, but might brush teeth after each meal.

Equation 2 defines the relative time (relTime) for an activity a_p where again $N = |V|$ is the total number of activities and V is the vector of activities.

$$relTime\ (a_p, a_q) = \sum_{i=1}^{N} g_i(a_p, a_q) \tag{2}$$

$$g(a_p, a_q) = \begin{cases} 1, if\ \ V(i) = a_p\ , V(i+1) = a_q \\ 0, otherwise \end{cases}$$

3.2.2 Spatial Features

Using the occurrence vector as defined in section 3.1 (see figure 3), a set of most likely activities may be analyzed based on the following arithmetic statistics [31]: the mean, the median, the range, the standard deviation, the skewness and the kurtosis.

The occurrence vector *o is* the number of activations for each sensor s_p which is defined as follows:

$$o(s_p) = \sum_{j=1}^{S} h_j(s_p) \tag{3}$$

$$h(s_p) = \begin{cases} 1, if\ \ s_p\ is\ on \\ 0, if\ \ s_p\ is\ off \end{cases}$$

where S is the total number of sensors in the window.

Arithmetic Mean

The arithmetic mean μ is the average value of the data, i.e., the sum of all occurrence vector fields o_i divided by the total number of sensors S $(i.e., the\ vector\ length)$:

$$\mu = \frac{1}{S} \sum_{i=1}^{S} o_i \tag{4}$$

Median

The median is the middle value in a sorted list of data:

$$median = \begin{cases} o_{\frac{S+1}{2}},\ if\ S\ is\ odd \\ \frac{1}{2}\left(o_{\frac{S}{2}} + o_{\frac{S}{2}+1}\right), otherwise \end{cases} \tag{5}$$

Range

The range is the difference between the largest value and the smallest value of a dataset. In our case, the difference between the largest value and the smallest value of the given occurrences vector:

$$o_{range} = o_{max} - o_{min} \tag{6}$$

Standard Deviation

The standard deviation is the square root of the variance. The variance is the sum of all squared differences from each occurrence value to the mean divided by the number of sensors S minus 1:

$$\sigma = \sqrt{\frac{1}{S-1} \sum_{i=1}^{S} (o_i - \mu)^2} \tag{7}$$

Skewness

The skewness γ is defined as the quotient of the third central moment m_3 of a dataset, and the cubed standard deviation. :

$$\gamma = \frac{m_3}{\sigma^3} = \frac{\frac{1}{S} \sum_{i=1}^{S} (o_i - \mu)^3}{\left(\sqrt{\frac{1}{S} \sum_{i=1}^{S} (o_i - \mu)^2}\right)^3} \tag{8}$$

Kurtosis

The kurtosis κ is defined as the quotient of the fourth central moment of a dataset m_4, and the standard deviation σ power 4:

$$\kappa = \frac{m_4}{\sigma^4} = \frac{\frac{1}{S}\sum_{i=1}^{S}(o_i - \mu)^4}{\left(\sqrt{\frac{1}{S}\sum_{i=1}^{S}(o_i - \mu)^2}\right)^4} \qquad (9)$$

In our approach, these statistical values (equations (4) to (9)) are interpreted as spatial features. Based here-on, we define the complete *feature vector* as follows:

occurrence vector with best fitting sensors (bfs)	spatial features (moments of bfs)	occurrence vector without bfs	spatial features without bfs

3.3 Multiclass Classification

Typically, AAL datasets have multiple activities (classes). Thus, we have a multiclass classification problem which is a major problem in machine learning.

The most common approach to multiclass classification is the one-versus-all approach which makes direct use of standard binary classifiers to encode and train the output labels [32]. It assumes that for each class there exists a single separator between that class and all the other classes.

Additionally, another common approach is all-versus-all which assumes the existence of a separator between any two classes.

In this paper, we choose the one-versus-all approach whose advantage is, that each class is represented by only one classifier; thus, it is possible to obtain knowledge about a specific class by checking out its corresponding classifier.

The classification model used is multinomial logistic regression, which generalizes logistic regression to multiclass problems [33]. The idea is to use ridge estimators in logistic regression to improve the parameter estimates and diminish the error made by further predictions.

4. Results

For our experiments and evaluation we used the Aruba CASAS[4] dataset [34]. The CASAS project considers AAL environments as smart agents through which the status of the residents and their spatial environment are perceived by using sensors. The Aruba dataset is collected in a house which consists of one bedroom, one bathroom, a kitchen, a living / dining room, and an office. The home is equipped with motion and temperature sensors.

For this dataset the number of best fitting sensors was evaluated to 5 based on the approach presented in section 3.1.

Weka tool is used for the classification [32], we conducted a 10-fold cross-validation of the dataset using the multinomial logistic regression model with a ridge estimator [33].

[4] http://ailab.wsu.edu/casas/datasets/aruba.zip

4.1 Aruba CASAS Dataset

In the Aruba CASA dataset, the activities are recorded by a single resident who acted from 2010-11-04 to 2011-06-11.

Sensor events are collected by using motion sensors, e.g., M003, M024, door closure sensors, e.g., D002, D004 and temperature sensors, e.g., T001, T002 (see Table 1). The total number of sensors is 34, but we excluded the temperature sensors; therefore, we took only 30 sensors into consideration.

In the dataset 11 activities are annotated but we took only 9 activities into account due to the low number of samples of the other two activities.

The following resident activities were considered within our evaluations: Sleeping, Bed to Toilet, Meal Preparation, Relaxing, House Keeping, Eating, Leave Home, Enter Home, and Work.

Table 1: Sample of sensor dataset

Date/time	Sensor ID	Sensor reading	Annotation
2010-11-04 00:03:50.209589	M003	ON	Sleeping begin
2010-11-04 00:03:57.399391	M003	OFF	
2010-11-04 00:15:08.984841	T002	21.5	
2010-11-04 00:30:19.185547	T003	21	
2010-11-04 00:30:19.385336	T004	21	

4.2 Activity Recognition

For activity recognition, an evaluation of features is applied to check their effectiveness in the intended classification task. For this purpose, we checked the Information Gain (IG) Attribute Evaluation method [29].

The quality of the spatial features varied between 0.13 and 0.58. The closer the quality is to one, the better it is.

In contrast to spatial features, temporal features did not change significantly the overall recognition rate. Therefore, these features were discarded from the final feature vector. This can be explained by the fact that the resident does not have specific temporal patterns while performing his/her daily life activities.

In the 10-fold cross-validation mentioned above, the data is randomly divided into ten equal-sized slices. Each slice is used as a test set and a training set. The test results are then averaged over the ten cases.

Table 2 shows the results of our approach presented in 6 different evaluation metrics, where,

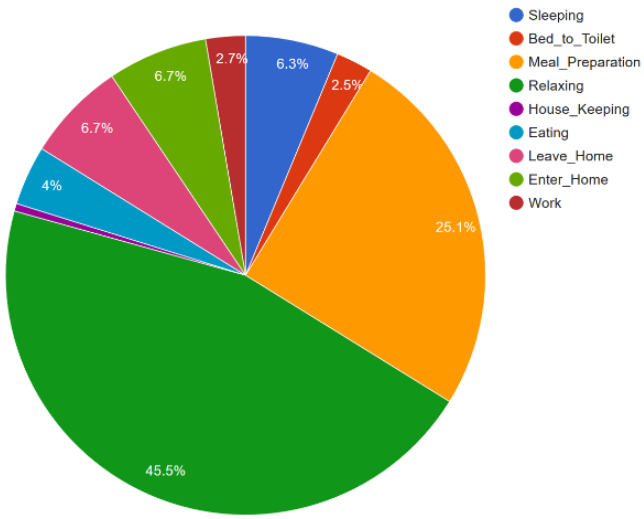

Figure 4: The overall distribution of all activities

- TP is true positives,
- FP is false positives,
- Pr is the precision,
- Re is the recall,
- F-M is the F-Measure, and
- ROC is the Receiver-Operating-Characteristic Curve.

The classes are:

- C1: Sleeping,
- C2: Go to Bed,
- C3: Meal Preparation,
- C4: Relaxing,
- C5: House Keeping,
- C6: Eating,
- C7: Leave Home,
- C8: Enter Home, and
- C9: Work.

The overall F-Measure value which is calculated based on the annotations of the given dataset (i.e. without dynamic windowing) is 0.959 although there are bad cases (worst: class C7 "Leave House" with value 0.179, second worst: class C5 "House Keeping" with value 0.714). This can be explained by Table 3 which shows the confusion matrix for all nine classes. For example, the misclassifications occurred due to the dominance of class C3 over C7 which is a consequence of its large number of occurrences in the dataset. Other misclassifications, e.g. C5 instead of C3 may be explained by the fact that these activities might share similar sensors.

Figure 4 shows the overall distribution of the activities. This distribution reflects the fact that the classes are imbalanced. However and despite this problem, still a high performance is ensured (see Table 2).

Table 4 shows the overall performance after applying our windowing approach, i.e., the approach we proposed for activity recognition based on real time sensor data streams. The classes C2 and C7 do not appear in the evaluation, because their data were "consumed" in the windowing phase. Clearly, our overall F-measure evaluated to 70.14.

To check other works that used windowing on the Aruba CASAS dataset, we found the recent results reported in [35]: within this paper, two methods have been proposed: (1) an extension of feature descriptors using mutual information-based weighting of sensor events within a window which is called SWMIex where its F-measure: 68.68, and (2) a method based on the last state of sensor within a window which is called SWLS where its F-measure: 69.24.

Table 2: The Overall performance without windowing

Aruba	TP	FP	Pr	Re	F-M	Roc
C1	0.98	0.002	0.98	0.98	0.98	0.987
C2	1	0.002	0.961	1	0.98	1
C3	0.983	0.024	0.915	0.983	0.948	0.986
C4	0.995	0.005	0.995	0.995	0.995	0.998
C5	0.714	0.002	0.87	0.714	0.784	0.961
C6	0.957	0.004	0.941	0.957	0.949	0.991
C7	0.179	0.001	0.174	0.179	0.286	0.902
C8	0.982	0.002	0.976	0.982	0.979	0.994
C9	0.955	0.001	0.985	0.955	0.97	1
Weighted Avg	0.966	0.008	0.957	0.966	0.959	0.991

Table 3: The confusion matrix for the overall performance without windowing

C	1	2	3	4	5	6	7	8	9
1	147	1	0	1	0	0	0	1	0
2	0	74	0	0	0	0	0	0	0
3	0	0	410	1	3	2	2	0	0
4	1	0	0	918	0	2	0	0	1
5	1	2	2	1	20	0	0	1	0
6	0	0	2	1	0	112	0	2	0
7	0	0	32	0	0	2	5	0	0
8	0	0	2	0	0	1	0	166	0
9	1	0	0	1	0	0	0	0	64

Table 4: The overall performance with windowing

Aruba	TP	FP	Pr	Re	F-M	Roc
C1	0.81	0.003	0.75	0.81	0.78	0.95
C3	0.98	0.35	0.93	0.98	0.95	0.85
C4	0.83	0.01	0.89	0.83	0.86	0.96
C5	0.25	0.002	0.62	0.25	0.36	0.84
C6	0.66	0	1	0.66	0.80	0.99
C8	0.42	0.001	0.76	0.42	0.54	0.87
C9	0.71	0.002	0.54	0.71	0.62	0.99

5. CONCLUSION

Activity recognition requires a detailed analysis and understanding of the domain in which activities occur. Within this paper, we proposed a dynamic windowing technique supported by different types of spatio-temporal features. We proved that the proposed approach is a solid basis for implementing a powerful tool in order to detect complex activities in smart homes.

In particular, the extracted features based on standard moments are suitable for characterizing activities in dataset and thus for recognition.

Additionally, we evaluated the overall quality of our features to ensure a high performance through the use Information Gain (IG) Attribute Evaluation.

Furthermore, we were able to test our method's accuracy by using the internationally well-known CASAS dataset. The importance of the dataset arises from the fact that all sensor data do mimic real life scenarios.

Our future work will focus on testing the proposed approach considering several residents.

Within the AAL system HBMS, activities are represented as "Behavioral Units" of a so-called Human Cognitive Model (HCM) using the domain specific modeling language HCM-L [5][5]. In addition to this, a case base of all observed and recognized activities will be realized. Consequently, the recognition component will be extended such that the knowledge available in the HCM and the case base can be exploited for a further improvement of the automatic recognition.

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