MULTIPLE PEOPLE ACTIVITY RECOGNITION USING SIMPLE SENSORS

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Abstract: Activity recognition of a single person in a smart space, using simple sensors, has been an ongoing research problem for the past decade, as simple sensors are cheap and non-intrusive. Recently, there is rising interest on *multiple people activity recognition (MPAT)* in a smart space with simple sensors, because it is common to have more than one person in real-world environments. We present the existing approaches of MPAT, such as Hidden Markov Models, and the available multiple people activities datasets. In our experiments, we show that surprisingly, without the use of existing approaches of MPAT, even standard classification techniques can yield high accuracy. We conclude that this is due to a set of assumptions that hold for the datasets that we used and this may be unrealistic in real life situations. Finally, we discuss the open challenges of MPAT, when these set of assumptions do not hold.

1 INTRODUCTION

Activity recognition aims to recognize the intention or actions of one or more people/residents. Their intentions are inferred from a series of sensed observations on the actions of the people/residents and the environmental conditions. It is also known as plan, intent, or behavior recognition. Depending on the application, good activity recognition requires the careful selection and use of hardware/sensor-based and software/algorithmic combinations, in order to produce cheap but accurate outcomes.

For the identification of the activities of different people, we can use either complex sensors or simple ones. Complex sensors employ technologies such as Ultra Wide Band (UWB) and Radio Frequency Identification (RFID) to reliably distinguish the identities of people without much inference (that is, learning and predicting each person's movement and activity patterns). However, complex sensors are generally expensive, and requires people to wear sensors or tags, which can be intrusive to the privacy of the people. In simple sensors, inference is required on the identification of the activities of the different people, and a combination of simple sensors is usually needed for reliable and accurate inferences, as they have limited sensing range. However, they are cheap, and are less intrusive to the privacy of the people. Examples of simple sensors are motion detectors, contact switches, pressure mats, and vibration sensors.

Almost all prior activity recognition work using simple sensors is on a single person, but it makes more sense in recognition of activities of multiple people, as humans are social creatures and it is common to have more than one person in an environment. Recently, multiple people recognition algorithms are developed in the area of computer vision, which use video cameras in outdoor or common environments. For example, there are some computer vision works in nursing home, where multiple people interactions in the corridor and dining room are monitored by video cameras and microphones (Chen et al., 2007; Hauptmann et al., 2004). However in many indoor and private environments, the use of video cameras is not practical due to:

- computational constraints
- privacy concerns (such as in the home and office situations),
- budgetary limitations (such as high unit, installation, maintenance cost of each video camera; and situations usually require multiple units), and
- accuracy challenges (such as distance from camera, occlusion, and requirement of correct facial and gait alignment to camera).

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Multiple People Activity Recognition (MPAR) using simple sensors is an emerging and multi-faceted research area; closely related to ambient intelligence, sensor networks, and data mining. Its key application is in home-based elderly care due to the availability of realistic simple sensor data of normal people living in smart homes, and also the reporting of good results by some algorithms in this application.

Common sense tells us that MPAR is more complex than the single person version due to the additional task of assigning the recognized activity to one of the *n* number of people. However, contrary to conventional wisdom, we show that MPAR using many simple sensors can be trivial. In other words, if we relax a number of assumptions in the current state-of-the-art studies, such as using very few simple sensors or reduce the dependency on person-specific activity labels for training, the existing techniques will yield either poor results or are infeasible to use.

This rest of this paper is organized as follows. First, we introduce existing approaches. Second, we list some available datasets, mostly in home-based elderly care applications. We apply the simplest techniques on the simplest dataset, and present early results to support our argument. Finally, we present and describe four open challenges in MPAR using simple sensors. This is in hope to see more researchers working on this interesting area of research, new techniques which address these open challenges, or become our future work.

2 EXISTING MULTIPLE PEOPLE ACTIVITY RECOGNITION (MPAR) APPROACHES USING SIMPLE SENSORS

2.1 Hidden Markov Models (HMMs)

The hidden Markov model (HMM) is the most common approach used for activity recognition of multiple people in smart spaces (Panangadan et al., 2010; Cook et al., 2010; Crandall and Cook, 2009; Singla et al., 2010; Wilson and Atkeson, 2005). The HMM is a suitable approach, as it can probabilistically model the complexities and dynamics of the activities of the multiple people in a smart space. Each person's activities (Chiang et al., 2010) or each activity (Cook and Schmitter-Edgecombe, 2009) can be represented as a Markov model, as the assumption is that different activities map to distinct probability distributions. The Markov model is shown to have slightly better accuracy that the naive Bayes classifier (Cook and Schmitter-Edgecombe, 2009), probably due to its ability to capture sequence information.

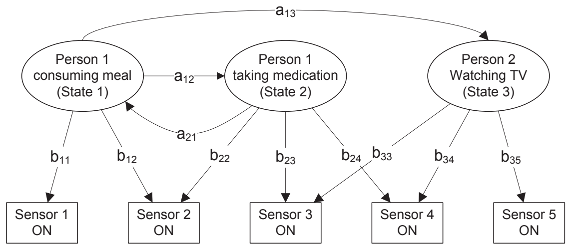


Figure 1: Example of a HMM modeling the activities of multiple people in a smart space. The activities of multiple people are represented as hidden states (circles) and sensor values are represented as observations. The edge labeled with a_{ij} is the transition probability from hidden state i to hidden state j, while the edge labeled with b_{ij} is emission probability of generating observation j in hidden state i.

Figure 1 shows an example of a HMM for activity recognition of multiple people. The HMM consists of hidden states and observable states. In the context of activity recognition, the activities are modeled as a Markov process, and they are represented as the hidden states, as the activities are not directly observable. The sensors values are modeled as observations, which are generated from the hidden states. The edges between the hidden states denote the transition probability between states (activities), while the edges from the hidden states to the observations denote the emission probabilities of generating the observations in the hidden states.

The HMM is first trained with the training data, and the Viterbi algorithm is used to detect the activities. Given a sequence of observations (sensors readings), the Viterbi algorithm is used to find the most likely sequence of hidden states (activities) that results in the given sequence of observations.

Note that the example shown in Fig. 1 is a simple example of how HMM is used, and different papers describe different variations of HMM to solve their own specific problems. For example, to detect human interaction, a HMM is used to model each person's activities, and two HMMs/people's activities are combined by considering the relationship between them; while parallel HMM does not consider any relationship (Chiang et al., 2010).

Although HMM is a popular approach in activity recognition, it has some limitations. First, HMM is not scalable to model large and complex smart spaces. As each activity of a person is modeled as a hidden state, a large number of activities and people will lead to an explosion of hidden states of HMM, which will decrease the efficiency of the model. Moreover, the Viterbi algorithm is a dynamic programming algorithm - expensive in running time and memory space.

Second, the activities and the number of people in the smart space must be known prior to the training of the model. Hence, the training data must be accurately labeled, which can be a time consuming process if manual annotating is used.

Third, HMM does not exclusively exploit the knowledge of multiple people to improve its accuracy, as it treats each hidden state equally, even though it is obvious that hidden states that correspond to a person should be related. Hence, there is no difference in modeling the activities of a person and the activities of multiple people.

Fourth, HMM has the stationary assumption, which means that the state transition probabilities do not change over time as system evolves. This is not realistic as activities of people may evolve over time, particularly for home-based elderly with dementia.

2.2 Emerging Patterns

Emerging patterns for activity recognition of multiple people has been proposed (Gu et al., 2009b). Let there be n datasets $D_1, \ldots, D_n$, where each dataset corresponds to the sensors readings of a person in the smart space. Each row R of a dataset D_i is the sensor readings of a continuous period of time, which corresponds to an activity. Each sensor and its reading is represented as an item, and so a row R represents a set of items. Let X be a pattern, which is a subset of row R. The support of pattern X, $sup_D(X)$, is $occ_D(X)/|D|$, where $occ_D(X)$ is number of rows in D containing X, and $|D|$ is total number of rows in D.

Definition 1. *Let D_i and D_j be datasets of two people i and j respectively. The growth rate of a pattern X from D_i to D_j is defined as $GrowthRate(X) = \frac{sup_j(X)}{sup_i(X)}$.*

In special situations, $GrowthRate(X) = 0$ if $sup_i(X) = 0$ and $sup_j(X) = 0$, and $GrowthRate(X) = \infty$ if $sup_i(X) = 0$ and $sup_j(X) > 0$.

Definition 2. *Given a growth rate threshold $\rho > 1$, a pattern X is an emerging pattern from a background dataset D_i to a target dataset D_j if $GrowthRate(X) \geq \rho$.*

An emerging pattern X with high support in target dataset D_j and low support in other background datasets D_i can be considered as a ‘signature’ of person j doing a particular activity. Therefore, for each person, each activity has its set of emerging patterns. Gu et al. then use these sets of emerging patterns to detect activities of multiple people in the smart space.

Using emerging patterns for activity recognition has some common weakness with HMM, such as the necessity that the activities and number of people must be known and the assumption that the activities of people do not evolve over time. Beside these, another weakness of emerging patterns is its sensitivity to the parameter ρ. Setting the appropriate ρ is a difficult task as it is not semantically meaningful and the user will most likely set it based on his or her biased assumptions. Thus, the emerging patterns are determined by the user, and they are not necessarily patterns that are intrinsically prominent in the data.

2.3 Filters

Rao-Blackwellised particle filter has been applied in MPAR using only motion detectors and contact switches (Wilson and Atkeson, 2005). The reported activity recognition accuracy is high - about 98% for 2-people and 85% for 3-people. Sigma-point Kalman filters have been proposed to fuse Infra Red sensors and binary foot-switches to track multiple people (Paul and Wan, 2008).

3 APPLICATIONS

MPAR using simple sensors are used in a wide range of applications, such as home-based elderly care, assistance of sick and disabled, environmental monitoring, security-related applications, logistics support, and location-based services.

Of the above applications, home-based elderly care is probably the most important and is the focus of this paper. This is because proven technology from MPAR using simple sensors can deliver large social and commercial impact. The social impact is to mitigate aging population and effects, particularly in developed countries. There are so many elderly to care for, but so few carers. For example, there is insufficient supply of nursing homes, trained geriatric nurses and doctors to handle the demand. The commercial impact is also significant. Long term home care and nursing home information systems market are projected to triple by 2016. The current home care and nursing home technology is applicable only to a single person, and key companies involved are QuietCare (GE Healthcare), Grandcare, and HealthSense.

3.1 Available Datasets

In Table 1, we describe and compare 6 MPAR datasets which and can be either downloaded from the Web or requested from the relevant researchers. The features are these 6 datasets are:

- Dataset ID refers to our naming convention where the last two digits refer to the year the data was collected. Most datasets are

Table 1: Some Available Datasets For Multiple People Activity Recognition Using Simple Sensors.

Dataset ID	*n*	**People profile**	**Sensor profile**	**Activity profile**	**Location profile**	**Label profile**
TWOR09 (Cook and Schmitter-Edgecombe, 2009)	2	1 couple, 1 dog	4 types of sensors (pressure, RFID, motion, door), about 90 sensors	about 8 2-people activities of daily living, about 800 occurrences for about 2 months	all locations in home	only activities labelled
TWORSUMMER09	2	same as *TWOR09*	in addition to *TWOR09*, 2 more types of sensors (temperature, electricity)	about 4-5 2-people activities of daily living	same as *TWOR09*	same as *TWOR09*
TULUM09	2	1 couple	2 types of sensors (motion, temperature), about 18 sensors	about 2 2-people activities of daily living, about 1000 occurrences for about 3 months	locations (pantry, dining, living rooms)	same as *TWOR09*
CAIRO09	2	same as *TWOR09*	2 types of sensors (motion, temperature), about 30 sensors	about 3 2-people activities of daily living, about 600 occurrences for about 2 months	same as *TWOR09*	same as *TWOR09*
YAMAZAKI05 (Yamazaki and Toyomura, 2008)	2	1 elderly couple in 60s	3 types of sensors (pressure, RFID, motion), about 1800 sensors	unknown 2-people activities of daily living for about 16 days	same as *TWOR09*	no labels (video provided for labeling)
WMD07 (Wren et al., 2007)	>2	many researchers and visitors	1 type of sensor (motion), about 200 sensors	unknown *n*-people office activities for about a year	research laboratory over 2 floors	no labels (map, calendar, weather data provided for labeling)

from Washington State University's CASAS lab's website, http://ailab.wsu.edu/casas/datasets.html. The CASAS datasets, TWOR09, TWORSUMMER09, TULUM09, CAIRO09, were all collected in 2009. More of their datasets, such as KYOTO and PARIS, have recently been made available online (Cook and Schmitter-Edgecombe, 2009). YAMAZAKI05 and WMD07 datasets are available from the researchers (Yamazaki and Toyomura, 2008; Wren et al., 2007), and are the largest datasets in terms of size and duration. The datasets used in the publications (Sim et al., 2010; Phua et al., 2009) can also be made available upon request.

- *n* is the number of people known to be in the dataset. Most of the multiple people datasets contain activities of mostly two people-of-interest; but there can be more than two entities captured by sensors, such as pets, visiting guests, and maid.
- People profile is typically a couple, except for WMD07, which has many researchers/visitors.
- All sensor profiles include motion sensors. The number of deployed sensors range from 18 to 1,800, where the majority are motion sensors.
- As for activity profile, the CASAS datasets typically have several activities with several hundred occurrences over a few months. YAMAZAKI05 and WMD07 datasets span 16 days and 1 year respectively.
- All activity recognition datasets are for home-based elderly care, except for WMD07, which is based on the office environment.
- All CASAS datasets have people-specific activity labels, while the rest are unlabeled.

In the next two subsections, using the TWOR09 dataset with activities from two residents R1 and R2, we demonstrate that MPAR using a large number of simple sensors can be trivial.

3.2 Data Preprocessing of TWOR09 Dataset

On the left side of Figure 2, the sensor layout for the upper and ground floor of the smarthome is shown. The sensors can categorized by:

- Mxx - motion sensor
- Ixx - item sensor for selected items in the kitchen
- Dxx - door sensor
- AD1-A - burner sensor, AD1-B - hot water sensor, AD1-C - cold water sensor
- Txx - temperature sensors (not used in TWOR09)
- P001 - electricity usage (not used in TWOR09) (Cook and Schmitter-Edgecombe, 2009)

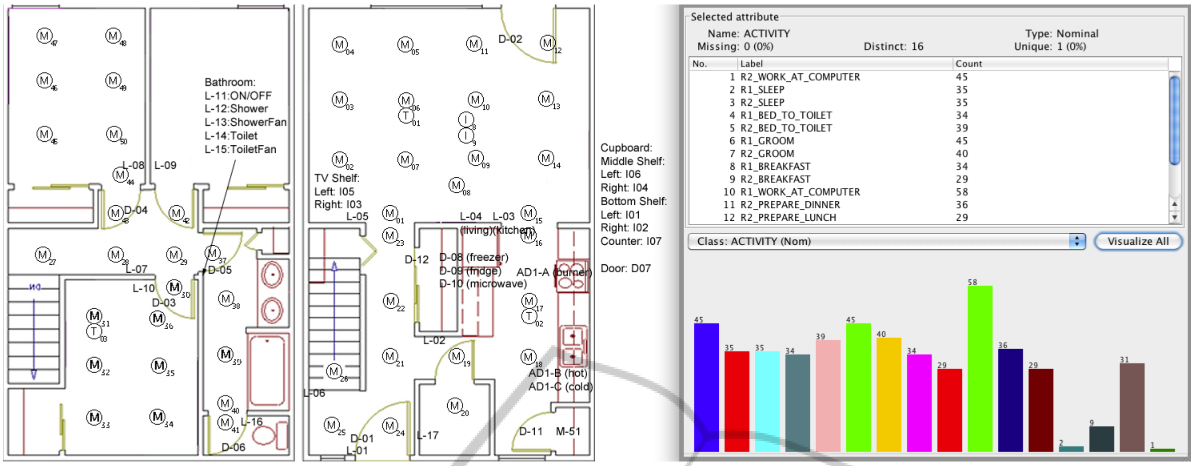


Figure 2: Sensor Layout in TWOR09 Dataset Smarthome (Cook and Schmitter-Edgecombe, 2009) and Some Person-Specific Activity Labels from WEKA.

On the right side of Figure 2, the bar chart shows 16 person-specific activity labels displayed using WEKA (Hall et al., 2009). For example, R1_SLEEP and R2_SLEEP are considered two separate activities. Most of the activities are preparing meals, eating, working, and sleeping; more than 80% of activities usually occur > 20 times.

On the left side of Figure 3, the raw TWOR09 data consists of 138,039 sensor events, 502 activity events, and 4 features. The raw features are timestamped with millisecond, sensor ID, sensor state, and the start/end label of activity event. The processed activity label is also transformed from a descriptive label to a nominal number starting from 0. For example, R2_GROOM is transformed by WEKA into number 9. The right side of Figure 3 shows there are 184 processed TWOR09 features, each representing a sensor state and the value is the sensor state frequency for a particular activity event. For example, R2_GROOM triggers M48 and M50 which are motion sensors presumably in the master bedroom.

3.3 Experiment Results on TWOR09 Dataset

We used a range of techniques for MPAR on the processed TWOR09 dataset, and we report results from classification algorithms (Naive Bayes, C4.5 Decision Tree, Support Vector Machine using sequential minimal optimization) with default parameters from WEKA (Hall et al., 2009). We also tried clustering (expectation maximization), and association rules (Apriori), but their results are too insignificant to be reported. The 3 subsets we used for 10-fold cross-validated experiments were:

- all 16 activities, 502 activity events
- 13 activities, each with at least 20 events (removed CLEANING, R1_WORK_AT_DINING_ROOM_TABLE, and WASH_BATHTUB), 490 activity events
- 3 activities, each with at least 40 events (left with R2_WORK_AT_COMPUTER, R1_GROOM, R1_WORK_AT_COMPUTER), 148 activity events

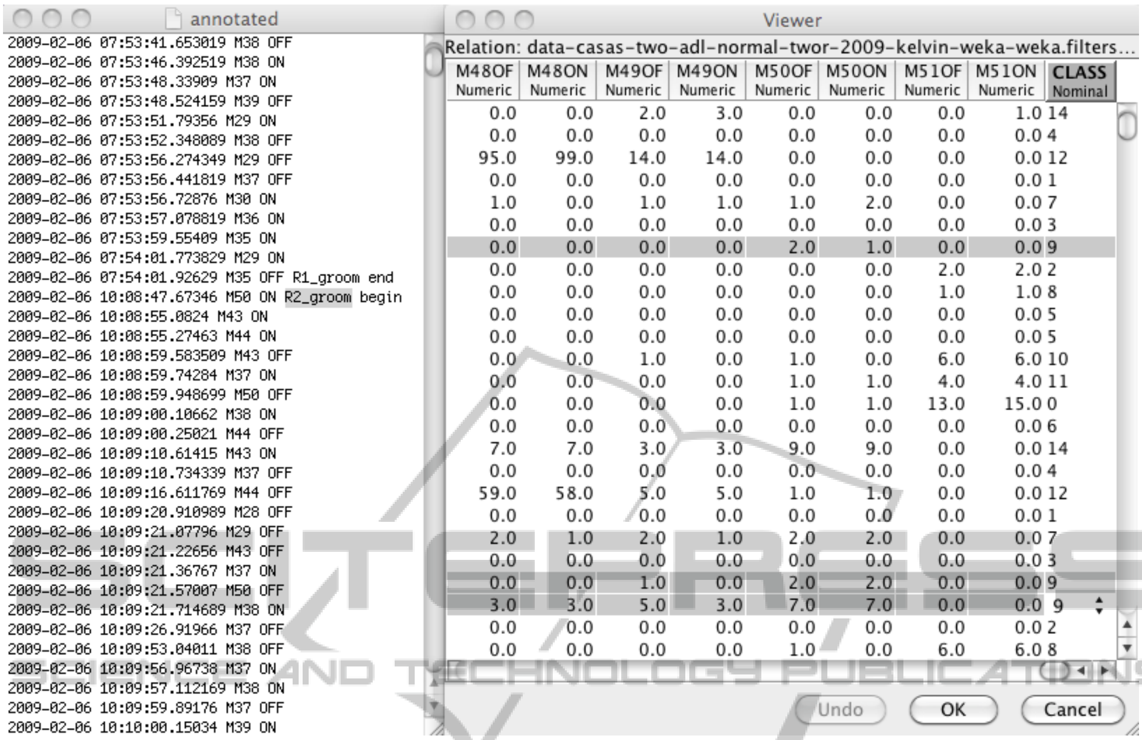
Table 2: Classification Accuracy.

Activities	Naive Bayes	C4.5 Decision Tree	Support Vector Machine
16	77.9%	76.5%	75.9%
13	80.8%	75.7%	75.9%
3	100%	100%	95.9%

Table 2 shows that Naive Bayes and C4.5 decision tree classifiers can achieve 100% accuracy in the 3 most common activities. Algorithm 1 shows the accurate and simple decision tree rules for the 3 most common activities.

Algorithm 1: C4.5 Rules on 3 Activities.

if $M37OF \leq 0$ **then**
  if $M45ON \leq 3$ **then**
    R1_WORK_AT_COMPUTER
  end
  if $M45ON > 3$ **then**
    R2_WORK_AT_COMPUTER
  end
end
if $M37OF > 0$ **then**
  R1_GROOM
end



annotated

```
2009-02-06 07:53:41.653019 M38 OFF
2009-02-06 07:53:46.392519 M38 ON
2009-02-06 07:53:48.33909 M37 ON
2009-02-06 07:53:48.524159 M39 OFF
2009-02-06 07:53:51.79356 M29 ON
2009-02-06 07:53:52.348089 M38 OFF
2009-02-06 07:53:56.274349 M29 OFF
2009-02-06 07:53:56.441819 M37 OFF
2009-02-06 07:53:56.72876 M30 ON
2009-02-06 07:53:57.078819 M36 ON
2009-02-06 07:53:59.55409 M35 ON
2009-02-06 07:54:01.773829 M29 ON
2009-02-06 07:54:01.92629 M35 OFF R1_groom end
2009-02-06 10:08:47.67346 M50 ON R2_groom begin
2009-02-06 10:08:55.0824 M43 ON
2009-02-06 10:08:55.27463 M44 ON
2009-02-06 10:08:59.583509 M43 OFF
2009-02-06 10:08:59.74284 M37 ON
2009-02-06 10:08:59.948699 M50 OFF
2009-02-06 10:09:00.10662 M38 ON
2009-02-06 10:09:00.25021 M44 OFF
2009-02-06 10:09:10.61415 M43 ON
2009-02-06 10:09:10.734339 M37 OFF
2009-02-06 10:09:16.611769 M44 OFF
2009-02-06 10:09:20.910989 M28 OFF
2009-02-06 10:09:21.07796 M29 OFF
2009-02-06 10:09:21.22656 M43 OFF
2009-02-06 10:09:21.36767 M37 ON
2009-02-06 10:09:21.57007 M50 OFF
2009-02-06 10:09:21.714689 M38 ON
2009-02-06 10:09:26.91966 M37 OFF
2009-02-06 10:09:53.04011 M38 OFF
2009-02-06 10:09:56.96738 M37 ON
2009-02-06 10:09:57.112169 M38 ON
2009-02-06 10:09:59.89176 M37 OFF
2009-02-06 10:10:00.15034 M39 ON
```

Viewer

Relation: data-casas-two-adl-normal-twor-2009-kelvin-weka-weka.filters...

M48OF Numeric	M48ON Numeric	M49OF Numeric	M49ON Numeric	M50OF Numeric	M50ON Numeric	M51OF Numeric	M51ON Numeric	CLASS Nominal
0.0	0.0	2.0	3.0	0.0	0.0	0.0	1.0	14
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4
95.0	99.0	14.0	14.0	0.0	0.0	0.0	0.0	12
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1
1.0	0.0	1.0	1.0	1.0	2.0	0.0	0.0	7
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
0.0	0.0	0.0	0.0	2.0	1.0	0.0	0.0	9
0.0	0.0	0.0	0.0	0.0	0.0	2.0	2.0	2
0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	8
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5
0.0	0.0	1.0	0.0	1.0	0.0	6.0	6.0	10
0.0	0.0	0.0	0.0	1.0	1.0	4.0	4.0	11
0.0	0.0	0.0	0.0	1.0	1.0	13.0	15.0	0
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6
7.0	7.0	3.0	3.0	9.0	9.0	0.0	0.0	14
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4
59.0	58.0	5.0	5.0	1.0	1.0	0.0	0.0	12
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1
2.0	1.0	2.0	1.0	2.0	2.0	0.0	0.0	7
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
0.0	0.0	1.0	0.0	2.0	2.0	0.0	0.0	9
3.0	3.0	5.0	3.0	7.0	7.0	0.0	0.0	9
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2
0.0	0.0	0.0	0.0	1.0	0.0	6.0	6.0	8

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Figure 3: Snapshots of Raw TWOR09 Data (Cook and Schmitter-Edgecombe, 2009) and Processed TWOR09 Data for Classification from WEKA.

In other words, MPAR using simple sensors can be very accurate if 3 assumptions are true:

- there are many simple sensors
- there is availability of people-specific activity labels
- there are few activities with high number of events

In the next section, we discuss if the above 3 assumptions do not hold true.

4 OPEN CHALLENGES

4.1 Handling Noisier Data with Fewer Sensors

Sensor readings are known to be noisy, as sensors are prone to breakdown and give erroneous readings. Readings will be even noisier with fewer sensors. Hence it is crucial that activity recognition approaches are able to handle noisy data. To the best of our knowledge, existing MPAR approaches do not handle noisy data, and this problem is yet to be solved even in activity recognition of single person. A possible solution is to treat the data in a probabilistic manner and represent the data as probability distributions, which is known as uncertain data. There is ongoing research on data mining techniques for uncertain data (Aggarwal and Yu, 2009), and techniques such as classification and clustering for uncertain data may be used for activity recognition in noisy data.

4.2 Less Dependency on Training and Labels

The paradigm of existing approaches requires a training phase on their models using a set of training data. This training data is collected from multiple people in the smart space where the model is to be deployed, with the assumption that the group of people in the smart space is unchanged after model deployment.

There are two weakness to this paradigm. First, the model needs to be trained when deployed in a smart space. Hence, the model is overfitting the smart space that it is trained on, and not on other smart spaces. A possible solution is to develop a model which is able to detect the activities of multiple people in a general sense, so that the model can be deployed across different smart spaces. A good start in this area is by (Rashidi and Cook, 2009), which proposed the usage of transfer learning in activity recognition of a single person. In transfer learning, knowledge or models from other smart spaces can be exploited to train the model of a targeted smart space, so that the trained model is accurate and not overfitted.

Second, this paradigm requires collection of training data from the smart space, and depending on the model, the data collection may range from minutes (Sim et al., 2010) to weeks (Crandall and Cook, 2009). Hence, this paradigm is not practical for large deployment in multiple smart spaces. Moreover, the training data has to be annotated in order for the model to understand it, and annotation of the data is usually manual and laborious work (Sim et al., 2010). Various studies addressed it with visualization or calendar/diary of activities (Szewcyzk et al., 2009; Wren et al., 2007) after data collection, video matching (Sim et al., 2010; Phua et al., 2009; Yamazaki and Toyomura, 2008) after data collection, or actors pressing their identity button on the keypad during data collection (Wilson and Atkeson, 2005).

4.3 Incorporating Complex Situations

The existing approaches do not recognize activities of multiple people in complex situations. In complex situations, a person may perform his or her activities in interleaved or concurrent manner. In interleaved activities, a person may perform two or more activities by switching between steps of the activities. An example will be watching TV while consuming food.

In concurrent activities, a person may perform two or more activities by concurrently conducting the steps of these activities. An example will be consuming food and drinking water simultaneously.

Activity recognition of a person in complex situations is a non-trivial task, and this task is further complicated when there are multiple people in complex situations; multiple people may be in the same location, and each of them may be performing either interleaved or concurrent activities. For example, two people may be in the living room, where one person is watching TV while consuming food, and the other person is reading a book.

Emerging patterns are proposed to detect interleaved and concurrent activities of a single person (Gu et al., 2009a). Perhaps, these complex activities of multiple people can be detected by extending this work.

4.4 Capturing Evolving Activities and Labels

The existing approaches have an important assumption which forms the cornerstone of their works. They assume that multiple people perform their activities in a habitual way and do not change over time. In their training phase, they basically attempt to capture the patterns that represent the activities of the multiple people, and use these patterns for future activity recognition. However, in real-world scenarios, it is possible that people may change their habits over time, and change the way they conduct their activities. This possibility is higher for home-based elderly with dementia, as their cognitive skills are dependent on the severity of their dementia. Therefore, there is a need for an approach which is able to continuously capture the evolving habits of the people and the way they conduct their activities.

5 CONCLUSIONS AND FUTURE WORK

Multiple people activity recognition (MPAT) using simple sensors is an emerging multi-faceted research area which is related to ambient intelligence, sensor networks and data mining. In this position paper, we discussed existing techniques of MPAT, and showed that standard classification techniques surprisingly yield high accuracy on MPAT using simple sensors, if (1) the number of simple sensors is large, (2) the training data is accurately labeled, (3) the activities are simple, and (4) activities are done in a habitual way. These assumptions may be unrealistic in real life situations, and we presented open challenges of MPAT using simple sensors, when the assumptions do not hold.

For future work, as the MPAR approaches we discussed are bottom-up (data-driven), another approach can be top-down using ontologies (Lecce et al., 2009). Also, we focused only on MPAR with identification of the individuals, but it might also be interesting to recognize the activities of subgroups of people without bothering to identify them.

REFERENCES

Aggarwal, C. and Yu, P. (2009). A survey of uncertain data algorithms and applications. *IEEE Transactions on Knowledge and Data Engineering*, 21(5):609–623.

Chen, D., Yang, J., Malkin, R., and Wactlar, H. D. (2007). Detecting social interactions of the elderly in a nursing home environment. *ACM Transactions on Multimedia Computing, Communications and Applications*, 3.

Chiang, Y.-T., Hsu, K.-C., Lu, C.-H., Hsu, J. Y.-j., and Fu, L.-C. (2010). Interaction models for multiple-resident activity recognition in a smart home. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.

Cook, D. J., Crandall, A., Singla, G., and Thomas, B. (2010). Detection of social interaction in smart spaces. *Cybernetics and Systems*, 41:90–104.

Cook, D. J. and Schmitter-Edgecombe, M. (2009). Assessing the quality of activities in a smart environment. *Methods of Information in Medicine*, 48(5):480–485.

Crandall, A. S. and Cook, D. J. (2009). Coping with multiple residents in a smart environment. *Journal of Ambient Intelligence and Smart Environments*, 1:323–334.

Gu, T., Wu, Z., Tao, X., Pung, H., and Lu, J. (2009a). epSICAR: An emerging patterns based approach to sequential, interleaved and concurrent activity recognition. In *Proceedings of the 7th IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 1–9.

Gu, T., Wu, Z., Wang, L., Tao, X., and Lu, J. (2009b). Mining Emerging Patterns for recognizing activities of multiple users in pervasive computing. In *Proceedings of the 6th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous)*, pages 1–2.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I. H. (2009). The WEKA data mining software: An update. *SIGKDD Explorations*, 11(1):10–18.

Hauptmann, A. G., Gao, J., Yan, R., Qi, Y., Yang, J., and Wactlar, H. D. (2004). Automated analysis of nursing home observations. *IEEE Pervasive Computing*, 3:15–21.

Lecce, D., Calabrese, V., and Piuri, V. (2009). An ontology-based approach to human telepresence. In *Proceedings of IEEE International Conference on Computational Intelligence for Measurement Systems and Applications (CIMSA)*, pages 56–61.

Panangadan, A., Mataric, M., and Sukhatme, G. (2010). Tracking and modeling of human activity using laser rangefinders. *International Journal of Social Robotics*, 2:95–107.

Paul, A. and Wan, E. (2008). Wi-Fi Based Indoor Localization and Tracking Using Sigma-Point Kalman Filtering Methods. In *Proceedings of IEEE/ION Position Location and Navigation Symposium (PLANS)*, pages 646–659.

Phua, C., Foo, V. S.-F., Biswas, J., Tolstikov, A., Aung, A.-P.-W., Maniyeri, J., Huang, W., That, M.-H., Xu, D., and Chu, A. K.-W. (2009). 2-layer erroneous-plan recognition for dementia patients in smart homes. In *Proceedings of the 11th International Conference on e-Health Networking, Applications and Services (Healthcom)*, pages 21–28.

Rashidi, R. and Cook, D. (2009). Multi home transfer learning for resident activity discovery and recognition. In *Proceedings of the 4th International workshop on Knowledge Discovery from Sensor Data (SensorKDD)*.

Sim, K., Yap, G., Phua, C., Biswas, J., Aung, A.-P.-W., Tolstikov, A., Huang, W., and Yap, P. (2010). Improving the accuracy of erroneous-plan recognition system for Activities of Daily Living. In *Proceedings of the 12th IEEE International Conference on e-Health Networking Applications and Services (Healthcom)*, pages 28–35.

Singla, G., Cook, D. J., and Schmitter-Edgecombe, M. (2010). Recognizing independent and joint activities among multiple residents in smart environments. *Journal of Ambient Intelligence and Humanized Computing*, 1(1):57–63.

Szewcyzk, S., Dwan, K., Minor, B., Swedlove, B., and Cook, D. (2009). Annotating smart environment sensor data for activity learning. *Technology and Health Care*, 17:161–169.

Wilson, D. and Atkeson, C. (2005). Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors. *Pervasive computing*, pages 62–79.

Wren, C. R., Ivanov, Y. A., Leigh, D., and Westhues, J. (2007). The MERL motion detector dataset. In *Proceedings of the workshop on Massive datasets*, pages 10–14.

Yamazaki, T. and Toyomura, T. (2008). Sharing of real-life experimental data in smart home and data analysis tool development. In *Proceedings of the 6th International Conference on Smart Homes and Health Telematics (ICOST)*, pages 161–168.