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An Adaptive Activity Recognition Approach in Smart Environments

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ABSTRACT
Smart Homes are smart spaces that contain devices are connected with each other to get information about user's activities; these devices can be controlled through one central point. Like door locks, thermostats, televisions, home monitor and lights. Behavior recognition in dynamic environments is one of the most challenging issues in this research area, each behavior has a specific number of activities to be performed. In this paper, a new approach to recognize the human behaviors based on finding the minimum number of activities to perform the behavior by determining the membership degree of each activity for each behavior. The proposed approach learns the performed behaviors and uses that knowledge to recognize the behavior through applying a threshold and Alpha cut concept on the membership degree of each activity. In addition, it can adapt to environment modifications, variations in human habits. The conducted simulation results show that the proposed approach achieves better performance than existing approaches in terms of accuracy, recall, and f-measure metrics.

General Terms
Smart homes, home automation, ambient-assisted living and activity recognition

Keywords
Smart home, activity recognition, Naïve Bayes

1. INTRODUCTION
Nowadays, there are a lot of new smart devices that homeowners are interested in, these technologies keep developing and become easier to use. The improvements in electronics and sensor technologies allow the development of new intelligent environments, where the combination of independence, constant supervision, and assistance takes place.When these devices are used to make the home automated, this is called Smart Home or home automation. Basically, smart home facilitates users with comfortable living, safety and energy management features as well as added benefits for assisting elders or people with special needs. For example, when a person enters his home, the roller blinds and curtains go up, lighting switch on, and so on.The system selects his favorite movie, music, or TV channel. He doesn't need to turn on air-condition on/off to or set the light level in the living room. When he leaves a home, after he has turned his key the alarm system goes on, the external blinds close, temperature is reduced, air-condition is closed, and all lights and appliances switch off automatically. Nobody is at home, so why use up costly energy. And what would happen if water from an open tap flooded the house. The system will automatically turn it off and calls him on his mobile phone. All of that can be automated though the collected data about homeowners and their habits this is totally depending on activity recognition systems.

2. RELATED WORK
IN recent years, a lot of activity recognition projects have been developed to help in different fields especially in healthcare field, elders care projects have been developed to have a combination of the benefits of Engineering and technology with healthcare. One such project is the Center for Eldercare and Rehabilitation Technology (CERT) [1] .This effort is a large interdisciplinary collaboration between electrical and computer engineers, gerontological nurses, social workers, physical therapists. The improvements in electronics and sensor technologies allow the development of new intelligent environments, where the combination of independence, constant supervision, and assistance takes place. One example of this combination is the project presented by Rantz et al. [2], at the University of Missouri. They develop a research that involves disciplines, such as nursing, electrical and computer engineering, social work, or health informatics, among others. The project is developed in a real nursing home, where the elderly are able to live independently. Their research is based on studying the data acquired from a huge number of motion, pressure, and sound sensors, or IR-cameras. This information is used to elicit some conclusions about the user: heart pulse, breathing, fall detection, etc. In [3], Lee et al. proposing an algorithm that combines a modified, fuzzy and competitive learning construction with a Bayesian decision rule that is capable to ignore any behavior of the user that is unintended.Other similar works that model human activities with Hidden Markov Models (HMMs) are [4,21,6]. Naeem and Bigham present in [7] an approach that is based on Multiple Behavioral Hidden Markov Models (MBHMM). They suggest creating the multiple hidden Markov models for any form of an action, so that the system is able to define the currently active tasks, even if the user did not complete the activity yet.
Other examples in the literature are MavHome project [8], the iDorm [9], the CASAS project [10], and the Georgia Tech Aware Home [11]. More projects concerning this research range are summarized in [12]. Recognizing normal and abnormal human behaviors for the elderly, to enhance their personal comfort and safety, and delay moving to a nursing home, is one of the most challenging issues related to home assistance.CARE (Context Awareness in Residence for elders) [13] is a distinguished study thatdeveloped in the University of Amsterdam. CARE gives the chance to elders to retain independence by living longer at home. They use sensors like switches or pressure mats, in order to observe the residents' behavior unobtrusively and provide both, families and elders with benefits by means of network services. Concentrating on people with special needs, in [14], the authors submitted a project to help people with mild dementia

to navigate using contextual information, wireless, mobile device technologies, including location-based services.There is an extensive study about avails and flaws of different probabilistic and statistical techniques for human activities recognition presented in [15]. Lately, some projects have emerged and they are involving various techniques for the problem of recognizing normal and abnormal behaviors. In [22], the authors propose an ambient intelligence approach, and develop a fuzzy computing system to learn and model human behaviors. Their work joins the advantages of a multifaceted framework with fuzzy control methods to progress the recognition process and constantly enhances the knowledge about the user and his/her environment. In [5] the authors have developed a system which is able to recognize human behaviors from current user activity by means of learning automata and fuzzy temporal windows. On the other hand, Rashidi et al. In [16] introduce a method which is unsupervised, to discover activities in a smart environment, using data mining techniques to find activity patterns and a clustering process to gather these patterns into activity definitions, and HMMs to clarify the activities and their diversity for their detection and recognition later on. Temporal information was contained by some other authors to extract valid patterns for each behavior. Instance, in [17,18], the authors suggest a learning machine to determine temporal relations between the daily activities in a smart home. Then these relations can be used for prediction, decision making, and anomaly detection of ADL. Further related projects are summarized in [19,20]. In spite of proceeded efforts for recognizing human activities in smart home environments, the need for information is always required to adapt the system to environmental or human habit changes.

3. ACTIVITY RECOGNITION PROBLEM

Activity recognition problem(ARP) is one of the key issues in smart home environments, this problem deals with how to learn user behavior and detect when the user performs this behavior in dynamic environments. In this section, the assumptions and models will be described then the formulation of ARP problem will be introduced.

3.1 Assumptions and Models

Assume that there is a smart home which contains a set of objects and each object has its own sensor, and there is a set of users, $U=\{ u_1,u_2,\dots, u_j \dots,u_n\}$, each user does a set of behaviors $B=\{b_1,b_2, \dots,bj,\dots ,b_n\}$, where each behavior $b=\{a_1,a_2, \dots ,a_i, \dots ,a_n\}$which can be represented by some of consecutive activities $a_i=(l_i,s_i,t_i,u_i)$ such that l_i is the label of touched sensor/object, s_i is the sensor id,t_i is the time When user touched the object and u_i is the user id who touched the object.

Example: Let us suppose that every morning, when the user goes to the work at approximately 7.30 A.m., he/she does some behaviors first (go to the toilet, make a breakfast then go to the work), to go toilet he/she opens the toilet, then touch the cold-faucet and do anything else the open the toilet door again to go out the bathroom, all these actions could be embraced as a unique routine: to go to toilet. Then he/she go to the kitchen, open the Kitchen door, Toaster, Microwave, Light switch, Refrigerator, Garbage and Sink faucet. Then, all these actions could be embraced as a unique routine: to make a breakfast.

4. ADAPTIVE ACTIVITY RECOGNITION APPROACH

4.1 Basic idea

Here, to improve the accuracy of activity recognition in smart homes, a new approach called *Adaptive Activity Recognition Approach* (AARA) is proposed. the basic idea of AARA is based on (1) extracting the minimum number of activities to represent the behavior by using alpha-cut concept, (2) ignoring behavior time in the day in case of different users can perform the same behavior in different times in the day, (3) determining the membership degree of each activity for each behavior, and (4) using Naive Bayes classifier to classify each activity based on its membership degree.

In the rest of this section, Naive Bayes Classifier, Membership Degree Function, and the steps of the proposed approach will be described in details.

4.2 Naive Bayes Classifier (NB)

A Naive Bayes classifier is a general probabilistic model which is based on the Bayes rule in addition of an assumption of independence.

Assume $T=(t_1,t_2,t_3,. . . t_n)$ to be a set of DB transactionsand $B=(b_1, b_2, b_3, . . . ,b_q)$ be set of classes/behaviors. Each of the n number of transactionsin $\boldsymbol{T}$ are classified into one of the q number classes/behaviors from set B. We classify T as the class which has the highest posterior probability $P(B|T)$. The probability of a transaction t being in class b using Bayes theorem is given by:

$$p(B|T) = \frac{p(T|B)P(B)}{p(T)} \quad (1)$$

To calculate $P(T|B)$ we calculate $P(w_k|B)$ for each word,

$$p(w_k|B) = \frac{n_k+1}{n+|vocabulary|} \quad (2)$$

where n is the number of actions in the class and n_k= number of times action$k$occurs in class and $|vocabulary|$ number of unique actions for all transactions.

4.3 Membership Degree Function

To determine the membership degree of each activity for each behavior, AARA uses Trapezoidal function. This function definedby a lower limit a, an upper limit d, a lower support limit b, and an upper support limit c, where a < b < c < d.There are two special cases of a trapezoidal function, which are called R-functions and L-functions:

R-functions: given by

$$\mu_{A(x)}=\begin{cases} 0, & x > d \\ \frac{d-x}{d-c}, & c \geq x \leq d \\ 1, & x < c \end{cases} \quad (3)$$

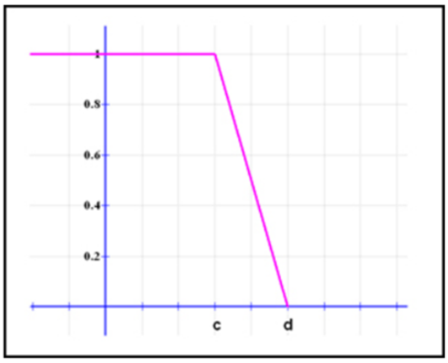

Fig. 1 R-functions: with parameters a = b = - ∞

L-Functions: given by

$$\mu_{A}(x) = \begin{cases} 0, & x > a \\ \frac{x-a}{b-a}, & a \geq x \leq b \\ 1, & x < b \end{cases} \quad (4)$$

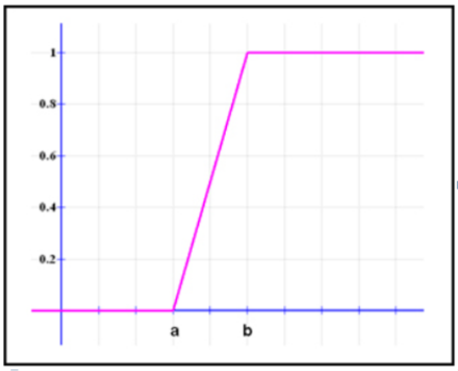

Fig. 2L-functions: with parameters c = d = + ∞

4.4 The proposed Approach

Based on the basic idea of AARA, the proposed approach consists of two phases: *learning phase* and *recognition phase*. These two phases are described as follows.

1- *Learning phase*

In this phase, AARA determines the minimum set of actions for each behavior based on the membership degree of each action and a predefined threshold τ. To get this set of actions for each behavior, AARA uses the following steps.

Table 1. Example for behavior (Preparing lunch) in DB

T_1	$(a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9)$
T_2	$(a_1, a_2, a_3, a_4, a_5, a_6, a_7,)$
. . .	. . .
T_n	$(a_4, a_5, a_6, a_7, a_8, a_9)$

(1) **Initialization**: In this step, AARA creates the list of the current behaviors is prepared with their own activities which happened in learning period for each behavior. This list is represented as a tuple of activities in the DB as shown Table 1.

(2) **Calculating membership degree**: AARA selects all behaviors from DB and calculates a membershipdegree for each activity using L-Functions trapezoidal fuzzy method and stores each behavior with its activities including the membership degree for each activity.Table2.shows these learning results.

Algorithm 1, shows the steps of this learning phase.

Algorithm 1 Algorithm to learn Specific Behavior (make a breakfast for example)

Behavior = Selected Behavior
For $b \in B$ = {all behaviors sequences} **Do**
 b count = count of *b*
 M = empty array (M is an array of activities and their count)
  For each action a_i in b do
   If $M[a_i]$ is exist **Do**
    $M[a_i]$ ++
   Else
   $M[a_i]$ =1
   End If
  End For
End For
For each action a_i in M **Do**
 calculate **M**embership**D**egree of a_i
 Save *Behavior* and am_i membership degree
End For

After applying learning algorithm, AARA gets this DB table.

Table 2. Exampleof learned behaviors in DB

Preparing lunch	(a_2, 0.85), (a_{10}, 0.39), (a_{15}, 1), (a_{18}, 0.07), (a_{57}, 0.15), (a_{31}, 0.39), (a_{11}, 0.46), (a_9, 0.08), (a_{53}, 0.08), (a_{42}, 0.23), (a_{30}, 0.23), (a_4, 0.54), (a_{29}, 0.15), (a_{45}, 0.08), (a_{58}, 0.08), (a_7, 0.15), (a_{56}, 0.08), (a_{27}, 0.14), (a_{26}, 0.07), (a_{22}, 0.23), (a_1, 0.31), (a_{23}, 0.46), (a_{28}, 0.77), (a_{40}, 0.07), (a_6, 0.31), (a_{12}, 0.39), (a_{16}, 0.08), (a_{21}, 0.15), (a_{39}, 0.08), (a_5, 0.15), (a_{59}, 0.08), (a_{41}, 0.08), (a_{17}, 0.08)
Watching TV	(a_5, 1), (a_{48}, 1), (a_2, 0.38), (a_{23}, 0.13), (a_{15}, 0.38), (a_{24}, 0.17), (a_{25}, 0.13), (a_{17}, 0.25), (a_{13}, 0.25), (a_{26}, 0.13), (a_9, 0.13), (a_{49}, 0.17), (a_{34}, 0.25), (a_{11}, 1), (a_6, 0.25), (a_1, 0.17), (a_{12}, 0.33), (a_{50}, 0.17), (a_{27}, 0.25), (a_{18}, 0.13), (a_4, 0.13), (a_{51}, 0.13), (a_{29}, 0.13), (a_{43}, 0.13), (a_{16}, 0.13), (a_{30}, 0.13), (a_{31}, 0.13), (a_{32}, 0.13), (a_{33},

	0.13), (a_{28}, 0.13), (a_{52}, 1)
.	.
.	.
.	.
Talking on telephone	(a_{54}, 1), (a_2, 0.25), (a_{51}, 0.25), (a_{34}, 1), (a_{31}, 1), (a_{28}, 1), (a_{15}, 1), (a_4, 1), (a_{23}, 1)

2- *Recognition phase*

In this phase, AARA uses the set of resulted behaviors from the learning phaseto recognize the set of current behaviors as follows.

(1) **Determination**: in this step, AARA applies a specific threshold on the membership degree for all behaviors to define the minimum number of activities which must be done to perform this behavior.

(2) **Retrieving**: in this step, AARA retrievesthe current set of behaviors which are subset of studying behavior, assume that $D$is astudying behavior, $H=\{\alpha_1,\alpha_2, \ldots, \alpha_n\}$ is set of all available actions, $B=\{b_1,b_2, \ldots, b_n\}$ is the set of learned behaviors, $b_i=\{\alpha_1,\alpha_2, \ldots, \alpha_m\}$ □HEquation 4.5 is used to get all subsets behaviors.

Algorithm 2, shows the steps of this recognition phase.

$$\beta = \{b_i \in B \mid \forall \alpha_j \in b_i, MembershipDegree(\alpha_j) \geq \tau \text{ and } \alpha \in D\} \quad (5)$$

(3) **Elimination**: in this step, AARA, removes all common actions between studying behavior and selected behaviors. As a result, the remaining set of actions is called *uncommon set* for the studying behavior D and is denoted as UC_D.

(4)**Classification**: in this step, AARA uses Naïve Bayes classifier method to classify thestudying behavior by using the matched behaviors,$\prod = \{b \in \beta \mid b(\alpha) \in B\}$ from the DB.

(5) **Updating**: in this step, AARA adds the new actions in the uncommon set of actions, UC_D, for the detected behavior and going to learning step to update the minimum number of actions which represent this behavior.

Algorithm 2, Algorithm to recognize specific behavior

1: D = Studied Behavior
2: $H=\{\alpha_1,\alpha_2, \ldots, \alpha_n\}$ *is set of all available actions*
3: $B=\{b_1,b_2, \ldots, b_n\}$ *is the set of learned behaviors*
4: $b_i=\{\alpha_1,\alpha_2, \ldots, \alpha_m\}$ □H
5: *Set the valoue of threshold*, τ// τ is the selected threshold
6: $\beta = \{b \in B \mid \forall \alpha \in b\ MembershipDegree(\alpha) \geq \tau$ and $\alpha \in D\}$ //select all behaviors from DB which activity membership degree is more than or equal τ
7: Get Matched behavior $\prod = \{b \in \beta \mid b(\alpha) \in B\}$ without applying *threshold* τ
8: Use $\prod$ as a learning data for Naïve Bayes Classifier
9: Test the studied D behavior to get the correct class b
10: Add the new behavior to the DB and call learning phase again

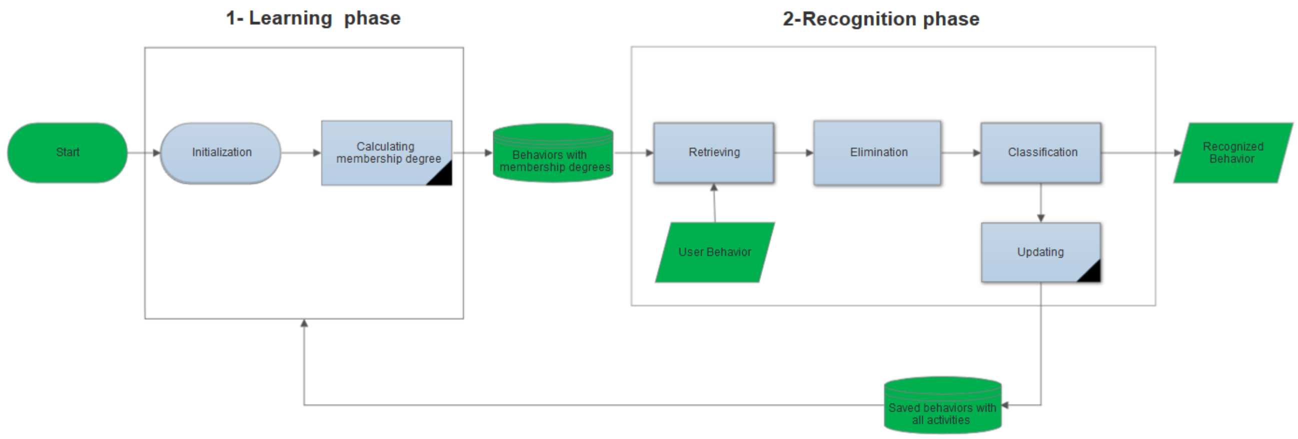

Fig 3.System work flow for AARA

5. SIMULATION AND RESULTS

5.1 Simulation Settings

To evaluate the proposed approach, AARA, a real dataset is used for a person who lived in the smart home for 16 days which contains 196 behaviors executed by thisperson.This dataset is divided tofourperiods by using 4 daysfor each period. These four periods are evaluated by using cross evaluation policy for learning and testing phases.Table 3 shows the selected periods and the number of existing behaviors in these periods for the cross-evaluation settings.

In addition, Node.js version v8.6.0 is used to design and build new application to evaluate AARA. Node is an open source development platform for executing JavaScript code server-side. Node is useful for developing applications that require a persistent connection from the browser to the server and is often used for real-time applications. Also, MongoDB version v3.4.4is used to manage the used dataset. MongoDB is a cross-platform and open-source document-oriented database, a kind of NoSQL database. As a NoSQL database, MongoDB shuns the relational database's table-based structure to adapt JSON-like documents that have dynamic schemas which it calls BSON.BSON makes data integration for certain types of applications faster and easier. MongoDB is built for scalability, high availability and performance from a single server deployment to large and complex multi-site infrastructures.

Table 3: Cross evaluation settings: selected periods and their# of behaviors

Learning phase		Testing phase	
periods	*# of behaviors*	*periods*	*# of behaviors*
1,2	95	3,4	101
1,3	82	2,4	114
1,4	99	2,3	97
2,3	97	1,4	99
2,4	114	1,3	82
3,4	101	1,2	95

5.2 Performance metrics

The classification is done with 196 behaviors. The classifiers performance has been analyzed by using *Precision*, *Recall* and *F-measure*, which are obtained from the confusion matrix as shown in table 5.2.1. These metrics are described as follows.

Table 4: Confusion Matrix

	p' (Predicted)	n' (Predicted)
p (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

(a) ***Precision***: measures the relevant behaviors found against all behaviors found i.e. the percentage of selected behaviors that are correct and is defined by the following equation.

$$Precision = \frac{\text{TruePositive}}{\text{TruePositive+FalsePositive}} \quad (6)$$

(b) ***Recall***: measures the relevant behaviors found against all relevant behaviors i.e. the percentage of correct behaviors that are selected and is defined by the following equation.

$$Recall = \frac{\text{TruePositive}}{\text{TruePositive+FalseNegative}} \quad (7)$$

(c) ***F-measure***: is weighted harmonic mean between precision and recall and is defined by the following equation.

$$F\text{-}measure = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision + Recall}} \quad (8)$$

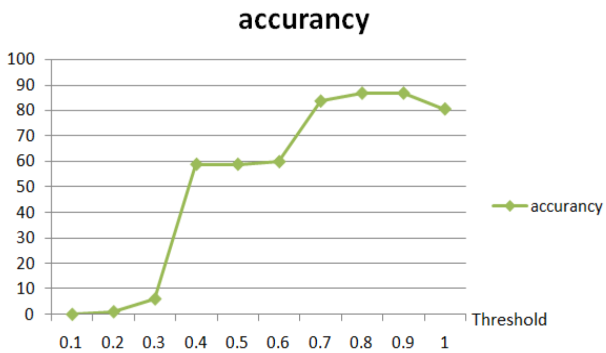

Fig. 4: result for different values for the Threshold for AARA

5.3 Results and Discussion

Here, the simulation results will be presented and discussed.The performance of AARA is compared with the proposed online recognition system in [5]. In case of the proposed AARA, different values of threshold havebeen studied and tested to measure the accuracy of AARA. These values were between 0.1 to 0.9and Fig 4 shows these results. As shown in Fig. 4, the best threshold for AARA was 0.9, so in the rest of simulation, this value is used to compare the performance of AARA with the online recognition system [5].

In preparing the dataset for simulation, some noises were found because some behaviors which happened with a little time and in the testing period only. So, this dataset is classified into two groups: (1) *with noises* and (2) *without noises*. The simulation results are shown for the two groups in Figures 5 to 16.

5.3.1 Results with Noises

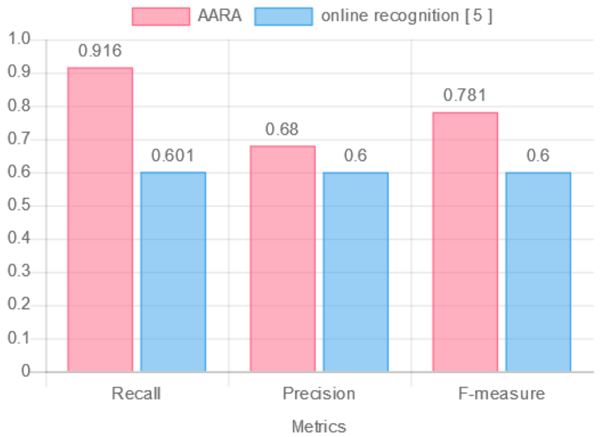

Fig. 5: the result for (95) behaviors for periods (1,2) as a training set and periods (4,3) as a testing set.

Fig. 5, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 5, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 91.6%, 68%, and 78.1%, respectively. While for the online recognition [5] were 60.1%, 60%, and 60%, respectively. As result, AARA improves the recall, precision, and F-measure by 31.5%, 8%, and 18.1%, respectively.

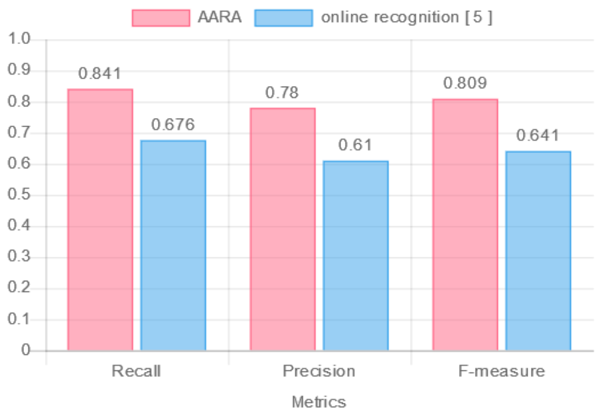

Fig. 6: The Result for (82) behaviors for Periods (1,3) as a Training set and Periods (4,2) as a Testing Set

Fig. 6, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 6, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 84.1%, 78%, and 80.9%, respectively. While for the online recognition [5] were 67.6%, 61%, and 64.1%, respectively. As result, AARA improves the recall, precision, and F-measure by 16.5%, 17%, and 16.8%, respectively.

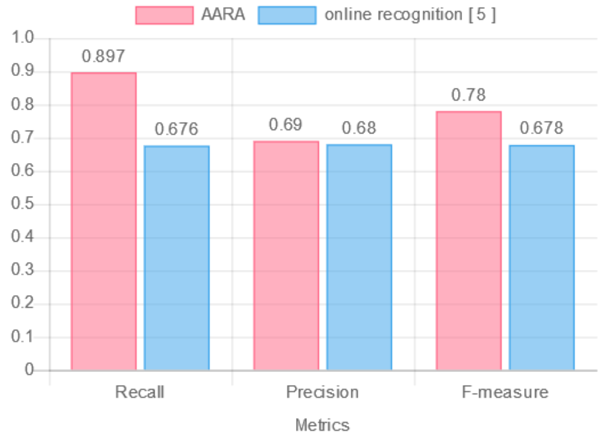

Fig. 7: The Result for (99) behaviors for Periods (1,4) as a Training set and Periods (3,2) as a Testing Set

Fig. 7, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 7, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 89.7%, 69%, and 78%, respectively. While for the online recognition [5] were 67.6%, 68%, and 67.8%, respectively. As result, AARA improves the recall, precision, and F-measure by 22.1%, 1%, and 10.2%, respectively.

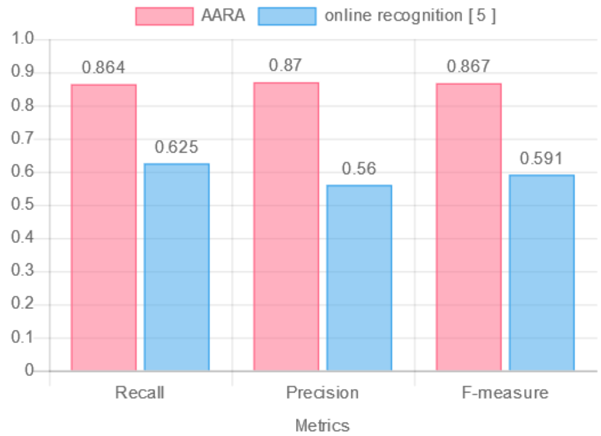

Fig. 8: The Result for (97) behaviors for Periods (2,3) as a Training set and Periods (4,1) as a Testing Set

Fig. 8, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 8, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 86.4%, 87%, and 86.7%, respectively. While for the online recognition [5] were 62.5%, 56%, and 59.1%, respectively. As result, AARA improves the recall, precision, and F-measure by 23.9%, 31%, and 27.6%, respectively.

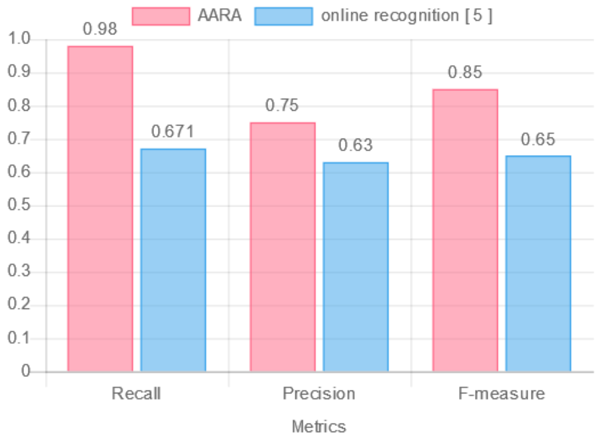

Fig. 9: the result for (114) behaviors for periods (2,4) as a training set and periods (3,1) as a testing set.

Fig. 9, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 9, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 98%, 75%, and 85%, respectively. While for the online recognition [5] were 67.1%, 63%, and 65%, respectively. As result, AARA improves the recall, precision, and F-measure by 30.9%, 12%, and 20%, respectively.

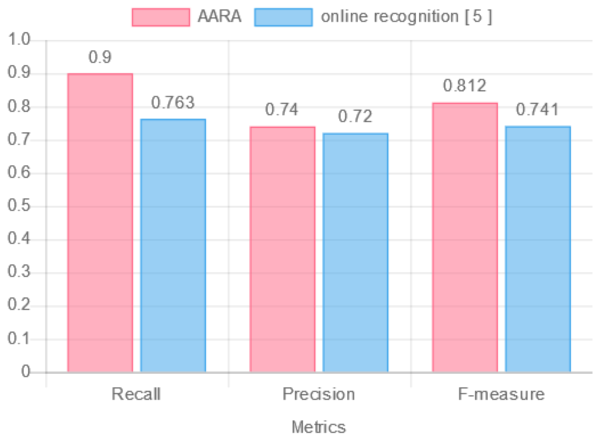

Fig. 10: the result for (101) behaviors for periods (3,4) as a training set and periods (2,1) as a testing set.

Fig. 10, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 10, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 90%, 74%, and 81.2%, respectively. While for the online recognition [5] were 76.3%, 72%, and 74.1%, respectively. As result, AARA improves the recall, precision, and F-measure by 13.7%, 2%, and 7.1%, respectively.

5.3.2 Results without Noises

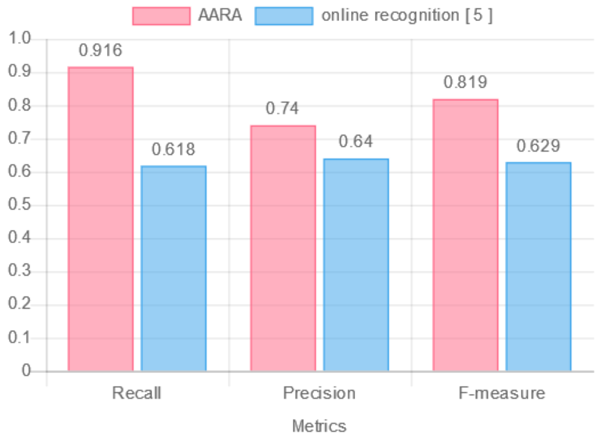

Fig. 11: The Result for (88) Behaviors for Periods (1,2) as a Training Set and Periods (4,3) as a Testing Set

Fig. 11, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 11, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 91.6%, 74%, and 81.9%, respectively. While for the online recognition [5] were 61.8%, 64%, and 62.9%, respectively. As result, AARA improves the recall, precision, and F-measure by 29.8%, 10%, and 19%, respectively.

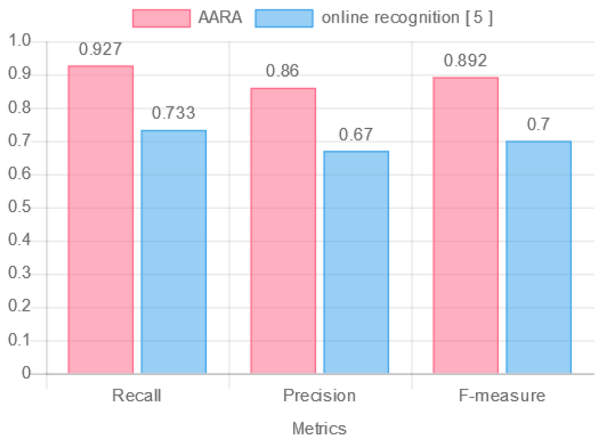

Fig. 12: the result for (73) behaviors for periods (1,3) as a training set and periods (4,2) as a testing set.

Fig. 12, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 12, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 92.7%, 86%, and 89.2%, respectively. While for the online recognition [5] were 73.3%, 67%, and 70%, respectively. As result, AARA improves the recall, precision, and F-measure by 19.4%, 19%, and 19.2%, respectively.

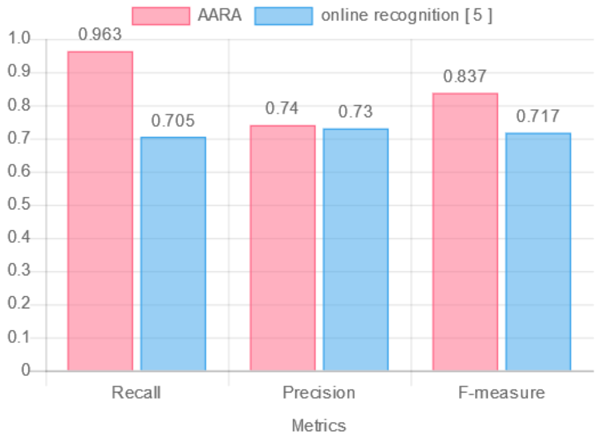

Fig. 13: The Result for (90) behaviors for Periods (1,4) as a Training Set and Periods (3,2) as a Testing Set

Fig. 13, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 13, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 96.3%, 74%, and 83.7%, respectively. While for the online recognition [5] were 70.5%, 73%, and 71.7%, respectively. As result, AARA improves the recall, precision, and F-measure by 25.8%, 1%, and 12%, respectively.

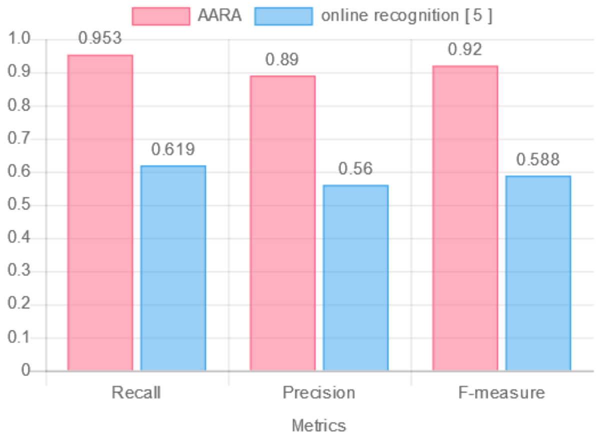

Fig. 14: The Result for (93) behaviors for Periods (2,3) as a Training Set and Periods (4,1) as a Testing Set

Fig. 14, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 14, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 95.3%, 89%, and 92%, respectively. While for the online recognition [5] were 61.9%, 56%, and 58.8%, respectively. As result, AARA improves the recall, precision, and F-measure by 33.4%, 33%, and 33.2%, respectively.

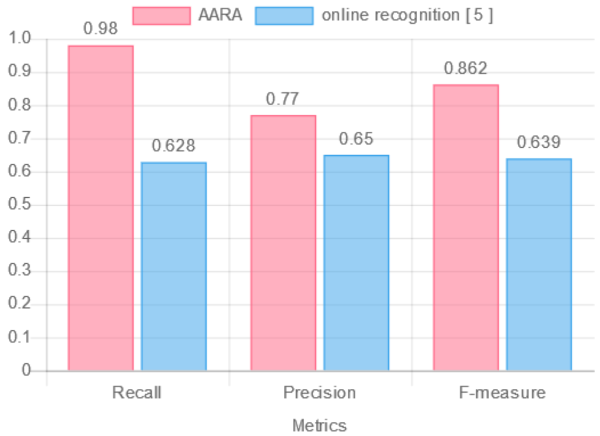

Fig. 15: The Result for (110) behaviors for Periods (2,4) as a Training set and Periods (3,1) as a Testing Set

Fig. 15, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 15, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 98%, 77%, and 86.2%, respectively. While for the online recognition [5] were 62.8%, 65%, and 63.9%, respectively. As result, AARA improves the recall, precision, and F-measure by 35.2%, 12%, and 22.3%, respectively.

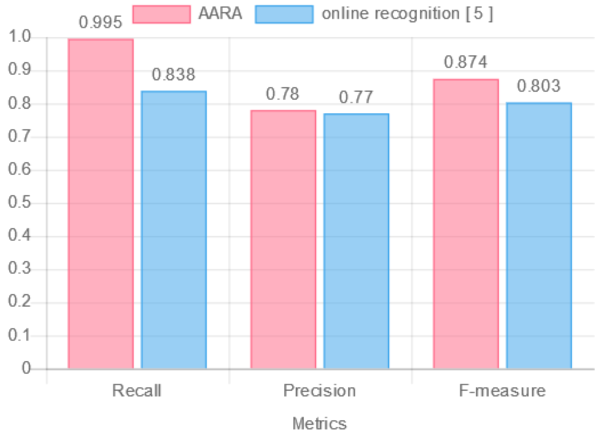

Fig. 16: The Result for (95) behaviors for Periods (3,4) as a Training Set and Periods (2,1) as a Testing Set

Fig. 16, shows the recall, precision, and F-measure for AARA and online recognition [5] when the threshold equal to 0.9. As shown in Fig. 16, AARA achieves higher performance than online recognition [5] where the recall, precision, and F-measure for AARA were 99.5%, 78%, and 87.4%, respectively. While for the online recognition [5] were 83.8%, 77%, and 80.3%, respectively. As result, AARA improves the recall, precision, and F-measure by 15.7%, 1%, and 7.1%, respectively.

6. CONCLUSION

In this paper a new approach called AARA was presented for improving the accuracy of activity recognition in smart environments. AARA can recognize behaviors based on finding the minimum number of activities which will be used to represent the behavior, trapezoidal fuzzy method, and Naïve Bayes Classifier. To measure the performance of AARA, a real dataset was used and a lot of simulation scenarios were conducted. AARA achieves higher performance than existing approaches in terms of precision, recall, and F-measure. In the future work, finding a dynamic threshold for AARA will be studied and improving AARA to be applied for a group activity recognition in smart environments.

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