A New Approach to Recognize Activities in Smart Environments Based on Cooperative Game Theory

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Abstract—These days, a lot number of elderly people need health care which may cause huge financial costs, especially in formal case. Machine Learning and the profound achievements in sensing technology provide the opportunities to monitor people living independently at home and can detect a distress situation affordably. Although there are some approaches to do recognize activities for this purpose, but there has not been any game-theoretic approach in order to select the most efficient sensors to reduce the system's overhead by decreasing the number of features. In this paper, we present a new classifier to recognize activities in a smart environment that is based on selection of most efficient sensors by cooperative game theory. The sensors are selected in which provide more information about the target classes. We show the performance of our algorithm by simulation.

Keywords—activity recognition; classification; game theory;

I. Introduction

The life expectancy in many countries has been increased by the advances in medicine. People, especially those experiencing difficulties such as elderly people or disabled ones need health care, and from financial point of view, it could impose huge costs to provide it in case of living independently. In contrast, researchers have found the achievements in machine learning and robust sensors can assist this situation by remote heath monitoring, and, as a result, people can remain in their own smart home.

To provide remote health monitoring, we need the individuals to do independently Activities of Daily Living (ADL) such as dressing, drinking, cooking in a complete form. Activity recognition takes a significant part in this system. We need to detect any distress by monitoring the behavior of individuals and their interactions with the smart environment to assist residents and enhance the quality of their life.

To response this need, there are variety of approaches to recognize activities designed by researchers. The generally accepted approach is to analysis data gained by the variety of sensors located in different places. However, there are some difficulties with this. First, the numerous data generated by varied sensors cause inordinate amounts of time for processing and it makes the system impractical in cases time is a significant factor. Second, using a lot number of sensors impose financial costs to residents and it may overtake that of formal health care. Last but not least, the need for an accurate classification is still underscored. For taking drug, for example, a false recognition may lead to irreparable harms.

In this paper, we introduce a new supervised method to recognize activities in a smart environment to address the above issues. For this purpose, first we select the efficient sensors to generate data by cooperative game theory and in the second step we create a boosted version of Decision Tree for activity recognition based on hyperplanes built by Support Vector Machine (SVM) for separation. By this approach we could employ only the efficient sensors in a smart environment for assistive living, along with an accurate algorithm for recognition, and, as a result we can provide an affordable system as well as doable for accurate performance.

Our contribution in this paper includes:

- We select the most efficient sensors to generate data from the smart environment by cooperative game theory
- We present a new method for activity recognition based on combine of Decision Tree and Support Vector Machines.
- We show simulation result and compare the accurate of our algorithm with traditional form of Decision Tree.

The reminder of this paper is organized as follow. Section II compares some activity recognition methods in smart environments, game theoretic approaches in this field, and related works. Section III presents our approach based on a boosted version of decision tree and choosing the efficient sensors to generate data. In Section IV, we show a simulation study on the presented algorithm and compare with traditional methods and analyze the result of our algorithm. The paper concludes in Section V.

II. II. Related Works

Recognize activities is not an untapped research area. With the increasing attention to activity recognition systems, researches have investigated methods based on 4 different applications [12] such as active and assistive living applications for smart

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homes, healthcare monitoring applications, security and surveillance applications, and Tele-immersion.

Varied methods have been investigated according to different machine learning classifiers for healthcare monitoring applications. Naïve Bayes classifiers have been applied to recognize activities with respect to conditional independence among features [1, 2, 3]. These approach could provide high accuracy with large amount of sample data. Other researchers, such as Maurer et al. [4], used Decision Tree to classify activities. It could offer good accuracy but the method is independent on precision of numeric data and it makes it brittle. Fleury et al. [5] presented a new approach to recognize ADL by using support vector machines. They were able to classify 7 different activities with only 75% of classification accuracy by the polynomial kernel. Similar research is presented in [6] using support vector machine to classify activities with the effort to deal with uncertainly generated information through decision-making process. In some approaches researchers used annotated data labeled with the equivalent activities to improve the accuracy rate. Szewcyzk et al [7] have investigated a new mechanism to annotate data generated by sensors; thus; there were able to achieve a higher accuracy rate from 66.37% to 75.15%. Although they have improved the accuracy rate, annotating data by their corresponding activities takes time and need the individuals' assistance.

With regards to game theoretic approach, there are only few attempts to improve the security of network systems such as Wireless Sensor Networks (WSN) for smart environments. In [9], a trust derivation for WSNs has been presented by adopting game theoretic approach. A little work has been done to use game theory in WSN for studying tradeoff between bandwidth and energy consummation [13] and for security implementation in eHealth systems. Similar approach has been used in [8] to evaluate employee performance automatically. They have discussed the game theoretic decision-making process for strengthening employee-employer relationship.

All of the aforementioned studies discussed varied aspects of smart environments by adopting game theoretic approach, and different machine learning methods to recognize activities in this. To our best knowledge, no specific study of sensor reduction for healthcare applications by employing game theoretic approach has been investigated.

III. Proposed Approach

We use the cooperative game theoretic approach introduced in [9] to reduce the number of sensors. It can significantly improve the high computational complexity of classification method and present an affordable system to recognize activities in a smart environment. In the next step, we introduce a new classification method based on boosted version of Decision Tree to recognize activities occurred in smart environment. The architecture of the system is presented in Fig. 1.

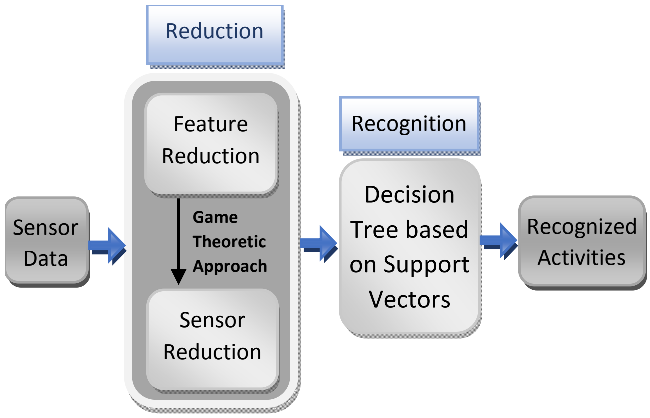

Fig. 1. Main components of proposed system activity recognition

A. *Reduction on Sensors by Cooperative Game Theoretic Approach*

Sensors located in different places in smart environment generate enormous amount of data to recognize activities. However, some of this information is not significant for this purpose. According to the redundant data, we can reduce the number of sensors to provide health monitoring system in which analyze data with acceptable computational complexity. We evaluate the power of each feature based on Mutual Information (MI). The MI $I(X;Y)$ is defined as follow:

$$I(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\log\frac{p(x,y)}{p(x)p(y)}.$$

According to the information theoretic measurements define in [9], we can distinguish different relationship among features as:

- *Redundancy*: A feature is called redundant if its relevance with the target class decreased by the knowledge of one or more of its correlated features.

  $I(f_j;class \mid f_i) < I(f_j;class)$.

- *Independent*: features f_i and f_j are independent when the relevance between f_j and target class can be increased by the knowledge of f_i .

  $I(f_j;class \mid f_i) > I(f_j;class)$.

- *Interdependent*: features f_i and f_j are interdependent when the relevance between any of them and target class cannot changed by the knowledge of other one.

  $I(f_j;class \mid f_i) = I(f_j;class)$.

As a similar approach to [9] we evaluate the power of each feature based on Banzhaf Power. Consider K as a candidate subset, we can evaluate the power of feature $f_i\,(f_i \notin K)$ by estimating its impact on Coalition K . To make it doable, we compute the number of independent or redundant features ($\eta_i(K)$) with f_i based on corresponding measurements, as well as computing the number of features are interdependent with f_i, $\mu_i(K)$.

The ratio $p = \mu_i(K) / \eta_i(K)$ shows the impact of feature f_i on coalition K.

Next, we evaluate the Banzhaf power to estimate the power of each feature based on proposed algorithm in [9], and, as a result, we will have optimal feature subset in which the members are relevant to the target class and interdependent on each other. It's noteworthy to mention that we have employed mRMR [10] as the feature selection algorithm in the final step according to the experimental results have been shown in [9].

In the final step, we have the optimal coalition that represent the efficient features for classification. According to this subset, we define sensors corresponding to the features do not exist in the final coalition. As a result, we remove redundant sensors by this definition:

Consider f_i as the information generated by sensor V_i, and coalitions S the final optimal feature subset. V_i will be redundant sensor if $f_i \notin S$.

B. Activities Recognition by boosted version of DT

In the recognition step, we use the features generated by selected sensors in the previous part and create a boosted version of Decision Tree to recognize activities occurred in smart environment.

We declare the set of optimal features (events) as $F = \{f_1, f_2, ..., f_d\}$, the set of samples as $O = \{o_1, o_2, ..., o_m\}$, and the set of target class (activities) as $T = \{t_1, t_2, ..., t_z\}$. For activity recognition, first we compute the hyperplane to seprate different activities based on support vector machines. To build hyperplane we have:

$$\begin{cases} \sum_{\alpha_k > 0} f\left(\alpha_k \langle x, x_k \rangle + \omega_0\right) > 0 \rightarrow f = 1 \\ \sum_{\alpha_k > 0} f\left(\alpha_k \langle x, x_k \rangle + \omega_0\right) < 0 \rightarrow f = -1 \end{cases}$$

In this equation we can classify a new vector x. α_k are the Lagrange multiplayers, and x_k are the support vectors, the one in each class to define the separation [14].

Based on the classification result in first step, we create corresponding decision tree. In the next step, we compute hyperplane for sepration with the similar approach on 2 subregion resulted by the previous step. Fig. 2 shows an example of final spliting based on hyperplances.

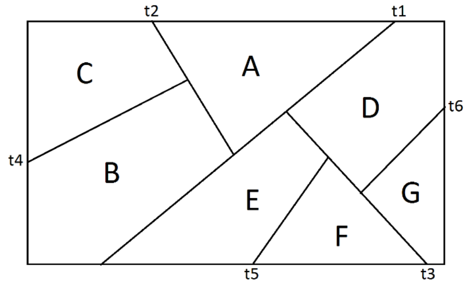

Fig. 2. Example of final spliting regions in proposed method

In Fig. 2, subset $T = \{t_1, t_2, ..., t_6\}$ represent hyperplanes in each step. For the sake of convenience, we have defined a threshold ω which introduce the number of computing hyperplanes iteratively. Here in this example ω=3, which means we have computed hyperplanes three times. It's clear that we stop computing hyperplanes for separation in sub regions in which there are only samples corresponding to one target class, such as sub region A in this example.

Fig. 3 shows the corresponding decision tree for sub regions in Fig. 2.

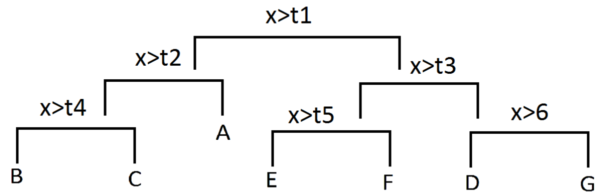

Fig. 3. Example of correspoing decision tree in proposed method

The proposed method combines decision tree classifier and support vector machines stated in general form. It is shown than the proposed method classify activities faster than traditional decision tree, since the deep of our decision tree will be significantly smaller than the original one. The accuracy of proposed algorithm is compared to algorithm support vector machines with different kernels in the Section IV.

IV. SIMULATION

We have studied the performance of our method in terms of accuracy classification by simulation.

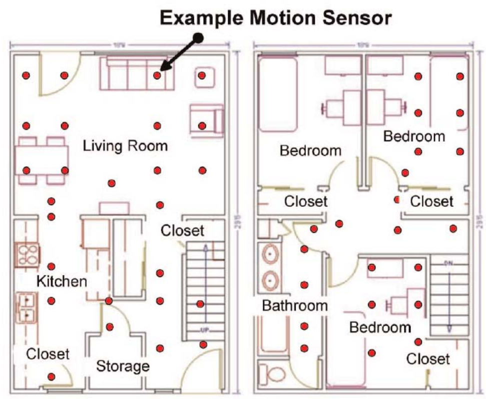

Fig. 4. Smart environment for our data collection. Circles indicate the location of motion sensors

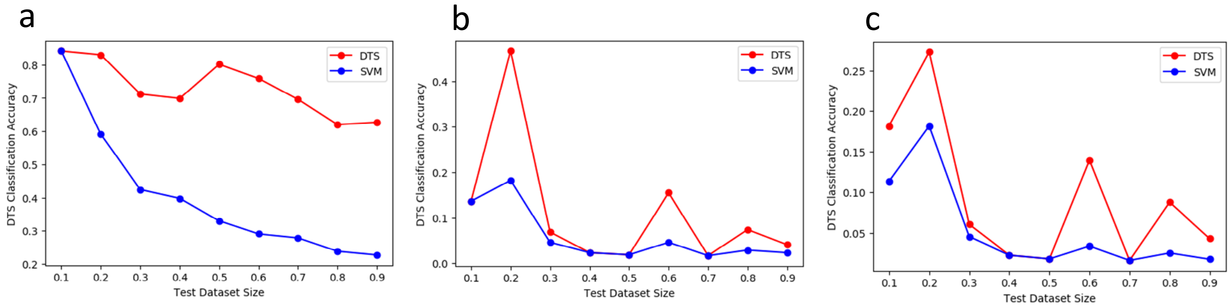

Fig. 5. Classification accuracy of our method against SVM on three different kernet: (a) Linear, (b) Guassian, (c) Polynomial

The testbed for this purpose accessed by the Washington State University campus that is part of ongoing CASAS smart home project [11]. A three-bedroom smart apartment used for collecting data and the position of motion sensors are indicated by circles in the Fig. 4.

We have tested the classification accuracy of our method using a linear kernel, a Polynomial kernel, and a Gaussian kernel and compared to original form of SVM with the same kernels respectively. The validation has been performed using the "k-fold cross validation".

Based on empirical studies, we can conclude than the proposed method can provide a good classification accuracy in compare with original SVM. Fig. 5 illustrates this by comparing our method (DTS) with SVM in 3 different kernel functions for different k values. Fig. 5(a) shows the accuracy classification in which kernel function is linear. We can see that DTS classification accuracy has significantly improved by different size of test datasets. For each dataset size, the classification accuracy is higher than that of original SVM. To explain this, our samples have somehow similar values for the same features, and as a result, SVM with a linear kernel is not suitable to separate these. For example, activities such as hygiene and toilet are close and it is difficult to separate these by linear kernel. Therefore, we can see significant difference between the accuracy of our method with SVM. It also can be seen from Fig. 5(b) that our method has the same classification accuracy with SVM by Gaussian kernel in the worst cases.

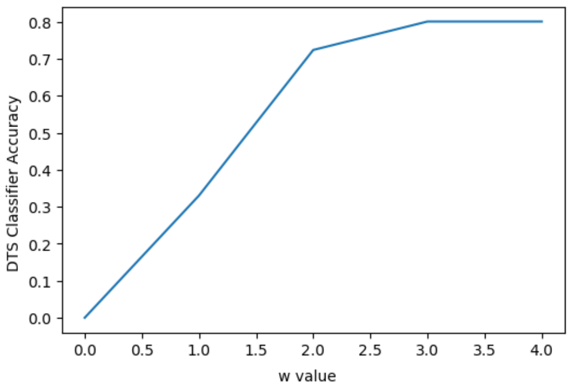

Fig. 6. Accuracies vs. different w values in proposed algorithm

However its performance has improved in some dataset sizes, especially when we have used 0.1 of our dataset as the test dataset and 0.9 as the train one. As the same empirical studies, Fig. 5(c) shows our method has improved the classification accuracy in compare with SVM by polynomial kernel as well.

In our method, parameter ω is introduced to improve the classification accuracy and reduce the computational complexity to make the algorithm finite. To investigate the impact of ω in classification accuracy we compare the classification performance of our method with different value of this parameter in Fig. 6.

We can see that our method achieves the highest classification accuracy, 0.84, when $\omega = 4$, which means we calculate support vectors in 4 iteration. It remains steady when reaches the peak, and it is understandable by the fact that, the higher values for ω can reduce generalization, and as a result, the classification accuracy.

V. Concluding Remarks and Future Prospects

To provide a robust smart environment for people living independently and experiencing difficulties, we need to consider methods to recognize activities with higher classification accuracy with reasonable computational complexity.

We introduce a boosted version of decision tree by evaluating hyperplanes for separation in SVM. To make our approach affordable with less computational complexity, we reduce the number of sensors by a proposed cooperative game theoretic approach which could select the most powerful features as the winner coalition. Our simulation study shows that the classification accuracy of our method has improved in compare with SVM in 3 different kernel functions; linear, polynomial, and Gaussian.

With regards to the future prospects, we can take contribution to solve these problems:

- Human behavior is complex and spontaneous. It is difficult to distinguish different activities. For example, they cooking while watching TV. So we can work to investigate a method to recognize these kind of activities.
- People do activities differently. For example, a person prefer to eat out, and another one prefer to cook. To make our system more practical, we can work on an unsupervised method for activity recognition.

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