Activity Recognition based on SVM Kernel Fusion in Smart Home

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Abstract. Smart home is regarded as an independent healthy living for elderly person and it demands active research in activity recognition. This paper proposes kernel fusion method, using Support Vector Machine (SVM) in order to improve the accuracy of performed activities. Although, SVM is a powerful statistical technique, but still suffer from the expected level of accuracy due to complex feature space. Designing a new kernel function is difficult task, while common available kernel functions are not adequate for the activity recognition domain to achieve high accuracy. We introduce a method, to train the different SVMs independently over the standard kernel functions and fuse the individual results on the decision level to increase the confidence of each activity class. The proposed approach has been evaluated on ten different kinds of activities from CASAS smart home (*Tulum 2009*) real world dataset. We compare our SVM kernel fusion approach with the standard kernel functions and get overall accuracy of 91.41%.

Keywords: Activity recognition, Smart home, SVM, Kernel fusion.

1 Introduction

Activity recognition is active area of research since the inclusion of smart home concept for providing ubiquitous lifecare services. It can provide a valuable health monitoring services for ageing society to improve their quality of life. In the recent years, several smart homes have been developed such as CASAS and MavHome [1] at Washington State University, Aware Home [2] at Georgia Tech University, Adaptive House [3] at University of Colorado, House_n [4] at Massachusetts Institute of Technology (MIT), and House A [5] at Intelligent Systems Laboratory. The nomenclature of the activity recognition has two broad categories, visual sensing and ubiquitous sensing technologies. In first category, camera based techniques are used to monitor the behavior of inhabitants. These are not practical due to privacy reason, day/night vision problem and jumble environment. In second category, ubiquitous sensors are embedded on the different objects to recognize the daily life activities. They are cost-effective, easy to install and less intrusive to the privacy of inhabitants. Activity recognition is a big challenge by using ubiquitous sensors due to complex and highly diverse life styles.

Several machine learning and statistical approaches have been proposed to recognize the human activities and achieves acceptable accuracy with particular attentions [6], [7]. This paper investigates the theoretically rich statistical method SVM due to its quality of generalization and ease of training as compared to traditional method artificial neural network. We adopt decision fusion mechanism to increase the accuracy of recognition rate. A kernel fusion method is introduced to transform the activity recognition problem into higher feature spaces. The output of each individual is combined for the final consensus about the activity class label. Our approach is able to recognize activities more efficiently in a reasonable amount of time using fast training method Sequential Minimal Optimization (SMO) instead of Quadratic Programming (QP). For empirical evaluation, we performed the experiments on the CASAS smart home (*Tulum 2009*) real world activity dataset. Results show that our approach yields a significant improvement in the accuracy as compared to the single kernel function.

We structure our paper as follow: Section 2 provides information about some of the existing approaches for human activity recognition. Section 3 presents our proposed approach for activity recognition in smart homes. In Section 4, we illustrate the experimental results followed by comparison and discussion. And finally the conclusion and future work are drawn in Section 5.

2 Related Work

There have been a number of machine learning methods for recognizing activities, such as Markov models [8], dynamic Bayesian network [9] and frequent activity patterns methods [10]. Rashidi et al. [10] track the regular activities to monitor functional health and to detect changes in an individual's patterns and lifestyle. They described activity mining and tracking approach based on Markov models and validates their algorithms on data collected in physical smart environments. Kasteren et al. [9] described the use of probabilistic model dynamic Bayesian network using less parameters to give better results. They showed how the use of an observation history of sensors increases the accuracy in case of the static model. Furthermore, the use of the observation history allows their model to capture more correlations in the sensor pattern. The authors in [11] proposed unsupervised approach to find frequent periodic activity patterns and resident implicit and explicit feedback can automatically update their model to reflect the changes. Their model did not take any assumptions into account about the activity structure, but leaves it completely to their algorithms and discover the resident's activity patterns in smart home environment.

Fusion techniques play an important role to achieve high accuracy as compared to single classifier and successfully produced more accurate results in different application domains such as image processing [12], gene functional classification [13]. In the context of sensory data, Xin at el. [14] address the fusion process of contextual information derived from the sensor data. They analyzed the Dempster-Shafer theory and merged with weighted sum to recognize the activities of daily living for inhabitants in smart homes. Their framework is capable to handle the sensors uncertainty and demonstrated the conjunction of sensors to support the reliable decision making. They demonstrate the concept of their work with the help of tutorial type exercise. They showed that the number of sensors and reliability of each sensor has a significant impact on the overall results in term of decision making.

In the previous works, it has been shown that many machine learning algorithms are proposed to recognize the daily life activities in the Smart homes. Our objective is to utilized theoretical rich model (i.e., SVM) and combines fusion technique to provide more robust and accurate activity recognition approach. We believe that, nature of the problem can be solved more precisely by fusion techniques along with SVM method.

3 The Proposed Approach

In our proposed approach, four individual SVM kernels are designed to use the preprocessed annotated smart home dataset in parallel. The output of each SVM kernel is a decision about the activity class label. In order to increase the confidence of final predicted class, decision fusion technique is applied to recognize the human daily life activities with more accuracy. The architecture of proposed approach is shown in Fig. 1 and details as follow.

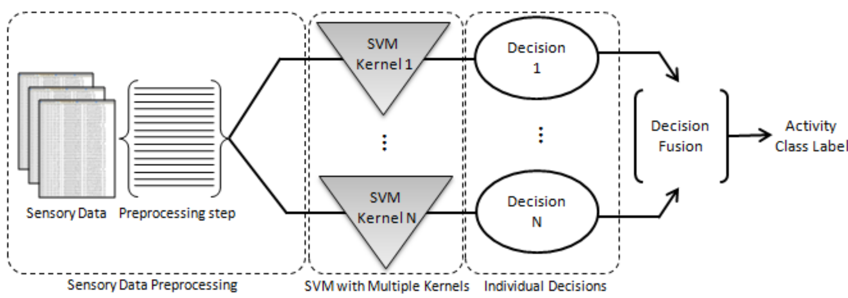

Fig. 1. The proposed architecture

3.1 Sensory Data Preprocessing

Ubiquitous sensors in the smart home continuously sense the environment and generate signals according to the subject interactions. Log files are maintained with attributes *start time, end time, sensor id* and *sensor value*. In order to recognize the performed activities, recorded dataset is preprocessed into the form of $\{(x_1, y_1), \ldots, (x_n, y_n)\}$. The x_i values are the vectors of form $\langle x_i, 1, x_i, 2, \ldots, x_i, m \rangle$ whose components are embedded sensors such as stove-sensor, refrigerator-sensor, and door-sensor. The values of "y" are drawn from a discrete set of classes $\{1, \ldots, K\}$ as a "Meal preparation", "Cleaning", "Laundry" and so on.

3.2 SVM with Multiple Kernels

Given training set of sensors value and activity pairs (i.e.,(x_i, y_i)), the SVM for the binary linear classification problem require the following optimization model including the error-tolerant margin.

$$Minimize\ \frac{1}{2}w^T w + C\sum_{i=1}^{n}\xi_i \tag{1}$$

$$Subject\ to: y_i(w^T x_i + b) \geq 1 - \xi_i, \quad and \quad \xi_i \geq 0 \tag{2}$$

Where "w" is a weight vector and b is bias. C is the error penalty and ξ_i are slack variables, measuring the degree of misclassification of the sample x_i. The maximum margin is obtained by minimizing the first term of objective function, while the minimum total error of all training examples is assured by minimizing the second term. Activity recognition is multi-class problem so we adopt "one-versus-one" approach for this purpose and trained the SVM through SMO for efficient performance [15]. The above optimization model can be simplified by using the Lagrangrian multiplier techniques and Kernel functions:

$$Maximize\ (w.r.t\ \alpha)\sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=0}^{n}\sum_{j=1}^{n}\alpha_i\, y_i\alpha_j y_j K(x_i, x_j) \tag{3}$$

$$Subject\ to: \sum_{i=1}^{n}\alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C \tag{4}$$

Where K is the kernel function that satisfies $K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j)$. It is a function that transforms the input data to a high-dimensional space where the separation could be linear [16]. SVM can provide a good generalization performance, but oftently far from the expected level of accuracy, due to their approximation algorithms and high complexity of data [17]. In order to achieve high accuracy in the classification, we trained following multiple kernels [15] and fused the individual results.

$$K(x_i, x_j) = x_i^T x_j \tag{5}$$

$$K(x_i, x_j) = (x_i^T x_j + 1)^p \tag{6}$$

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{(2\sigma^2)}\right) \tag{7}$$

$$K(x_i, x_j) = tanh(kx_i^T x_j - \delta) \tag{8}$$

Equations 5, 6, 7, and 8 shows the linear, polynomial, Gaussian (RBF) and multi-layer perceptron (MLP) kernel functions respectively. An "ideal" kernel function assigns a higher similarity score to any pair of objects that belong to the same class. In this problem domain, kernel function behaved differently on the performed activities due to complex situation that may arise because of so many ways of doing an individual activity. The level of accuracy for performed activities is dependent on the different kernel function and discussed more in the evaluation and results section.

3.3 Decision Fusion

The output of the SVM kernels are the class labels and it has very clear inference about the activity. Each kernel sources are independent of each other and contain the class label about the certain activity. Before assigning the final class label, we get the confidence with the help of max rule as below:

$$Activity\ Label = argmax\left(\sum_{i=1}^{4} SVM(K_i)\right) \tag{9}$$

4 Evaluation and Results

We performed experiments over the CASAS smart home dataset (*Tulum 2009*) collected in a Washington State University family apartment with full-time residents [4]. Twenty different kinds of temperature and motion sensors are deployed at various locations. Two volunteer was performing the common house hold activities during the eighty three days stay. In that time, volunteer's annotated activities are preparing breakfast, lunch, snack, wash dishes, watch television, group meeting, and leave home. During our experiments, we recognized activities of both volunteers according to uniquely assigned labels in the annotated file. The approach has been implemented in MATLAB 7.6. The configuration of the computer is Intel Pentium(R) Dual-Core 2.5 GHz with 3 GB of memory and Microsoft Window 7. We used 70% of dataset for training and 30% data for testing as an evaluation criterion for recognizing the daily living activities. Fig. 2 shows the average accuracy of kernel fusion in comparison to recognition rate as compared to the individual kernel functions.

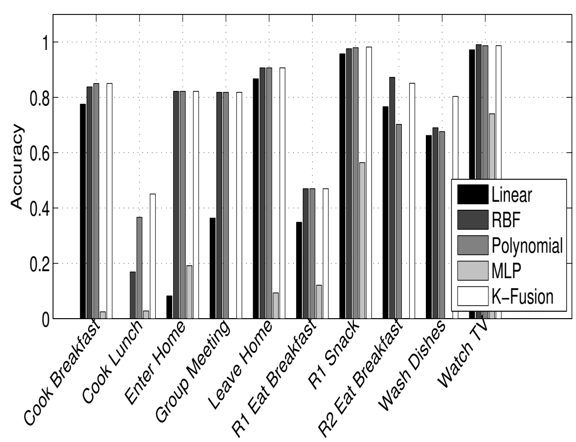

Fig. 2. Individual class accuracy of different kernel functions

In Fig. 2, different kernel functions show the performance variations for the recognition of same activities. The overall performance of “MLP” is low as compared to other individual kernel functions. “RBF” usually perform well in most of the cases but “kernel fusion” outperforms all individual kernel methods. In the proposed method, fusing the individual decisions, strengthen the confidence to assign final activity class label. Although, “RBF” is better than “kernel fusion” in case of “*R2 Eat Breakfast*” activity but its overall accuracy, 90.41%, is significantly better than “RBF” and other individual kernel functions as shown in Table 1.

Table 1. Overall kernel functions accuracy

Kernels	Accuracy
Linear Kernel	81.03%
RBF Kernel	88.89%
Polynomial Kernel	88.49%
MLP Kernel	46.33%
Kernel Fusion	**90.41%**

Table 1 illustrates the accuracies achieved by different kernel functions along with our proposed kernel fusion method. We analyze from our experiments nature of the different activities differ in different situations and may learn properly over the different kernel functions. A significant improvement is achieved by fusing the individual kernel outputs.

5 Conclusion and Future Work

Although a lot of work has been done to recognize daily life activities but few methods investigated fusion techniques that can help to improve the accuracy. In this paper, we investigate the fusion of kernel methods to overcome the learning effects of different kernel function for individual activities. We proposed a method to train independent kernel functions with support vector machine and the decision of each individual’s is combined at decision level by max rule. Our study found that it increases the overall accuracy of recognized activities and also performs well in case of those activities where single kernel methods suffer from accuracy problems. To investigate further, we intend to define our own activity domain specific kernel function to refine the accuracy rate.

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