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# A Human Activity Recognition System Based On Sensory Data Related to Object Usage

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***Abstract*—**Sensor-based Activity Recognition systems usually accounts which sensors have been activated to perform an activity. The system then combines the conditional probabilities of those sensors to represent different activities and takes the decision based on that. However, the information about the sensors which are not activated may also be of great help in deciding which activity has been performed. This paper proposes an approach where the sensory data related to both usage and non-usage of objects are utilized to make the classification of activities. Experimental results also show the promising performance of the proposed method.

***Keywords*—**Naïve Bayesian-based classification, Activity recognition, sensor data, object-usage model.

## I. Introduction

HUMAN activity recognition deals with the problem of identifying what a person is doing (e.g. cooking, eating breakfast, bathing, etc.). This is used to monitor the activities of people. One of the major applications of human activity recognition system is monitoring the old people living alone at homes or in old homes. This can also be used in many diverse applications such as medicine and healthcare. Hence, human activity recognition has attracted many researchers in recent years due to its strength in providing personalized support for in different applications in different scenarios [17]-[19].

Different groups of researchers have been investigating on how to construct smart living environments targeting at the care to the individuals as focus. Intel Research group in Seattle and the University of Washington have built a prototype system that can infer a person’s activities of daily livings (ADLs) [5]. University of Rochester has been working on building the Smart Medical Home, which is a five-room house equipped with infrared sensors, computers, bio-sensors, and video cameras for use by research teams to work with research subjects as they test concepts and prototype products [6]. Georgia Institute of Technology builds an Aware Home as a prototype for an intelligent space [7]. Massachusetts Institute of Technology (MIT) and TIAX are working on the PlaceLab initiative, which is a part of the House_n project [8]. The mission of House_n is to conduct research by designing and building real living environments—“living labs”—that are used to study technology and design strategies in context. Many projects are building body networks for the collection of vital signs, such as AMON. All these systems demonstrate the excitement and need for activity recognition systems [9]. Tapia et al. [10] employed simple and ubiquitous sensors for activity recognition. The authors provided the ESM in a PDA to the user to annotate their daily activities. Naïve Bayes classifier was used to recognize activities. They have showed an excellent promise, even though their mechanism suffers from low recognition accuracy. Kasteren et al. [11] used the similar settings, except their annotation technique was quite innovative. They employed predefined set of voice commands to start and end points of an activity through a bluetooth enabled headset combined with speech recognition software. Perkowitz et al. [12] introduced the notion of mining the generic activity models from the web. They have shown that it is possible to convert natural-language recipes into activity models. And these models can be used in conjunction with RFID tags to detect activity. Their model consists of a sequence of states and is based on a particle filter implementation of Bayesian reasoning.

In video-based human activity recognition, a person’s full body is first segmented in video frames, and then different context-based analysis is applied to classify the activity based on the pose in one or more frames over times. The main problem in such approaches is that the available segmentation approaches cannot always segment the human body much accurately, which is required for the further analysis of activities.

In sensor-based activity recognition systems, every object in a home is equipped with one or more sensors. In the simplest case, an object may be monitored by a sensor, which can recognize whether the object is in use or not. Based on such data gathered from a set of sensors, an activity recognition system usually combines the conditional probabilities of the active objects’ usage when an activity is performed [1], [2]. The final decision is then taken in favor of the activity whose probability attains the highest value among a set of all possible activities.

Many available activity recognition systems [11]-[14] utilize the Object-usage Based Model (OBM) to classify activities. The downside of such an approach is that as the number of activities to monitor grows, the number of distinguishing objects between activities decreases. In such scenarios, such systems would produce more confusion between activities.

Traditional human activity recognition systems make use of only the sensory data related to the objects that are used in an (test) activity. An unused object’s data is not used. However, an unused object may provide with the important information that a particular activity may not has been performed. This helps in the classification that this particular activity is less probable to have performed. This paper focuses on this important observation.

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In this paper, a new approach of activity recognition is proposed. The proposed method uses the sensors' signal regarding whether different objects are used or not used to perform the test activity at hand to classify. Experimental results show that the proposed system outperforms the traditional ones in terms of accuracy.

The rest of this paper is organized as follows. The proposed as well as the traditional approaches of classifying human activities are described in Section II in detail. Then the experimental results are presented in Section III. Finally, Section IV concludes the paper with the future research direction where the proposed approach may be utilized more effectively.

## II. The Proposed Approach

In this section, the formal definition of the classification problem, which is intended to solve in the sensory data-based activity recognition systems, is first described. Then the traditional approach of solving the problem is presented followed by the proposed method.

### *A. The Problem Definition*

Let O = $\{o_1, o_2, o_3, \ldots, o_m\}$ be the set of objects, each of which is equipped with sensors capable of detecting whether the object is in use or not and A = $\{a_1, a_2, a_3, \ldots, a_n\}$ be the set of activities that may be performed by the person/people being monitored. Now suppose that an activity $x$ is performed employing a set of objects E = $\{e_1, e_2, e_3, \ldots, e_t\}$ where E is a subset of O. Now the problem is to classify $x$ to one of the available classes in A.

### *B. The Traditional Approach*

For fusion of the conditional probabilities related to the activated sensors, naïve Bayesian-based classification scheme is very popularly used in different fields [1], [2]. Such techniques use (1) in general.

$$\underset{i}{argmax} \quad P(a_i)\prod_{k=1}^{t} P(e_k|a_i) \tag{1}$$

where $P(a_i)$ is the prior probability of the activity $a_i$ and $P(e_k|a_i)$ is the conditional probability that the object $e_k$ is used in the activity $a_i$.

In the traditional approach, when an object is used, its infers the possibilities of the occurrences of different activities based on the corresponding conditional probabilities that are calculated beforehand (during the so called training phase) using a set of known activities along with the data related to the usage of different objects. Thus the activation of each object contributes to the accumulated probabilities of different activities, and the final decision is taken in the support of the activity that gains the maximum probability, among the all the activities under consideration, according to (1).

In a Naïve Bayes-based classifier for activity recognition, the model parameters are usually approximated using the relative frequencies of the object-usage in a training set. This is called likelihood estimation of the probabilities. If a given activity and the object-usage value never occur (unseen object) together in the training set then the estimated likelihood will be zero. This is problematic since it will wipe out all information in the other object-usage probabilities when they are multiplied. To prevent such estimation problem, the authors in [15] proposed a smoothing technique which is based on the Jelinek-Mercer (JM) [16] (also referred as the linear interpolation language model) smoothing technique used in Information Retrieval.

The supports of only the objects, which are in favor of an activity, are thus considered in such approaches. Such a method risks misclassifying an activity when more than one activity involve almost similar objects (and differ only at a very few objects).

### *C. Proposed Method*

The proposed method considers the contribution of all the objects whether used or not. It uses (2), which is basically a slightly modified form of (1).

$$\underset{i}{argmax} \quad P(a_i)\prod_{k=1}^{m} p_i^k \tag{2}$$

where $p_i^k$ denotes the support (or resistance) provided by the object $o_k$ in favor of (or against) the activity $a_i$, and is calculated using

$$p_i^k = \begin{cases} P(o_k|a_i) & \text{if } o_k \text{ is used in } x \\ 1 - P(o_k|a_i) & \text{otherwise} \end{cases} \tag{3}$$

In (1), a higher value of $p_i^k$ means more support for the activity $a_i$ while a lower value of it denotes less support. Since all the values are in the range (0, 1], a value of $p_i^k$ almost always (other than when it is 1) decreases the aggregated value in (2). The decrease is smaller (bigger) for higher (lower) values of $p_i^k$. Thus a smaller $p_i^k$ acts as an opposing force in (2). Equation (3) utilizes this fact. A high value of $P(o_k|a_i)$ denotes that the use of the object $o_k$ is very important to perform the activity $a_i$. When such an object is not used in an activity $x$, it infers that $x$ may not mean the activity $a_i$, and hence a small value $1 - P(o_k|a_i)$ is used to decrease the aggregated value. Similar explanation can be made when an object with lower conditional probability is not used. In such a case, $1 - P(o_k|a_i)$ becomes higher, and does not oppose the aggregated value much. Thus the use of a frequently used object in an activity provides more support for the activity while the not using a frequently used object in an activity makes much protest against voting for that activity. On the other hand, the support for as well as oppose against an activity provided by a non-frequently used object in that activity becomes smaller in

(3), as expected.

The proposed approach thus incorporates both the supports and the resistances provided by the sensory data coming from different object. And hence, it gives a very good accuracy other than the traditional approaches that only use the supporting values provided by the sensors.

## III. Experimental Results

To evaluate the performance of the proposed method in comparison to the traditional approaches, the well-known MITes [3], [4] benchmark datasets has been used. It provides two datasets namely subject1 and subject2. For each of the datasets, a 4-fold cross validation test has been applied. Each dataset has been randomly divided into four equal parts. At each pass of the cross validation, three of them have been used for training (i.e., calculating the conditional probabilities), and the other one has been used to validate the performances of the proposed as well as the traditional approach.

The accuracies yielded by the traditional as well as the proposed approach are presented in Fig. 1. Each value presented here is the averages of the accuracies in the corresponding four passes of a 4-fold cross validation experiment.

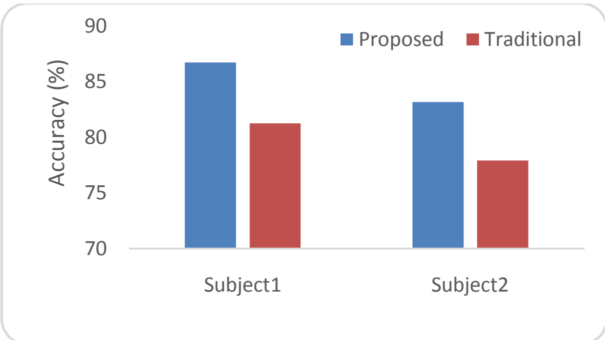


Fig. 1 Accuracies of the proposed and the traditional approaches

## IV. Conclusion

This paper proposes an activity recognition approach for human activity recognition. The proposed approach relies on the data provided by the sensors based on whether some objects are used or not. A use of an object contributes to the probability of the related activities while an absence of the usage of an object penalizes the activities which are usually done making use of the object. Thus the proposed approach reasonably aggregates the data from the sensors and can make a better classification than the traditional approach.

This paper, however, presents the proposed approach using the very much straightforward naïve Bayesian-based classification. The performance enhancement in the accuracy done by the proposed approach is promising. It may also be applied along with other classification schemes as well. Use of some other datasets to evaluate the performance may also help to more clearly show the performance of the proposed approach. These are left here as future works.

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