Smart Classifier Selection for Activity Recognition on Wearable Devices

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Abstract: Activity recognition is a key component of human-machine interaction applications. Information obtained from sensors in smart wearable devices is especially valuable, because these devices have become ubiquitous, and they record large amounts of data. Machine learning algorithms can then be used to process this data. However, wearable devices impose restrictions in terms of computation and energy resources, which need to be taken into account by a learning algorithm. We propose to use a real-time learning approach, which interactively determines the most effective set of modalities (or features) for classification, given the task at hand. Our algorithm optimizes sensor selection, in order to consume less power, while still maintaining good accuracy in classifying sequences of activities. Performance on a large, noisy dataset including four different sensing modalities shows that this is a promising approach.

1 INTRODUCTION

Recognizing everyday activities is an active area of research in machine learning and context-aware computing. Classical work for estimating user behavior in activity recognition is based on high dimensional and densely sampled video streams (Clarkson and Pentland, 1999). However, these approaches are intrusive and power-inefficient when monitoring in real-world conditions over a long period of time. For such situations, real-time sensory information obtained through smart wearable devices is preferable, because such devices have become ubiquitous. Many of these devices come equipped with sensors such as GPS, accelerometer, digital compass, gyroscope, barometer, WiFi and infrared, which can query the local environment and yield information about the user's activities. For example, mobile phone sensing can be used in personal health-care, safety and fitness, by monitoring and analysing the daily physical activities and body movement of a user.

Most existing work includes as many sensory modalities as possible to produce a large, complex feature vector, including low-level features like frequency content, or higher-level measures like number of objects detected by the proximity sensor (Choudhury et al., 2008; Mannini and Sabatini, 2010; Subramanya and Raj, 2006). Then, feature selection is needed to determine which of these features are useful for classification. The techniques of sensor selection can be broadly classified into two main categories (Zhang and Ji, 2005). The greedy search-based approach regards sensor selection as a heuristic search problem (Kalandros et al., 1999). The decision-theoretic approach regards sensor selection as a decision making problem (Castanon, 1997). However, both approaches suffer from combinatorial explosion. Moreover, if a real-time activity detection task runs on a smart phone, all the sensors are typically always on, and a lot of additional computing power is required by the heavy-duty feature extraction and feature selection tools. While these approaches work well, at the end all algorithms select a single feature vector (including features from all sensors) to classify every different type of activity, which often requires all the sensors to be engaged all the time. This is suboptimal from the point of view of energy and computation load on the device.

We propose a real-time activity recognition algorithm which actively selects a smaller subset of sensors that are the most informative, yet cost-effective, for each time frame. We use a greedy process to discover sets of sensor modalities that most influence each specific activity. These subsets of sensors are then used to build different models for the activities. We use these models to develop an algorithm that decides on-line which model is suitable for recognizing the activity in each given time frame. Our algorithm has the flavor of active learning (Settles, 2010), but instead of asking for labels on new data points, we

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start the recognition task with a small set of sensors and then interactively send queries for more features, as needed. In this way, we can afford to run the activity recognition engine on a low-powered device without sacrificing the accuracy. We present empirical results on real data, which illustrate the utility of this approach.

2 METHODOLOGY AND DATA

The data set used for the feature selection experiment was collected by Dieter Fox (Subramanya and Raj, 2006), using the Intel Mobile Sensing Platform (MSP (Choudhury et al., 2008) that contains several sensors, including 3-axis accelerometer, 3-axis gyroscope, visible light photo transistor, barometer, and humidity and ambient light sensors. Six participants wore the MSP units on a belt at the side of their hip and were asked to perform six different activities (walking, lingering, running, climbing upstairs, walking downstairs and riding a vehicle) over a period of three weeks. Ground truth was acquired through observers who marked the start and end points of the activities. The working data set was 50 hours of labelled data (excluding the beginning of each recording which was labelled as *unannotated*) and also some long sequences (over 1 minute) labelled as *unknown*. There were also some short unlabelled segments, which we smoothed out using a moving average filter. We computed the magnitude of the acceleration $\sqrt{x^2+y^2+z^2}$ based on components sampled at 512 Hz. We also used the gyroscope (sampled at 64Hz), barometric pressure (sampled at 7.1Hz) and visible light (sampled at 3Hz). These four measures were all up-sampled to 512Hz in order to obtain time series of equal length. To prevent overfitting to characteristics of the locations, we did not include the humidity and temperature sensors, as they could potentially mislead the classifier to report a false correlation between location and activities. For example, if a lot of *walking* data were collected under hot sun, the classifier would see temperature as a relevant feature to walking.

For the classification task, we used random forest (Breiman, 2001), a state-of-the-art ensemble classifier which also provides a certainty measure in the classification. The random forest algorithm builds many classification trees, where each tree votes for a class and the forest chooses the majority label. Assume we have N instances in the training set and there are M tests (based on the features) for each instance. In order to grow a tree, N instances are sampled at random with replacement and form the training set. At each node, $m \ll M$ tests are randomly chosen and the best one of these is determined. Each tree grows until all leaves are pure, i.e. no pruning is performed. A subset of the training set (normally about one-third of the N instances) are left out to be used as a validation set, to get a running estimate of the classification error as trees are added to the forest. The error on this out-of-bag (OOB) data gives an unbiased error estimate. This classifier is very efficient computationally during both training and predicting, while maintaining good accuracy.

We also need an probabilistic certainty measure, which should reflect how confident the classification is. We will use this quantity to manage the sensor selection procedure. When using random forests, for any given sample in the validation set, the classifier not only predicts a label, but also reports what proportion of the votes given by all trees matches the predicted label. We used this ratio as a certainty measure.

3 INITIAL EXPERIMENTS WITH SENSOR SELECTION

Table 1: Individual classifiers. The bold line in each section denotes the classifier with the highest accuracy.

No.	Feature Set	Accuracy
1	$\{Acc, Bar, Gyro, VisLight\}$	**86.16**
2	$\{Acc, Bar, Gyro\}$	75.16
3	$\{Acc, Bar, VisLight\}$	**86.50**
4	$\{Acc, Gyro, VisLight\}$	84.33
5	$\{Bar, Gyro, VisLight\}$	78.33
6	$\{Bar, Gyro\}$	54.00
7	$\{Acc, Gyro\}$	69.50
8	$\{Acc, Bar\}$	74.83
9	$\{Acc, VisLight\}$	**77.66**
10	$\{Bar, VisLight\}$	74.00
11	$\{Gyro, VisLight\}$	74.00
12	$\{Acc\}$	**48.16**

First, we wanted to verify the effect of different subsets of sensors on the accuracy of recognizing the six different activities. We began by examining all possible combinations of sensors on the entire data set. We treated each time sample as an instance and used raw sensor data as features for classification task. We performed cross-validation over users (leaving in turn each user's dataset aside as the test set and combining and randomizing all other datasets to use as training set) The accuracy of the classifiers for all 12 possible combination sets of four sensors[1]

[1]Single features except the accelerometer are excluded from the results due to poor performance.

is given in Table 1. From now on, instead of full sensor names, we use abbreviations *Acc*, *Bar*, *Gyro* and *VisLight* for accelerometer, barometric pressure, gyroscope and ambient visible light, respectively.

The overall results are competitive with prior activity recognition results that used complex feature sets, even though we used the raw sensory values. It is also clear that not all sensors are contributing equally to the performance. For example, comparing results from classifiers No.1 and No.3 in Table 1 clearly shows that data from the gyroscope did not provide useful information about this set of activities. Moreover, this sensor seems to lead to a similar or less improvement than the barometer sensor. So we decided to prune the gyroscope.

The contribution of each sensor varies among different activities. For example, accelerometer data is key in discriminating physical activities such as running and walking. However, the classifier using only accelerometer data (No.12) performs poorly while recognizing some activities like riding a vehicle or while distinguishing activities with similar dynamics (e.g. upstairs vs. downstairs). However, this classifier is the cheapest one in terms of energy consumption and it is reliable enough to be used as a default classifier for our active learner. There is smaller subset of sensors which models well this set of activities. Classifiers No.3 and No.9 achieved 86.5% and 77.66% accuracy rate, respectively, whereas the classifier No.1 (using all sensors) only obtained 86.16%. Hence, we identified subsets that can be used instead of the full set of sensors.

4 PROPOSED APPROACH FOR SENSOR SELECTION

In this section we introduce a real-time algorithm that optimally selects the best classifier for each time frame. The main idea is to start the activity recognition task by acquiring data just from the single most informative sensor and building a cheap classifier. The certainty measure provided by this classifier is then used to identify points in time when uncertainty is high, so using more sensors could be beneficial. Other classifiers can then be invoked. Figure 1 presents an overview of the information flow.

The algorithm begins by training a set of classifiers, each using a feature set selected in advance, based on application-specific criteria. The experiment in previous section is an example of how the best feature sets can be chosen, though one would not need to be so exhaustive. In general, the set of classifiers should contain at least one cheap classifier that can run all the time, and an expensive classifier with very good accuracy. Also, if there is a large number of sensor modalities, it is useful to have some classifiers that use different types of resources, not only for energy consumption, but also to ensure that the application is robust with respect to sensor failure, or unusually noisy readings.

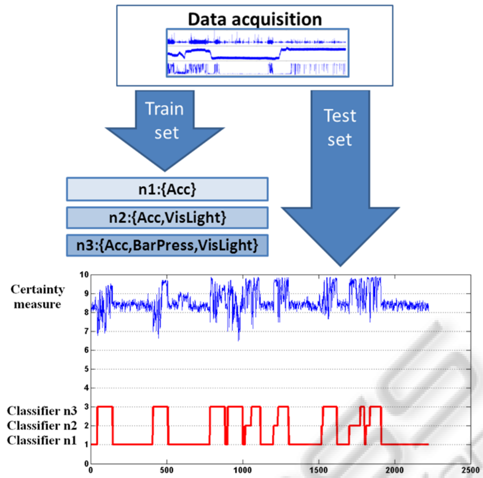
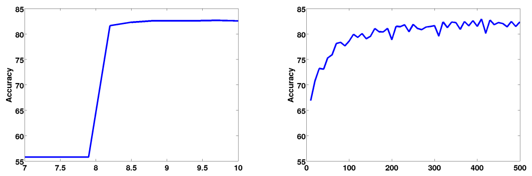


Figure 1: Overview of the algorithm.

When the training phase is over, the algorithm will have to process new time series. It starts by sliding a fixed-width window (of length w), with 10% overlap, over the data, in order to obtain data intervals. We would like to keep the length of these intervals as small as possible, in order to avoid mixtures of activities, but large enough to capture the essence of the activity. Each interval is initially labelled by the cheapest classifier. We compute the running average of the certainty measure over each frame, to indicate if the classifier is confident enough about the labelling decision or not. If the measure drops below a given threshold, the algorithm will query other sensors, and upgrade the classifier to a more complex one, which works with the new information.

The algorithm will switch back to a cheaper classifier as soon as its certainty measure rises above the threshold. To do this, the algorithm simultaneously computes and compares the confidence level of both classifiers at each time frame, and switches back when the threshold is exceeded again. Ideally, we want the algorithm to have smooth transitions between classifiers, so we also use a control parameter, which allows the algorithm to switch from one model to another only after δ frames.



(a) (b)

Figure 2: Influence of θ (left) and δ (right) on performance.

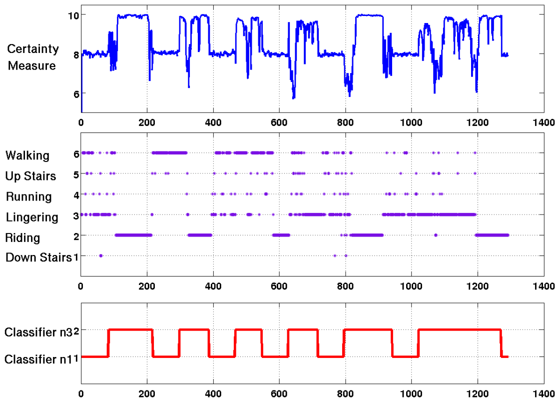


Figure 3: Algorithm performance on a segment of data. The top and middle figures show the the certainty measure of the classifier in use and the corresponding true activities at each time frame. The bottom figure shows the algorithm's decision of the best classifier to use.

5 RESULTS AND DISCUSSION

We evaluated the proposed algorithm on the data set and selected subsets from the experiment in Sec. 3. The number of classifiers used is $N = 3$, where the classifiers to be tried are $n_1 = \{Acc\}$, $n_2 = \{Acc, VisLight\}$ and $n_3 = \{Acc, Bar, VisLight\}$. Hence, the algorithm will first use only the accelerometer data for classification, then incorporate visible light, and in the worst case, barometric pressure as well. In both training and testing we used 10 trees in the forest

There are two parameters that were chosen empirically, and which influence the results:

- δ, the number of frames before switching to another classifier is allowed
- θ, the threshold for the certainty measure, which may depend on the overall accuracy rate

Figure 2 shows how δ and θ affect the overall accuracy of the system. One can see that performance is stable for a fairly large range of these parameters.

In practice, we found that switching between two classifiers, instead of three, yields better accuracy and smoother transitions. This happens because the algorithm does not stay with n_2 for long and tends to switch between n_1 and n_3. Figure 3 shows a run of the algorithm on a segment of data from one specific user, using classifiers trained on the other users' data.

Table 2: Comparison of recognition accuracy.

Algorithm	Accuracy	Proportion of time
Classifier n_1	48.16	100%
Classifier n_2	77.66	100%
Classifier n_3	86.50	100%
Active alg.(n_1, n_2, n_3)	71.78	9%,32%,59%
Active alg.(n_1, n_3)	80.14	35%,65%

Table 2 shows the classification results of the proposed algorithm and the baselines from the first experiment, as well as the proportion of the time the algorithm used each classifier. The overall accuracy of the active algorithm (combination of 2 classifiers) is just 6% lower than the best baseline(n_3) while consuming 35% less energy. This is significant savings for a low-powered device.

6 FINAL REMARKS

We presented an approach that can be used to select among classifiers with different features (and power consumption) in activity recognition tasks. the active-learning-style idea is to use a certainty measure in the result of the classification to decide if a more "expert" classifier should provide labels. However, no input from a user is required, as the algorithm is fully automatic. The empirical results show that our approach can successfully switch between complex and simple classifiers, on-line and in real time, yielding power savings without significant loss in accuracy. In future work, we aim to further explore the empirical and theoretical properties of this algorithm. We are also exploring the use of reinforcement learning, instead of active learning, for this problem. Reinforcement learning has the advantage of being able to incorporate and balance in a quantitative fashion power savings and accuracy changes.

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