Opportunistic Human Activity Recognition: a study on Opportunity dataset

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ABSTRACT
A lot of research has been done for human activity recognition. But most of it uses a static and immutable set of sensors known beforehand. This approach does not work when applied to a ubiquitous or mobile system, since we cannot know which sensors will be available in the users' surroundings. This is why we consider here an opportunistic approach, where each sensor individually trained are able to bring its own knowledge. Inspired by the Opportunity project, we propose to evaluate both the effectiveness of using a Random Forest (RF) classifier to train the sensors and the robustness of fusing the results using a weighted majority vote. We found that RF gave better and more robust results than the other classifiers formally tested by Opportunity.

CCS Concepts
• **Computing methodologies~Machine learning** • *Computer systems organization~Reconfigurable computing*

Keywords
Activity recognition; Multi-sensors; Body worn sensors; Wearable computing; Opportunistic sensing.

1. INTRODUCTION
Progress in integration of different types of sensors in objects and in wearable devices, such as bracelets, phones, etc. has created a new specific research field in human actions recognition. Traditional human activity recognition approaches rely on mapping sensor signals to activity classes. The main drawback of these approaches is that the inputs and outputs are predefined at design stage of the system, with a specific precise and fixed set of sensors (body-worn sensors or sensors in the environment) coupled with the methods used to recognize activities.

However, the availability of different worn sensors in everyday life (sensors included inside wearable objects) and the increasing addition of embedded sensors in physical objects in the environment (ambient sensors) requires defining and designing a new approach for recognizing activities. This approach must exploit all the available sensors, which can be heterogeneous, and can spontaneously appear (or disappear) in the surrounding environment or on the user. This emergence of new resources participating in the activity recognition process reverses the traditional and static approach where all the possible information is known at the design stage of the system. The need to develop a dynamic adaptation of opportunistic sensor configurations [3] has been studied by the Opportunity European project. They defined a framework to enable the opportunistic use of sensors to achieve human activity recognition.

In this paper we study the results obtained from the Opportunity dataset using different classification approaches [1] and we propose to introduce the use of Random Forest (RF) that was not evaluated within this approach. We will show the advantages of this method and evaluate the performance resulting from an opportunistic strategy and compare the results to other learning methods.

2. RELATED WORKS
Once the input data is recorded from all the sensors, the recognition process is first based on sliding windows, overlapping from one position to the next, in order to gather some temporal consistency. In these windows, the raw signal is transformed into a feature vector that will be given to the classifier. There are many different supervised or unsupervised classifiers: Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Nearest Cluster classifier (NCC), Classification trees, Neural Networks, Random Forest (RF), etc.

From the different datasets that have been created for human activity recognition from sensors data [4], the Opportunity project proposes a rich dataset collecting information about realistic daily life activities in a sensor rich environment: "*72 sensors of 10 modalities in 15 wireless and wired networked sensor systems in the environment, in objects and on the body*" [5]. This dataset, acquired from 12 subjects while performing morning activities, can be used to recognize different families of activities: locomotion and gestures. It has been used in an activity recognition challenge to compare different methods of recognizing these families using body-worn sensors. In [1], Chavarriaga et al. obtained better results with 1-NN and 3-NN methods compared to NCC, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). Nevertheless, these results were obtained by training a fixed sensor set.

Amongst all the possible approaches for human activity recognition, those based on multi-classifiers seem to be very promising. One example, of these, is the highly acclaimed from the work of Shotton et al. on Microsoft Kinect [6]. Similarly RF has been used for sensor data with very promising results [2]. RFs are based on two important notions: Bagging (each tree of the forest is built with a randomly chosen subset of the data) and Random feature selection (the node of each tree is selected from a subset of the features characterizing the data).

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Our approach is based on RF, like in [2]. But unlike those studies, we do not only consider all the sensors simultaneously for the learning phase. We put ourselves in a totally ubiquitous process (the sensors aren't known beforehand, they can appear and disappear, leading to dynamic configurations) by training each sensor independently with a RF and then combining the decisions from each RF (i.e. each sensor) in a specific manner.

3. EXPERIMENTS

We selected a subset of all the available sensors in the Opportunity dataset, in order to match it with the one the Opportunity team chose to perform their sensor by sensor activity recognition [3]. We considered all the sensors from the same body area as one group. The groups we obtained are: RKN (Right Knee), SHOE, LUA (Left Upper Arm), LLA (Left Lower Arm), RUA (Right Upper Arm), RLA (Right Lower Arm) and BACK.

Within the recognizable activities we chose to carry out our tests on the modes of Locomotion: Stand, Walk, Sit, Lie and a null class that represents the transition states that cannot be categorized in any of the four former classes.

3.1 Learning

To embrace the opportunistic activity recognition introduced by the Opportunity project, we trained seven sensor groups separately. A classic learning process was applied, split into three different and distinct steps: signal processing, features extraction and training the classifier. We used the data from subject 1, 2 and 3, using ADL1,2,3 and Drill to train and ADL 4 and 5 to test.

We first applied a spline interpolation to handle missing values (4.10% of data missing in the learning set and 2.10% in the test set). We used the min, the max, the entropy, the mean and the variance features and modified the sliding window, with a window size of 60 instants and sliding step of 15 instants, which gave better results.

Finally, we trained each one of our sensor groups with the features extracted. We chose to compare three classifiers: 1-NN and 3-NN (since they are the ones that obtained the best results in the Opportunity Challenge [1]), and a RF classifier. As shown in Table 1, RF outperformed the K-NN classifiers for five out of the six sensor groups, and when the K-NN was better, it was only by a very small amount.

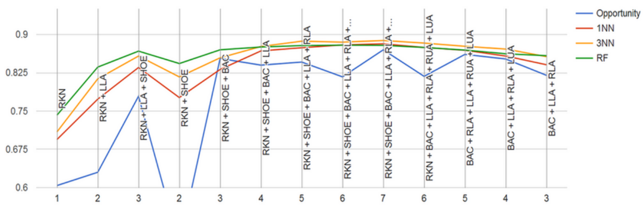
Table 1. Individual sensor training results

	RKN	SHOE	LUA	LLA	RUE	RLA	BACK
Opportunity	0.604	0.698	**0.858**	0.719	0.769	0.709	0.761
1NN	0.694	0.708	0.834	0.792	0.811	0.785	0.811
3NN	0.709	0.719	0.835	0.795	0.814	**0.798**	0.813
RF	**0.742**	**0.774**	0.835	**0.896**	**0.820**	0.797	**0.855**

3.2 Fusion

Once each sensor has learned individually, we simulated an opportunistic approach considering only specific sensor combinations at a given time. We applied the thirteen different combinations used by Opportunity in their tests [3]. In order to recognize the activity for each sensor combination, we needed to combine the decisions given by each sensors' classifiers. Since we were simulating an opportunistic approach we could not use fusion techniques that required training. This is because combinations are not static and can (and will certainly) change at runtime in a ubiquitous system. Consequently we opted for the same non trainable combiner as Opportunity: a majority vote. We tried out four different ways to perform this majority vote accounting for: (1) the winning class from each classifier, (2) the scores given to all classes by each classifier, (3) weighting the scores by the overall classifier's accuracy, (4) weighting the scores by the classifier's accuracy on the corresponding class.

Figure 3. Accuracy comparison for sensors configurations



The fourth approach provided by far the best results. As show in Figure 1, we can see that when the sensors are trained with the Random Forest classifier, we have very stable results, given any combination. Furthermore, when the number of sensors in the combination gets too high (more than 3 here), 3-NN, that had worse results than RF on individual sensors, of obtains slightly better results than the latter.

4. CONCLUSION AND FUTURE WORK

In this paper we studied the results presented by the Opportunity project on the different machine learning approaches to perform activity recognition. We put ourselves in a similar setting to Opportunity, training the sensors individually and then combining their decisions according to which ones are available. We compared the results obtained using our Random Forest approach to the best results from the Opportunity benchmark. A multi-classifier approach enables better raw results and a better accuracy stability when combining the classifiers.

In our future work, we will study the possibility combining results from different kinds of classifiers and fusion techniques. Indeed, by training each sensor independently, we can train them with specific classifiers to obtain better individual and combination results.

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