Fraunhofer PORTUGAL

RESEARCH CENTER FOR ASSISTIVE INFORMATION AND COMMUNICATION SOLUTIONS

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1 *Some of the activities that belong to the dataset: turn on and off the light; open and close the door; open and close the window; type the keyboard; mouse moving and clicking; answer the telephone; clapping; brush teeth; bite the nails and open and close the faucet.*

HDHAM – BRINGING HIGHER DEFINITION TO HUMAN ACTIVITY MONITORING

Expand the range of activities possible to detect through smartphone and wearable sensors

Motivation

Human activities comprise all actions present in our daily routine. In diverse areas, recognition of human activities has been sought due to the information it can provide about the user's state and better assist his needs. Today, smartphones are ubiquitous. These devices possess multiple accurate sensors which makes them prime candidates for monitoring human activities in a cheap and unobtrusive way.

The inherent complexity of Human behavior tends to promote well-defined motions which are repeated on everyday basis. In this sense, several areas of the biomedical field could benefit from the recognition of detailed activities. In health care, an earlier detection of movement's changes by tracking movements based on contextual information may contribute for a positive and earlier detection of stress agents that may affect the patient's health. Also, it can evaluate the user's lifestyle and help on incorporating healthy habits. For hospitals and families that have elderly at their care, this tool can be a way of monitoring their health at distance without the need of having the elder to interact with the device.

There are several applications with smartphone and wearable sensors, able to correctly discriminate between physical activities (walking, running). Previous studies can successfully recognize daily activities, like cooking or cleaning, but need restrains like location or time of the day. Besides, studies that embrace discrimination of finer and short time activities, such as opening a door or answer the phone are scarce.

Proposed solution

In this work, a framework for detailed human activities recognition is developed, recurring to smartphone sensors signals and machine learning algorithms. Since the goal was to capture finer activities, which mainly depend on hand movement, the sensors were placed on the dominant wrist.

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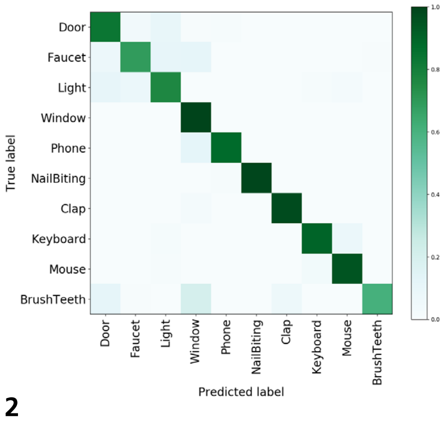

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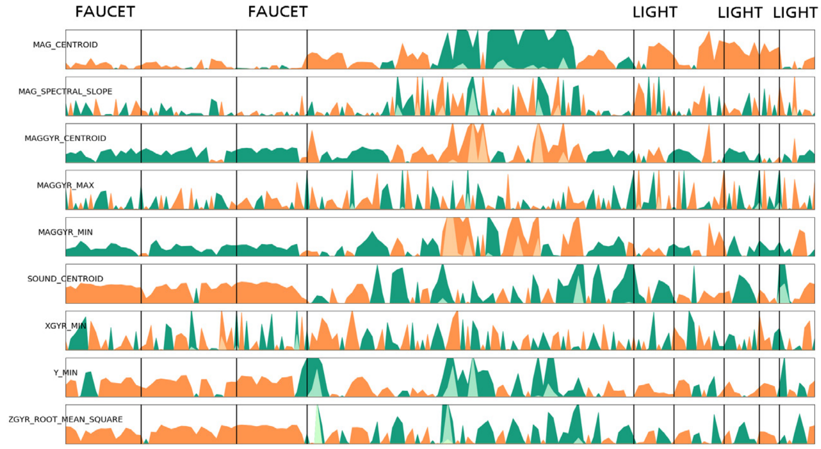

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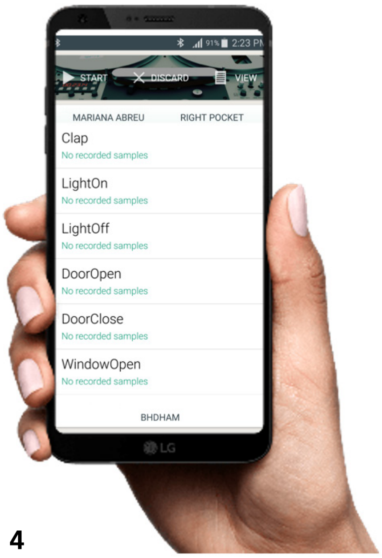

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4 *Pandlets Recorder app for the data acquisition protocol.*

The signals from accelerometer, gyroscope, magnetometer and microphone are divided in very small windows (0.25 second), from where a set of features is extracted. Each individual activity will therefore be represented by a group of sequenced windows that provide the time evolution for each feature.

Training Phase: The chosen classifier was Hidden Markov Models (HMM) due to its ability to interpret time sequences as a sequence of states. In this method, each activity has its own model. The number of states for each model is chosen recurring to a clustering algorithm applied to the training group.

Testing Phase: Each activity sequence from the test group is given to all models to calculate which model is the most probable one of generating that activity sequence. The most probable model's activity is chosen as the prediction.

Ongoing and Future Work

The first challenge was to be able to use this method on a specific finer dataset, containing the activities described on Fig. 1. The difficulties arise in the discrimination between opening and closing doors or windows or turn on and off the light, since the movements are very similar. For that reason, both activities such as open door and close door were considered the same activity 'Door'. Since this was a controlled case, the beginning and end of the activity sequence was known, and an accuracy of 86% was reached (Fig. 2).

Afterwards, a continuous acquisition was tested. This data simulates a real-life routine, where other unknown activities are present, such as walking. On Fig. 3, a horizon plot shows the features' evolution over the data stream. Here the activity monitoring is more difficult when compared to the first case, since it is unclear when the activity starts and when it finishes. An activity sequence can be well distinguished when its size is known, but parts of it could also be similar to other activities which hinders the correct classification. While type the keyboard and clap are activities well recognized, Light and Door show more confusion. However, models' probabilities show an increase when there is a similar movement to its activity. For these reasons, new methods of discrimination are currently being explored to produce solid results.

This solution is built to work not only with isolated activities, but also with continuous data containing several activities, since its future purpose would be a real time application. In this case, new activities could be added. However, increasing the number of activities being monitored could be too intrusive and a reasonable balance must be considered. Nevertheless, this solution can detect activities very short in time, without the need of video cameras. It can be applied not only for healthcare solutions, but also to enhance the precision of indoor location systems and the monitoring of complex activities in smart homes.

In the future, this algorithm will be tested with a public activity dataset, to have some degree of comparison to the current literature.

2 *Normalized confusion matrix for the dataset.*

3 *Horizon plot with the features selected for continuous acquisition.*