Demo: Hybrid Data-Driven and Context-Aware Activity Recognition with Mobile Devices

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ABSTRACT

We have designed and implemented a real-time hybrid activity recognition system which combines supervised learning on inertial sensor data from mobile devices and context-aware reasoning. We demonstrate how the context surrounding the user, combined with common knowledge about the relationship between this context and human activities, can significantly increase the ability to discriminate among activities when machine learning over inertial sensors has clear difficulties.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Computing methodologies → Knowledge representation and reasoning**; *Machine learning*.

KEYWORDS

activity recognition, hybrid reasoning, context-awareness

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1 THE PROBLEM

Activity recognition with mobile devices has been an active research area for several years [2]. While the majority of approaches showed to be effective on classifying a few physical activities (e.g., walking, running, biking, etc.), their effectiveness on more complex and context-dependent activities is still unclear. Moreover, discriminating those activities which have similar motion patterns is problematic even when we use both smartphone and smartwatch on-board sensors, like in our setting. For instance, activities like *walking* and *taking the stairs*, or *standing still* and *standing on a bus* are easily confused by purely statistical methods based on inertial sensors. The context which surrounds the user is valuable information to mitigate these issues [3]: a rich description of the user's context (e.g., semantic location, weather, traffic condition, speed, etc.) has the potential to discriminate among activities that exhibit similar inertial signal patterns. Directly using context-data as additional features in the machine learning process is not as effective as expected. Indeed, on one side it is unlikely that a labeled training set includes each activity performed in all the possible context conditions, and on the other side the connection between low level context data and possible activities typically requires reasoning with domain knowledge. Another aspect to consider is that not every context source may be continuously available at the same time. Using context as features may lead to missing values in the feature vectors which may negatively impact the recognition rate. Another aspect is whether it becomes necessary to include additional context data while the system is running. In the case of using context as features, there is the need for re-training the model from scratch with new labeled data.

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2 OUR METHOD

The architecture of our method is depicted in Figure 1. We address the above mentioned issues in two steps. The first step is called Statistical Prediction Module. This module pre-processes raw inertial sensor data from the user's smartphone and smartwatch in order to enable a supervised classifier to associate to each feature vector a probability distribution over the possible activities.

The second step of our algorithm is called Semantic Refinement Module. This module applies knowledge-based reasoning to context data in order to exclude from the statistical prediction those activities which are not consistent with the current context. In particular, context data needs to be pre-processed and translated into high-level facts, which are mapped to an ontology that models activities and contexts. Knowledge-based reasoning is then applied to evaluate which activities are *context-consistent*.

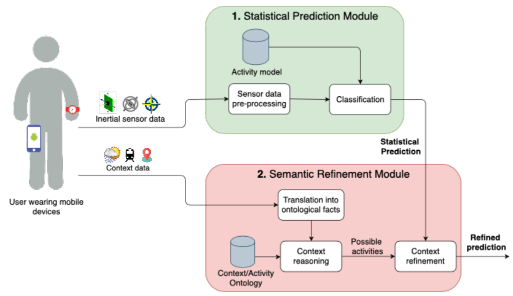

Figure 1: The overall architecture of our approach

3 THE DEMONSTRATION

We demonstrate our system by first asking the user to keep a smartphone in a pocket and a smartwatch on the wrist. The devices run custom applications which transmit inertial and context sensor data to a server, which executes our method in real-time. A web dashboard shows every step of our approach while it is recognizing activities (see Figure 2).

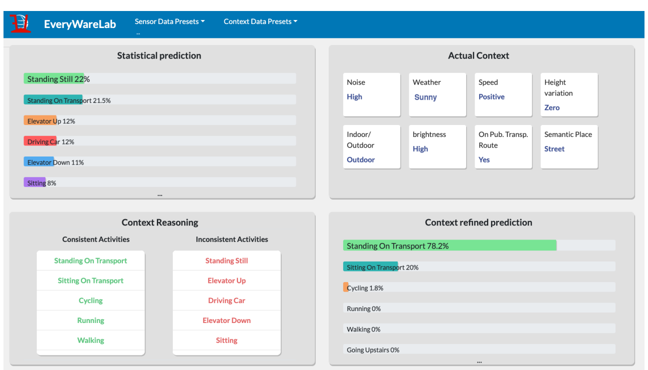

Figure 2: Our dashboard

The dashboard shows:

- In the top-left box, the output of the machine learning module
- In the top-right box, the pre-processed context-data
- In the bottom-left box, the list of consistent and inconsistent activities as derived by context reasoning. By clicking on an activity it is possible to see the ontological definition.
- In the bottom-right box, the context-refined probability distribution of activities

We will ask the user to perform simple activities. Considering the constraints at the conference venue, we will simulate different contexts and inertial data patterns to show our method in action. However, our system implements real data acquisition and processing which will be demonstrated during the demo. Moreover, the participants may experiment with different context and inertial data by using the presets menus from the dashboard.

Example 3.1. At the conference venue, among many examples, we will also simulate that the user is standing on a bus using inertial sensor data obtained from a real dataset of activities. In this case, the supervised classifier shows uncertainty between *Standing Still* and *Standing on Transport* activities. This is consistent with theoretical results obtained on real datasets [1]. Among the several context sources, we simulate GPS positions and we use a well-known Web Service to derive as high level context data that the user is following a public transportation route and that he is moving with a certain speed. According to the ontology, *Standing still* is not context-consistent since it should be a static activity. Hence, the system derives as most likely context-refined activity *Standing on Transport*.

4 CONCLUSION AND FUTURE WORK

Our demo shows the impact of context-reasoning for human activity recognition. We are currently conducting experiments which show that context reasoning is particularly useful when combined with semi-supervised classifiers, thus allowing to significantly reduce the amount of training data and the number of questions triggered by active learning methods [1]. While we are currently evaluating our method on a dataset we collected with volunteers, we will also consider different well-known datasets, like the one proposed in [4].

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