An Approach for Context-based Reasoning in Ambient Intelligence

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Thesis Summary

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This paper presents a summary of the doctoral dissertation of the author, which addresses the task of context-based reasoning in ambient intelligence.

Povzetek: Prispevek predstavlja povzetek doktorske disertacije avtorja, ki obravnava kontekstno sklepanje v ambientalni inteligenci.

1 Introduction

Ambient intelligence (AmI) is a scientific field that refers to environments consisting of smart devices (sensors and actuators) that can sense and respond to the presence of people [1] . The availability of small, wearable, low-cost, power-efficient sensors, combined with advanced signal processing and information extraction, is driving the revolution in AmI domain. This revolution has enabled novel approaches and technologies for accurate measurements in the area of healthcare, enhanced sports and fitness training, and life-style monitoring.

Early AmI systems included a single type of sensors that has made it possible to develop the first proof-of-concept applications. As the field has matured, these systems have gained additional sensors, resulting in the development of advanced and more accurate multi-sensor techniques and applications. However, combining multiple sources of information from multiple sensors is a challenging task. The first issue is that each sensor has its own technical configuration (for example, the data sampling rate) and requires different data-processing techniques in order to first align the different sensor data, and later to extract useful information. The second issue is that even if the multi-source data is aligned, it can be challenging to find an intelligent way to combine this multi-source information in order to reason about the user or the environment. While several approaches for combining multiple sources of information and knowledge have been developed (such as Kalman filters, ensemble learning, and co-training), these approaches have not been specialized for AmI tasks.

The doctoral dissertation [2] addresses the problem of combining multiple sources of information extracted from sensor data by proposing a novel context-based approach called CoReAmI (Context-based Reasoning in Ambient Intelligence). In particular, CoReAmI creates a multi-view perspective, in which each source of information is used as a context separately.

2 The CoReAmI approach

The CoReAmI approach is shown in Figure 1. At the top are the sensors $\{s_1, \dots, s_m\}$, which provide the raw data. The multiple sensors data is usually represented by multivariate time-series with mixed sampling rates, which are input to CoReAmI. The CoReAmI consists of three phases: (A) context extraction, (B) context modeling and (C) context aggregation.

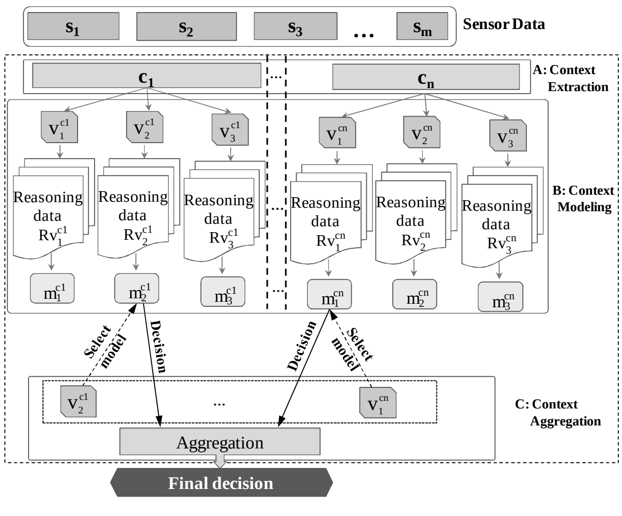

Figure 1. The CoReAmI Approach.

In the first phase (A) the raw sensor data are acquired and the multiple contexts are extracted $\{c_1, \dots, c_n\}$ using different types of techniques: data-preprocessing techniques, data synchronization, data segmentation, etc. In CoReAmI context represents information about the user which is extracted from the sensor data, e.g., user's activity extracted from wearable accelerometer data. This phase is similar to the feature extraction phase in machine learning (ML). Moreover, the contexts in CoReAmI are features that represent context information. Therefore, each context has values (v^c), which can be numerical or categorical (e.g., "sitting" for the "activity" context).

The second phase B, contains the main logic of the CoReAmI approach. In this phase the context modeling about the problem (activity, fall, energy expenditure, etc.) is performed using the contexts defined in the previous phase. First the context-based partitioning of the dataset is performed, i.e., the dataset is partitioned according to each context and its values. Therefore, for each context value a reasoning model (m^c) is constructed using its reasoning data − the reasoning data is a subset of the whole dataset that has that particular context value (Rv^c). For example, the reasoning data for the "sitting" model will be constructed using the data instances that contain the value "sitting" for the activity context. This way, the approach considers multiple views on the data using each of the features as a context.

In the final phase C, for a given testing data instance, the decisions from each context individually are aggregated and the final decision is provided. In this phase different aggregation techniques can be used, e.g., majority voting, plurality voting, averaging, choosing the median and similar.

The CoReAmI is a general approach for context-based reasoning and can be adapted to a range of tasks in AmI by adapting each of the phases to the particular task.

3 Case studies

The feasibility of the CoReAmI approach was shown in three AmI domains that have emerged as essential building blocks in AmI: activity recognition, energy-expenditure estimation, and fall detection.

The first problem domain, Activity Recognition (AR), can generally be defined as a process of recognizing activities through the analysis of sensor data. In recent years AR gained a lot of research attention, because it provides one of the basic information about a person that is monitored by an AmI system. In our study, we studied the state-of-the-art approaches in AR and observed that it is almost impossible to distinguish standing from sitting activity using a single accelerometer placed on the torso. However, by adapting and applying the CoReAmI approach, we have managed to significantly improve the recognition of these two activities, achieving 86% accuracy − which is for 24 percentage points better than conventional ML approach [4] .

Human Energy-Expenditure (EE) estimation is the process of calculating the amount of expended energy while performing everyday activities. It directly reflects the level of physical activity which makes it important for sports training, weight control, management of metabolic disorders (e.g., diabetes), and other health goals. We adapted and applied the CoReAmI approach to estimate the human energy expenditure using multiple sensor data (accelerometer, heart rate, breath rate, etc.). The CoReAmI significantly improved the estimation performance compared to conventional ML approaches and approaches that are based on single context (such as the activity of the user). Additionally, the CoReAmI provided better energy expenditure estimations than the BodyMedia device, which is a state-of-the-art commercial device for energy expenditure estimation [5] .

The third problem domain on which we applied the CoReAmI approach is the fall detection (FD). FD is a really important application in AmI because falls are among the most critical health problems for the elderly. We adapted and applied the CoReAmI approach to detect human falls. CoReAmI significantly improved the detection performance compared to conventional approaches, such as: threshold-based approaches and approaches based only on ML [6] .

4 Conclusion

This paper summarized the dissertation [2] and presented the main idea and findings of the same. The proposed CoReAmI approach was adapted and tested on three problem domains. The results show that CoReAmI significantly outperforms the competing approaches in each of the domains. This is mainly due to the fact that, by extracting multiple sources of information and combining them by using each source of information as a context, a multi-view perspective is created, which leads to better performance than with conventional approaches.

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