Distributed Collaborative Reasoning for HAR in Smart Homes

Extended Abstract

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ABSTRACT

Distributed Human Activity Recognition (D-HAR) is an active research issue for pervasive computing that aims to identify human activities in smart homes. This paper proposes a fully distributed multi-agent reasoning approach where agents, with diverse classifiers, observe sensor data, make local predictions and collaborate to identify current activities. Experimental tests on Aruba dataset indicate an enhancement in terms of accuracy and F-measure metrics compared either to a centralized approach or a distributed approach from the literature.

KEYWORDS

Distributed activity recognition; multi-agent system; smart homes.

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1 INTRODUCTION

Most HAR approaches are centralized and integrate a recognition model already built and identify activities as the environment changes. Nevertheless, connections between sensors and the centralized system are not always guaranteed. Moreover, handling the huge incoming sensor data deployed in the smart home, decreases the system performance. Thus, a fully decentralized approach seems to be a necessity for distributing both sensor data and reasoning process. Due to the dynamic and open nature of smart homes, the following main challenges must be considered when dealing with distributed HAR: *C1: scalability*: how to deal with fast and huge data arrival from deployed sensors? *C2: data freshness*: how to avoid outdated data? *C3: accuracy*: how to increase the activity recognition accuracy? *C4: identification*: how to identify current activities based on past person behaviors *C5: heterogeneity*: how to handle the diversity of sensor data? *C6: uncertainty*: how to trust data coming from other sensors ?. The literature review revealed few approaches [1, 2, 7–9, 13] that have considered distributed reasoning for HAR in smart homes. However, these few works only deal with some challenges discussed above. In this work, we consider the six aforementioned challenges as requirements to achieve and propose the Distributed Collaborative Reasoning (DCR) approach for HAR.

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2 RELATED WORKS

Few recent studies have focused on distributed HAR approaches. They can be grouped according to their architecture: client-server [2, 4], hierarchical distributed [1, 7] and totally distributed [8–11, 13]. All these approaches propose a distributed HAR where sensor data are processed in a bottom-up manner to detect activities. However, they present some limitations: a)- all approaches (except [2] that uses a multi-agent system) do not use an appropriate distributed system. They use wireless sensor networks which are resource constraints and are limited in data transformation [6]; b)- all entities (agents or nodes) adopt the same type of reasoning model; c)- in [8], they present a communication with all nodes; d)- Uncertainty is not addressed in these approaches. Entities trust all data provided from the others when collaborating.

In this regard, we propose the DCR approach having the following benefits: *P1*: a fully distribution of the reasoning process; *P2*: A bottom-up approach to guarantee the data freshness; *P3* A dynamic set of agents that collaborate; *P4*: Agents are enriched with classifiers as activity models; *P5*: Depending on the nature of sensor data, agents may hold different types of classifiers; *P6*: A trust degree is assigned to recognized activities.

3 THE DCR APPROACH

Actually, DCR models a smart home as a multi-agent system $MAS = \{A_{l_1}, A_{l_2}, ..., A_{l_n}\}$ where each agent A_{l_i} is assigned to a location l_i (kitchen, bedroom, etc.). Agents are autonomous and have the same functionalities. Each agent $A_{l_i} \in MAS$ is defined as a tuple $A_{l_i} = (id_{A_{l_i}}, clf_{A_{l_i}}, ACT_{A_{l_i}}, ACQ_{A_{l_i}})$ where:

$-$ $id_{A_{l_i}}$: is the identifier of the agent A_{l_i} in the location l_i.

$-$ $clf_{A_{l_i}}$: is a classifier based on reasoning mechanism of the agent A_{l_i}. We distinguish different classifiers such as Random Forest (RF), Decision Tree (DT) and Extra-Trees (ExT), based on forward chaining mechanism and Bayes Naive (BN) which is based on probabilistic reasoning.

$-$ $ACT_{A_{l_i}} = \{< a_{1_{(l_i)}}, d_{1_{(l_i)}} >, ..., < a_{m_{(l_i)}}, d_{m_{(l_i)}} >\}$: is a list of couples of $m_{(l_i)}$ recognized activities by the classifier $clf_{A_{l_i}}$ with their trust degrees $d_{1_{(l_i)}}, d_{2_{(l_i)}}, ..., d_{m_{(l_i)}}$. These ones express the truth degree of an activity. The set of activities is fixed when building the classifier $clf_{A_{l_i}}$ and the trust degree is computed using the F1-score metric [12] for each recognized activity in l_i.

$-$ $ACQ_{A_{l_i}}$: is the acquaintance list of the agent A_{l_i}. It is dynamically adjusted and contains agents who can recognize the local predicted activity by A_{l_i}.

Each agent A_{l_i} has a basic life cycle which includes the following steps to recognize activities:

– Given as input a feature vector FV, A_{l_i} (called the starter agent S) interrogates its $clf_{A_{l_i}}$ to get the predicted activity $pa_{A_{l_i}}$.
– After that, the agent S determines the trust degree d_{pa} related to the activity $pa_{A_{l_i}}$ from $ACT_{A_{l_i}}$ list.
– According to d_{pa} value, we distinguish two cases:

- If $pa_{A_{l_i}}$ is well recognized with a degree $d_{pa} >= \delta$ (δ is a detection threshold chosen by the designer), the agent S will generate as output the activity $pa_{A_{l_i}}$.
- If $pa_{A_{l_i}}$ is recognized with a degree $d_{pa} < \delta$, the agent S will collaborate with other agents and proceeds by the following steps:
  - Building its acquaintance list $ACQ_{A_{l_i}}$. This one contains agents who can recognize $pa_{A_{l_i}}$.
  - Sending its input to some agents in $ACQ_{A_{l_i}}$. These ones are selected if their trust degree of the corresponding activity is higher than d_{pa}.
  - Receiving foreign activity predictions with their trust degrees from selected agents.
  - Applying conflict resolution strategies when the local prediction and foreign predictions are in a disagreement.
  - Generating as an output the final activity which can be different from $pa_{A_{l_i}}$.

Conflict resolution strategies: two aggregation strategies are used by the starter agent S to resolve conflicts as follows:
1)–The *maximum trust degree* strategy (max-trust): the starter agent chooses the most confident activity which means the one having the higher mean of trust degrees.
2)–The *most frequent* strategy (max-freq.): the starter agent considers activity frequency. Thus, it chooses the most frequent activity.

4 SIMULATION AND EVALUATION

4.1 Preprocessing of Aruba dataset

We used the Aruba dataset from CASAS smart homes [3]. Performed activities for 220 days are: Bed_to_Toilet (id 1), Eating (id 2), Enter_Home (id 3), Housekeeping (id 4), Leave_Home (id 5), Meal_Preparation (id 6), Relax (id 7), Resperate (id 8), Sleeping (id 9), Wash_Dishes (id 10), Work (id 11) and Other (id 12). The purpose of Aruba dataset preprocessing is to prepare data for performing the DCR approach. It involves four main steps (we used results of the two first steps provided by [14]):
Segmentation step. In [14], authors used the sensor-based windowing technique to deal with streaming sensor data. Each window contains an equal number of events which is fixed to 10.
Feature extraction step. Each window can be transformed into a FV. In [14], authors used the *baseline method* as a feature extraction method [5]. Thus, a collection of FV and their activities become the training data on which the classifiers of each agent are built.
Adding location feature step. We distinguish 10 locations: livingroom, kitchen, dining, bedroom 1, bedroom 2, bathroom 1, bathroom 2, exit, corridor and office. FV contains the occurrence number of each triggered sensor within the window. These triggered sensors belong to different locations in the smart home. The final location of the FV is the location of the triggered sensors having the maximum occurrence number.

Table 1. DCR approach vs other approaches

Agents	Central.	CASE System	W-DCR	DCR		
				max-trust	max-freq.	UB
A_l	-	63.52%	76.04%	76.38%	76.4%	76.97%
	-	63.46%	75.43%	75.38%	75.61%	76.37%
A_d	-	51.54%	65.81%	67.25%	67.44%	70.60%
	-	51.32%	64.24%	62.62%	64.13%	68.25%
A_k	-	52.17%	58.81%	50.41%	51.45%	83.17%
	-	52.5%	58.97%	49.77%	50.88%	83.16%
A_o	-	53.51%	62.76%	62.68%	63.19%	76.52%
	-	54.61%	63.16%	54.38%	63.43%	74.08%
A_c	-	75.67%	84.13%	85.21%	85.24%	86.89%
	-	75.29%	80.76%	79.71%	80.3%	82.67%
A_{bed1}	-	49.82	65.81%	65.16%	67.01%	77.97%
	-	51.22%	65.75%	58.37%	64.7%	76.04%
A_{bed2}	-	85.72%	91.99%	92.57%	92.52%	92.77%
	-	85.51%	91.18%	91.25%	91.35%	91.60%
A_{bath1}	-	78.18%	80.10%	77.78%	83.53%	86.36%
	-	76.79%	76.48%	75.69%	78.36%	83.03%
A_{bath2}	-	90.92%	92.34%	93.39%	93.99%	94.07%
	-	91.02%	91.71%	92.31%	92.55%	92.66%
A_e	-	57.4%	73.86%	73.17%	74.24%	76.97%
	-	57.25%	72.34%	68.52%	72.35%	74.98%
Global	72.94%	65.84	75.16%	74.4%	75.5%	82.23%
	71.80%	65.89%	74.0%	70.8%	73.36%	80.28%

Creating sub datasets per location step. Adding *location* feature in the vector aims to split the Aruba dataset into different sub datasets according to the *location* feature. Thus, each sub dataset corresponds to a specific location, contains all related FVs and then can be assigned to an agent in that location.

4.2 Experimental evaluation

We have to initialize agents with their $clf_{A_{l_i}}$ and their $ACT_{A_{l_i}}$.
Building $clf_{A_{l_i}}$: The RF classifier presents the best accuracy and also for the F-measure for all sub datasets Therefore, all agents will adopt an activity model built upon the RF classifier.
Building $ACT_{A_{l_i}}$: is a set of recognized activities by the classifier and their trust degrees. The latter corresponds to the F1-score measure for each activity. We can cite as an example the activities list of the agent *kitchen* A_k: ACT_{A_k} = {(2, 19.62%), (3, 100.0%), (4, 25.2%), (5, 11.11%), (6, 74.6%), (7, 64.37%), (9, 81.58%), (10, 23.56%), (11, 0.0%), (12, 68.78%)}

After MAS initialization step, DCR can be launched. It is performed with 10 folds cross-validation. The threshold δ is chosen at 80%. DCR is evaluated with accuracy (first line) and F-measure (second line) metrics of each agent's sub dataset in MAS (Table 1).

DCR outperforms the centralized approach and the CASE system [2] in terms of metrics. It slightly improves the W-DCR approach (it is a degraded version of DCR without considering agent collaboration). DCR (UB) represents the maximum values computed (upper bound) of metrics that an aggregation method can achieve. Therefore, a new aggregation strategy may lead to results more closer to DCR (UB).

5 CONCLUSION AND FUTURE WORKS

This paper proposes DCR as a novel Distributed Collaborative Reasoning approach to recognize human activities from a continuous sensor sequence in smart homes. Our DCR approach achieves discussed requirements. In our ongoing work, we plan to propose a new aggregation strategy based on negotiation (argumentation theory) to help the starter agent to take the best decision. Another future work is to apply a dynamic learning over time by considering feedbacks resulted from collaborations between learning agents.

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