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Modelling of distributed activity recognition in the home environment

(Invited Paper)

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***Abstract*—Distributed ambient and on-body sensor systems can provide a suitable basis for recognizing complex human activities in daily life. Moreover, distributed activity recognition systems have high prospects for handling processing and communication loads more effectively than centralized solutions. A key challenge is to construct distributed activity recognition systems that make efficient use of the resources available for the recognition task, considering scalability and dynamic system reconfiguration.**

In this work, we present an approach to distributed activity recognition by introducing an activity-event-detector (AED) concept. We show formally how to construct and use AED for distributed recognition systems based on directed acyclic graphs. We illustrate essential properties for system scalability and efficiency using AED graphs. Results from a home monitoring study targeted at monitoring daily life activities are presented to illustrate the AED-based model regarding applicability and reconfiguration.

I. Introduction

Monitoring activities and user context using ubiquitous systems is often considered to be a base functionality, which can enable advanced service for novel assistive tools in smart environments. Famous examples of approaches to create such aware environments include the the Place Lab [1] and others, targeted at investigating activity monitoring solutions [2]. A distributed, parallel monitoring using several sensors can provide fine-grained information on the user's activity in these settings.

Generally, extracting activity and contextual information in smart environments essentially benefits from distributed monitoring and information fusion using ambient and worn sensors. These sensors are often battery-powered and thus, minimizing their energy consumption is vital to ensure acceptable system lifetime. As opposed to sending continuous data streams, energy can often be saved when performing local processing and only communicating event-type information on recognized activities when needed [3], [4]. Besides energy saving, reduced communication bandwidth moreover eases joint use of one wireless frequency band. However, due to the potential diversity of human activities and the number of available objects, a distributed recognition system can imply complex information flows and large number of nodes. Nevertheless, particular sensing and activity detection nodes may not be required or available at all times. Consequently, effective energy saving should incorporate knowledge on the actual need for a detector node to be present and when it is safe to turn off.

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Similarly, nodes may not be able to distinguish certain activities as they occur in real life, while the entire system may well identify them using the distributed approach. As an example, assume that a cooking pot is being used and that the pot could detect movement events, such as being picked up and placed down. While this pot could register these events by measuring and recognizing patterns of an attached inertial sensor, the pot's information does not reveal whether it is being cleaned or used for cooking. The latter would provide essential structural information regarding the performed activity sequences. Fusion and sequence matching among events reported from multiple distributed detectors can be used to discriminate more complex activity sequences, referred to as activity composites [4]. Our previous works showed that indeed performance and energy efficiency can be gained in a distributed settings, by operating sensor nodes selectively [3]. Nevertheless, it remains challenging to describe relations between activities, events derived from them, and distributed detector nodes.

In this present work, we introduce a graph-based modelling approach for describing activity-event-detector (AED) structures in distributed activity recognition systems. Our approach is based on directed acyclic graphs, which lend themselves well to denote dependencies between activities that can be observed, events that can be detected, and physical detector nodes used to report these events. Among others, AED graphs allow us to denote benefits of reconfiguration in a distributed system, as we demonstrate in this work. In summary, the following contributions are made:

1) We introduce the formalism to derive AED-graphs and detail specific constrains in the graph topology. With AED-graphs, we show how reconfiguration situations can be handled.
2) We present an evaluation of the AED-graph approach in modelling observational data from a home activity monitoring study. The evaluation targeted daily activities in a home kitchen environment.

A. Activity-event-detector (AED) concept

Activities are often captured in a hierarchical recognition stack to manage activity and behavior complexity. At its lowest layer, a stack would process raw sensor data to identify *atomic activities*, which are considered basic, non-dividable activity units in the considered recognition stack. Examples include "picking up a book" and "maneuvering a pot". Higher layers may subsequently be used to agglomerate atomic activities into more complex activity sequences (composites), representing workflow expressions. It is important to note that representing

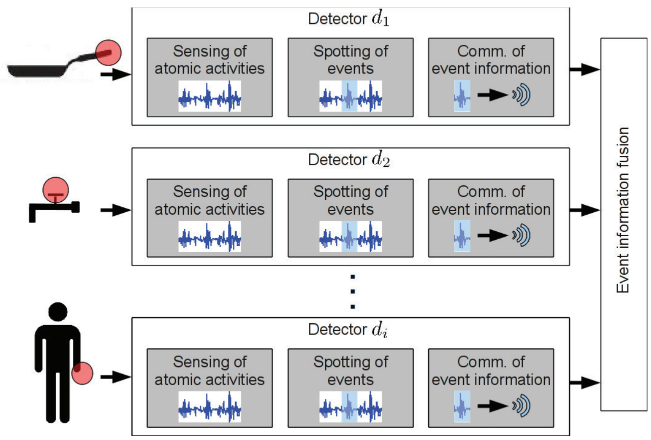

Fig. 1. Concept of the activity-event-detector (AED) distributed activity recognition approach. Each detector in a distributed recognition system performs local data acquisition, atomic activity spotting, and communicates event-type information to other network nodes.

and recognizing atomic activities deviates fundamentally from algorithms used to recognize activity at higher layers.

The AED recognition approach is shown in Figure 1 for an example of three distributed detectors. In the AED concept, a set of distributed sensing and detection nodes (for simplicity in this paper we refer to *detectors*) are considered, composed of the following functionalities:

- **Sensing of atomic activities.** Each detector performs sensing of one or more modalities to capture contextual data related to non-dividable units of user activity. The particular set of atomic activities is not constrained. Often one atomic activity is observed by more than one detector and one or more sensor modalities.
- **Spotting of events.** A detector searches and identifies pattern *events* in acquired sensor data, corresponding to the atomic activities. Several atomic activities may map to one event, eventually reported by a detector. As an example of this function, consider the cooking pot case described above. The AED concept does not require particular pattern properties to denote events, and work equally for simple state changes and temporal patterns in sensor data.
- **Communication of event information.** Once events are spotted by a detector, communication to other nodes in the distributed system is initiated for further processing. The AED concept does not impose constraints on the network topology, i.e. whether a centralized or distributed system is considered.

In the AED concept, detected events are communicated among the distributed detector nodes such that they can be further processed, e.g. in a event fusion scheme [4]. However, the AED concept does not constrain system topology to centralized or distributed schemes. In this present work, we focus on the modelling of AEDs regarding the mappings between atomic activities, events, and detectors.

II. Related works

Various hierarchical abstraction techniques have been considered to capture complex human activities. These approaches differ in granularity of abstractions and recognition goals. For example, Kawanaka et al. [5] used a hierarchy of interacting hidden Markov models to represent sequences of activities. Reconfiguration of sensor networks was not specifically addressed in these works. Moreover, these works did not consider the distribution problem, where mapping of activities and events for effective recognition and efficient communication are essential.

This present work relates to the hierarchy abstraction approaches, as further abstractions can be added on top of the events described here. Several relevant event fusion techniques had been investigated in our previous work [4].

Using location information as a results' filter allows designers to address the complexity problem in distributed activity recognition. Naya et al. [6] used an infrared location estimation system to mask location-dependent activities. Osmani et al. [7] use a concept where sensor nodes join a zone if they can contribute with events to the inference engine executed for this zone. Temporal relations between subsequent activities can be used as well to rule out impossible sequences of activities, as shown e.g. in [8].

At the network level, redundancy between sensor nodes was exploited to turn off unneeded sensor nodes. Ghasemzadeh et al. [9] provided bounds for selecting the smallest number of sensor nodes while maintaining service quality.

III. AED-graph based modelling

In this section we describe the AED concept and graph-based modelling approach.

A. AED architecture formalism

The catalog of atomic activities $\mathcal{A}$ is represented by $a_k \in \mathcal{A}$ set members, where $a_x \cap a_y = \emptyset, \forall\ x \neq y$ and $1 \leq x, y \leq |A|$. For distributed detectors, atomic activities may yield different signal patterns. Conversely, for a particular detector, several atomic activities may need to be represented by one event, if their signal patterns are similar. As an example, consider the cooking pot situation for discerning usage from cleaning, as described in Sec. I. While the pot could distinguish between atomic activities for being picking up and being placed down, the object itself could not make out whether it is used for cooking. A synchronous complementary information, e.g. regarding stove usage could disambiguate the situation. Consequently, in a distributed architecture the atomic activities of this example could be discerned, although not from individual detectors as the pot.

To represent these relations, we map atomic activities to events of detectors $d_i \in \mathcal{D}$. All detectors in a system deliver events $e_{i,k} \in \mathcal{E}$, which can be interpreted as local observations of a performed atomic activity k. It is important to note that $e_{x,k} \cap e_{y,k} = \emptyset \forall\ x \neq y$ where $x, y \in \mathcal{N}$. For simplicity in this paper, we enumerate all events and refer to e_j if the relations to a particular detector is implicit. The set of all disjunct events processed by detector i forms the set $\mathcal{E}_i$ and that of all events in an AED system is consequently denoted by $\mathcal{E}$.

B. AED digraphs

In the AED scheme, each event e_j represents a set of one or more atomic activities a_k that are locally observed and have similar signal patterns. This relationship can be represented by directed biparate graphs, such that $\mathcal{A} \mapsto \mathcal{E}$. In other words, $\mathcal{E}$ dominates $\mathcal{A}$, while no edges point to activities, thus $(\mathcal{E}, \mathcal{A}) = \emptyset$. Similarly, the relations between events and detectors can be modelled using the biparate digraph approach, where $\mathcal{E} \mapsto \mathcal{D}$ and $(\mathcal{D}, \mathcal{E}) = \emptyset$. Neither graphs ($AE$, ED) may have cycles or loops.

Corresponding to the strict directedness, the in- and out-neighbors of any detector d_i are:

$$N^{-}\{d_i\} \quad = \mathcal{E}_i,\ \mathcal{E}_i \subseteq \mathcal{E},\ \forall i \in \mathcal{N} \tag{1}$$
$$N^{+}\{d_i\} \quad = \emptyset,\ \forall i \in \mathcal{N}. \tag{2}$$

Similarly, the directedness implies for events e_j:

$$N^{-}\{e_j\} \quad = \mathcal{A}_x,\ \mathcal{A}_x \subseteq \mathcal{A},\ \forall x \in \mathcal{N} \tag{3}$$
$$N^{+}\{e_j\} \quad = \{d_y\},\ \forall x \in \mathcal{N}. \tag{4}$$

Using the notions of in- and out-degree (denoted by $\Omega^{-}(\cdot)$ and $\Omega^{+}(\cdot)$ respectively), the graph reveals the number of edges linking events with atomic activities and detectors. The degrees allow us to estimate the recognition complexity of the model, as the degree correspond to the number of atomic activities pooled in an event and the number of events pooled in a detector. The following basic constraints of an AED digraph can be described using the degree notation:

$$\Omega^{-}\{a_k\} = 0, \quad \Omega^{+}\{a_k\} \geq 1,\ \forall k \geq 1 \tag{5}$$
$$\Omega^{-}\{e_j\} \geq 1, \quad \Omega^{+}\{e_j\} = 1,\ \forall j \geq 1 \tag{6}$$
$$\Omega^{-}\{d_i\} \geq 1, \quad \Omega^{+}\{d_i\} = 0,\ \forall i \geq 1. \tag{7}$$

Furthermore, the graph notation allows us to describe subgraphs. We assume that the complete distributed activity recognition system can be denoted by $(G, L(G))$ where G represents all vertices of the system and $L(G)$ all edges corresponding to:

$$L(G) = \bigcup_k a_k + \bigcup_j e_j + \bigcup_i d_i \tag{8}$$

A subgraph is defined as having all end-vertices in a region $H \subseteq G$, thus:

$$L(H) \subseteq L(G). \tag{9}$$

Using the subgraph feature, we can formulate the principles of reconfiguration as described below.

C. Practical properties of AED digraphs

In the following, we consider an example to illustrate the AED digraph properties. Table I lists a potential set of atomic activities for the example activity sequence "heating water". As the list shows, several atomic activities involve multiple objects that may hold detectors with contact switches (for cupboard doors and stove manipulation), and detectors with inertial sensors (e.g., to spot picking up, maneuvering, and placing the pot).

TABLE I
EXAMPLE ACTIVITY SEQUENCE "HEATING WATER" DESCRIBED USING THE AED SCHEME. DETECTORS COULD INCLUDE CONTACT SWITCHES AND INERTIAL SENSORS TO REALIZE THE RECOGNITION STEP.

$\mathcal{A}$	**Description**	**Detectors (event-detector edges)**
a_1	Take out pot from cupboard (implies cupboard door manipulation).	Cupboard (e_1, d_1), pot (e_2, d_2)
a_2	Pour water into pot.	Pot (e_3, d_2), water tap (e_5, d_3)
a_3	Place pot on stove.	Pot (e_4, d_2), stove (e_6, d_4)
a_4	Turn on stove.	Stove (e_7, d_4)

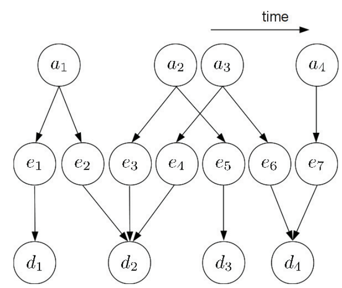

Fig. 2. Example AED digraph for the activity sequence "heating water". Elements a_k correspond to atomic activities, e_j to events recognized, and d_i to detectors embedded in objects or infrastructure. See Tab. I and main text for details.

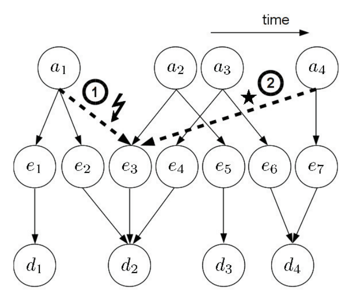

Fig. 3. Illustration of key properties of AED digraphs for the example activity sequence "heating water". The edges marked with ⊙ refer to special conditions: (1) marks an impossible edge, (2) marks a feasible edge that could provide additional information. See main text for details.

Figure 2 shows the full AED digraph for atomic activities, events, and detectors corresponding to the activity sequence and edges listed in Tab. I. Following the notations described above, we can derive in-degrees of the system for detectors assuming equal edge weights, $\mu(\cdot) = 1$:

$$\Omega^{-}\{d_1\} \quad = \mu(e_1, d_1) = 1 \tag{10}$$
$$\Omega^{-}\{d_2\} \quad = \mu(e_2, d_2) + \mu(e_3, d_2) + \mu(e_4, d_2) = 3 \tag{11}$$
$$\Omega^{-}\{d_3\} \quad = \mu(e_5, d_3) = 1 \tag{12}$$
$$\Omega^{-}\{d_4\} \quad = \mu(e_6, d_4) + \mu(e_7, d_4) = 2. \tag{13}$$

Two key properties can be identified from the AED architecture and digraph: firstly, an additional constraint of the AED scheme is that an atomic activity, e.g. a_1 in Figure 3 may not be linked to element e_3 since an edge (a_1, e_2) already exists and both, e_2 and e_3 are connected to d_2. Practically, this means that the signal patterns represented by e_2 (picking the pot) and e_3 (handling the pot) are expected to be sufficiently different, such that they represent different event information for d_2 (detector attached to the pot).

Nevertheless, the atomic activity a_4 may well link to e_3 in addition to the edge (a_4, e_7), as e_3 contributes to d_2. In this situation, e_3 should expect a sufficiently similar sensor signal for a_4, as for a_2.

D. Modelling of reconfigurations

In distributed activity recognition systems, it is often helpful to reconfigure the system to a current situation. This adaptation could include duty-cycling sensors or changing detector pattern models depending on the recognition needs.

In the example described above, only a subset of atomic activities $\mathcal{A}_{Loc} \subseteq \mathcal{A}$ are applicable if the location within the kitchen is known. Figure 4 shows an example for activities related to the location "stove". Note that the events have been reordered compared to Figs. 2 and 3. In this illustration, a subgraph H becomes apparent. The detector in-degrees of H are reduced to $\Omega^{-}\{d_2\} = 1$ and $\Omega^{-}\{d_4\} = 2$. Clearly, d_1 and d_3 are not required for activity recognition in this situation. Thus, given that appropriate location triggers are available, the AED graph can be substantially reduced.

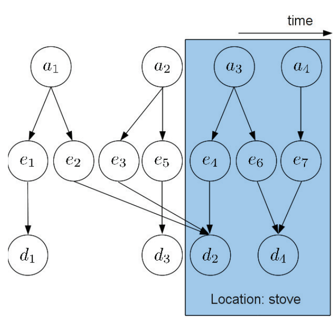

Fig. 4. Illustration of the AED digraph reconfiguration for the activity sequence "heating water". A reconfiguration for the location "stove" is shown. Note that the events have been reordered compared to Figs. 2 and 3.

IV. Application evaluation

We applied the AED graph-based modelling in a distributed activity recognition scenario for food preparation in a kitchen. The analyzes results presented below are based on an earlier study [3], from which we selected the kitchen setting.

The activities performed in the kitchen involved the following instructions: heating water, adding soup, cook soup, slice bread, use computer, prepare table, eat, clean up dishes. In total, the set amounted to $|\mathcal{A}| = 44$ atomic activities that were recored from detectors with inertial sensors attached to right and left wrists of the user, scissors, knife, and stirring spoon. PIR and light sensor modalities were used to capture location and object-related activity, including dishes, utensils, pots, food cupboards and drawers. From the computer, mouse and keyboard usage was registered. In total, $|\mathcal{D}| = 11$ detectors was considered.

Objects used in this evaluation typically provided 1 to 3 events, such as picking up, using, and placing down an object, hence $\Omega^{-}_{Tools}\{\cdot\} \leq 3$. In contrast, $\Omega^{-}_{Body}\{\cdot\}$ for wrists was larger, as the user was involved in all activities. When considering a location-specific reconfiguration, e.g. for the location stove, $\mathcal{A}_{Loc}$ was $\sim$10% of its initial size. In this setting, the activities were constrained to heating water, adding soup, cook soup.

V. Conclusions

This work showed that AED graphs can be used to model distributed activity recognition systems. Our work specifically focused on the mapping of atomic activities, events, and detectors. The AED approach considers a tight coupling of sensing and information compression using activity pattern spotting. AED graphs can be considered independent from the underlying sensing, recognition, and communication functions, and aims at providing scalable descriptions in distributed systems.

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