A collaborative situation-aware scheme based on an emergent paradigm for mobile resource recommenders

Giovanna Castellano · Mario G. C. A. Cimino · Anna Maria Fanelli · Beatrice Lazzerini · Francesco Marcelloni · Maria Alessandra Torsello

Abstract Today, handheld devices can accommodate a large amount of different resources. Thus, a considerable effort is often required to mobile users in order to search for the resources suitable for the specific circumstance. Further, this effort rarely brings to a satisfactory result. To ease this work, resource recommenders have been proposed in the last years. Typically, the recommendation is based on recognizing the current situations of the users and suggesting them the appropriate resources for those situations. The recognition task is performed by exploiting contextual information and preferably without using any explicit input from the user. To this aim, we propose to adopt a collaborative scheme based on an emergent paradigm. The underlying idea is that simple individual actions can lead to an emergent collective behavior that represents an implicit form of contextual information. We show how this behavior can be extracted by using a multi-agent scheme, where agents do not directly communicate amongst themselves, but rather through the environment. The multi-agent scheme is structured into three levels of information processing. The first level is based on a stigmergic paradigm, in which marking agents leave marks in the environment in correspondence to the position of the user. The accumulation of such marks enables the second level, a fuzzy information granulation process, in which relevant events can emerge and are captured by means of event agents. Finally, in the third level, a fuzzy inference process, managed by situation agents, deduces the user situations from the underlying events. The proposed scheme is evaluated on a set of representative real scenarios related to meeting events. In all the scenarios, the collaborative situation-aware scheme promptly recognizes the correct situations, except for one case, thus proving its effectiveness.

Keywords Collaborative context awareness · Multi-agent system · Emergent paradigm · Context awareness · Fuzzy information granule · Mobile resource recommender

G. Castellano · A. M. Fanelli · M. A. Torsello
Computer Science Department, University of Bari
"A. Moro", Bari, Italy
e-mail: castellano@di.uniba.it

A. M. Fanelli
e-mail: fanelli@di.uniba.it

M. A. Torsello
e-mail: torsello@di.uniba.it

M. G. C. A. Cimino (✉) · B. Lazzerini · F. Marcelloni
Department of Information Engineering,
University of Pisa, Pisa, Italy
e-mail: m.cimino@iet.unipi.it

B. Lazzerini
e-mail: b.lazzerini@iet.unipi.it

F. Marcelloni
e-mail: f.marcelloni@iet.unipi.it

1 Introduction

The number of available resources for mobile devices is continually growing. Today, mobile marketplaces host thousands of applications for all kinds of user needs. Further, the capability of storing applications and documents in mobile devices is rapidly increasing, thus expanding the personal information space of a mobile user in terms of dimensionality and variety. For an average user, finding the desired resource can be very time consuming.

Mobile Recommendation is a new paradigm that sensibly increases the usability of mobile systems, by proactively providing personalized and focused access (Ricci

2011). A *resource recommender* is a software application which aims to recommend resources when the user needs them. The front-end of a recommender can be thought of as an intelligent bookmark toolbar, whose items are automatically updated. In general, recommenders aim to suggest the most relevant items to the user, usually based either on information about the item (*content-based approach*) (Terveen and Hill 2001) or on the relationships of the user with other users *(collaborative filtering approach)* (Resnick et al. 1994; Sarwar et al. 2001), or on both these information sources (Burke 2002). Only recently, the recommendation process has been performed by using situation-awareness. *Situation-awareness* is a computing paradigm in which applications can sense and explore the situation of a user in order to identify her/his demand at a certain time (Terveen and Hill 2001; Ciaramella et al. 2010a). The fundamental vehicle to determine the situation of a user is the *context*, i.e., suitable circumstance information captured from a physical or logical environment. This form of autonomous perception implies reasoning, decision, adaptation, and other features of cognitive systems (Vernon et al. 2007), as well as dealing with an intrinsic uncertainty in data (Ciaramella et al. 2010a; De Maio et al. 2011).

A variety of recommender systems proposed in literature embed some kind of contextual information in order to determine useful recommendations (Adomavicius and Tuzhilin 2010). One of the first papers that have acknowledged the importance of context in recommendation is (Herlocker and Konstan 2001). Here task-specific recommendations have been proposed. A task is identified by a set of sample items related to the task itself. For instance, if the user provides a hammer as example item in a shopping recommender, the system can recommend buying nails. Such associations can be easily identified automatically by the system, via association rules. The increasing need to integrate context-awareness into identity management within the field of ubiquitous computing has been strongly argued in (Arabo et al. 2009, 2011). In this context, environment contextual information may be properly exploited in order to ensure users having reliable, fast and secure access to resources and services in a dynamic and adaptive manner without asking for explicit user intervention. In (Jiang et al. 2011) the authors proposed ContextRank, a method to recommend travel locations by exploiting different context information of photos such as textual tags, geotags, visual information and user similarity. Such context information is employed to predict the user preferences for a location and, finally, a ranking algorithm is used to combine the different preference predictions to provide final recommendation to the user. In (Naganuma and Kurakake 2005) a task-oriented service navigation system that supports users in finding appropriate services by browsing rich task ontology has been proposed. Such ontology contains a variety of real-world structured tasks and related services. In (Luther et al. 2008) the navigation system has been extended by taking the user situation into account, in order to suggest tasks and services actively, without the need for initial input from the user. A system that exploits situation awareness to provide user with the desired information and services has been proposed in (Weißenberg 2006). In this approach, a situation describes a user demand that occurs at a certain time and is formed by a sequence of contexts defined as logical expressions. Both situation inference and service selection are based on ontologies for inferring, first, a set of situations and, then, a set of services which may be relevant in such situations. The user may be in none, one or many situations in parallel, but no ranking is given to help the user to choose the most suitable situation, or to list the recommended services in an appropriate order. Recently, in (Petry et al. 2008) the authors have proposed ICARE, a recommendation system that returns references to experts in requested domains using contextual information. More specifically, the system improves its recommendations by using the contexts of both the user and the expert, privileging those experts who better fit current needs of the user. Examples of contextual information employed are expert's availability and approachability, social distance, etc. Contextual rules are defined to set appropriate weights in order to decide, given the context of the user, which contextual information should be favored. Hence, the recommendations are different for each user, according to her/his context.

The main weakness of all the afore-mentioned context-aware systems is that they do not consider uncertainty that characterize contextual data in order to infer the current situation of the user. Fuzzy logic has proved to be a promising approach to manage the natural uncertainty that affects contextual data. In (Cena et al. 2006) fuzzy logic has been employed in a context-aware tourism recommender. The system exploits personalization rules to suggest services (e.g., restaurants, places to visit, etc.) tailored to the profile and context of the user. User profile is generated from: (1) explicit user data, such as age, gender, general interests, etc.; (2) data inferred via fuzzy rules based on domain knowledge, such as propensity to spend, specific interests, etc.; (3) user current needs and wishes, by observing the sequence of user interactions with the system, such as printed pages, on-line booking, etc. Based on the interests, stored in his/her profile, and position of the user, the system computes an overall score for each service and recommends services in an order depending on the score. Thus, the context is limited mainly to the location of the user, which acts as a filter to recommend services. Moreover, proactivity of the recommendations is not supported, but only envisioned as future work. A context-aware music recommendation system that employs fuzzy Bayesian networks and utility theory has been proposed in (Park et al. 2006). In particular, a fuzzy system is exploited to pre-process contextual data from various sensors and the Internet, in order to have quantized inputs for the Bayesian network. Based on these inputs, the network can infer the user context and assign a probability. Finally, recommendations are proposed depending on a final score, which is computed taking the inferred context and user preferences into account. In this approach, no semantic aspects of the contextual information are considered. Moreover, the inference process is entirely based on the Bayesian network, resulting in a not easily accessible mechanism for average users.

In some recent papers (Ciaramella et al. 2010a, b), we have proposed a Situation-Aware Resource Recommender (SARR) for mobile users. SARR is based on a cognitivist approach (Vernon et al. 2007), i.e., it is a representational system based on symbolic information processing. More specifically, in SARR user data collected from mobile devices are communicated to a server-side system that exploits a semantic web engine to infer one or more current situations. If multiple possible situations are inferred, a fuzzy engine computes a certainty degree for each situation, taking the intrinsic vagueness of some conditions of the semantic rules into account. Finally, the specific current situation together with contextual information is used to recommend services. Fig. 1 shows the two macro processes of SARR, that represent the core modules of any situation aware resource recommender. They are the *Situation Recognition* (SR) process and the *Resource Recommendation* (RR) process. According to the user's current situation provided by the SR, the RR proposes specific resources that are also implicitly parameterized in terms of the context. Thus, the RR process can be considered as a resource classifier which is modulated by both the user context and situation, whereas the SR process is a pattern recognizer which generates the user's current situation as a higher level concept, starting from context sources. While the RR process is defined according to the specific application domain, the SR process can be modeled as a general purpose element for any situation aware application. For this reason, in this work we focus on the SR process, which is independent on the specific application. The interested reader is referred to (Ciaramella et al. 2010a) for further details on the RR process.

In SARR, the SR process is modeled by a rule-based paradigm, via fuzzy and crisp logic. Indeed, context sources include vague information, such as location and time of meetings. The structure of rules has been designed according to a upper situation ontology which is domain-independent. The calendar of the user acts as a reference for the parameterization of such fuzzy rules for each user.

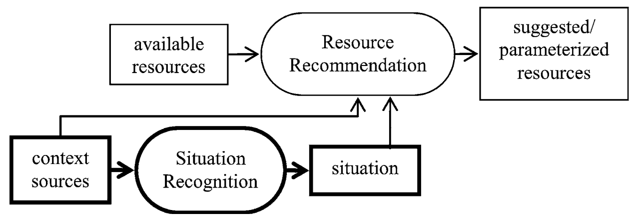


Fig. 1 Macro processes of a situation-aware resource recommender

Hence, the current situation of the user is inferred via (i) the *dynamic instantiation* of abstract fuzzy rules over concrete location and time references coming from the agenda of the user, and (ii) the *execution* of such rules with the current location and time as values for base variables. Thanks to fuzzy logic, SARR is able to detect events even if they occur with shifted time and/or location. This can be easily achieved by implementing linguistic variables over fuzzy sets with a sufficient support to cover a broad spatial/temporal region. However, the higher the uncertainty in fuzzy linguistic variables is, the lower the responsiveness of the system is. To cope with this problem, in (Ciaramella et al. 2010b) context history is employed as a training set for a genetic algorithm which aims to adapt fuzzy sets to the actual behavior and habits of the user, increasing the accuracy and responsiveness of the situation assessment. Nevertheless, the use of a calendar to make a reference schedule is an *explicit* input required to the user. On the contrary, context information should be collected in terms of *implicit* input, coming from changes in the environment. Further, the calendar is a common tool for business and not for personal use, and hence it cannot be guaranteed in many real world scenarios.

To avoid using explicit inputs as context sources in SARR, in this paper we propose an approach based on an *emergent* paradigm (Vernon et al. 2007) for detecting events and therefore recognizing situations. Emergent paradigms are based on the principle of self-organization (Heylighen and Gershenson 2003), which means that a functional structure appears and keeps spontaneously. The control needed to achieve results is distributed over all participating entities. In the literature, the mechanisms used to organize these types of systems and the collective behavior that emerges from them has become also known as swarm intelligence: a loosely structured collection of interacting entities (Barron 2005). The fact that simple individual behaviors can lead to a complex emergent behavior has been known for decades. More recently, it has been noted that this type of emergent collective behavior is a desirable property in pervasive computing (Barron 2005; Cimino and Marcelloni 2011). Biological paradigms have inspired a lot of research, not only in robotics and communication networks, but also in pattern detection and classification (Barron 2005). For example, in (Rao 2010) a swarming agent architecture for distributed patterns detection and classification is presented, providing robustness, scalability and fast convergence. In (Brueckner and Van Dyke Parunak 2005) an agent-based distributed data mining technique is proposed for smart space and ambient intelligence application areas. In general, pervasive computing environments can easily generate enough activity to enable a stigmergic mechanism (Park et al. 2006). Indeed, people and smart devices roam around the environment, interact with their neighborhood and produce some change on it, satisfying the minimal requirements set by Holland et al. to support stigmergy (Holland and Melhuish 1999).

In this paper we present how this form of collaborative situation awareness can be implemented by focusing on an important class of events, namely social events (e.g., meetings, conferences, festivals, entertainment, and so on). We discuss a collaborative multi-agent scheme for the detection of such events, structured into three levels of information processing. The first level is managed by a stigmergic paradigm, in which marking agents leave marks in the environment in correspondence to the position of the user. The accumulation of such marks enables the second level, a fuzzy information granulation process, in which relevant events can emerge and are captured by means of event agents. Finally, in the third level, a fuzzy inference process, managed by situation agents, deduces user situations from the underlying events. The combined use of the emergent paradigm and fuzzy logic in our context-aware scheme offers several advantages for the development of recommender systems. First of all, the self-organizing mechanisms underlying the stigmergic paradigm avoid the requirement of explicit input to the user in order to collect contextual information. In our approach context information emerges implicitly in the form of changes in the environment. This alleviates the user from inputting any kind of information, making the mobile device application more friendly and easy to use. Using the mechanisms of fuzzy granulation and fuzzy rule inference, the framework detects the flow of situations without requiring any information nor action from the user. Moreover, unlike other approaches that require pre-processing steps (e.g., clustering) to extract and synthesize a context model from the available contextual information, in our approach the context model is created on the fly, with no necessity of further elaboration, and situations are recognized in a very simple way, without requiring time-consuming processes. This lightweight feature is necessary for enabling a situation recognition framework to operate dynamically and adaptively in mobile devices having limited resources (i.e. low computing power and small memory). Also, using fuzzy logic, the proposed scheme can take into account the uncertainty that affects contextual data, thus detecting situations correctly even if they occur with shifted time and/or location. Another advantage coming from the use of fuzzy logic is the possibility to detect many situations simultaneously for a user by providing grades of certainty for each situation. As a consequence, different resources can be recommended to the user at the same time, using a ranking based on different certainty degrees. In this way, our scheme enables the development of proactive recommender systems, that can recommend resources as soon as a situation is detected, unlike other approaches that usually wait for the requests of the users in order to provide the desired recommendations.

The proposed scheme is tested on three representative real scenarios, considering four different types of situation. For each scenario, the scheme has proved to be able to recognize the four types of situation just approximately at the instants when these situations occur.

The paper is organized as follows: Sect. 2 describes the ontological and architectural views of the proposed collaborative situation-aware scheme. Section 3 introduces the three levels of information processing. Section 4 shows some results obtained on the three different scenarios. Finally, Sect. 5 draws some conclusions.

2 The proposed approach: ontological and architectural views

Social events are natively based on self-organizing social processes. The collective positioning information that arises from people can enact spontaneously some type of *stigmergic* information process (Barron 2005). Further, the output of this process can be subject to a fuzzy granulation able to discover, via fuzzy inference, the situation as an emergent phenomenon. There are some works in the literature showing that fuzzy modeling may be suitable for addressing *biomimicry*, that is, the development of artificial machines that mimic biological phenomena, in a systematic manner (Sipper 2002). Indeed, many animal and human actions are intrinsically "fuzzy", hence fuzzy modeling seems an appropriate tool for studying such behaviors (Margaliot 2008). Moreover, it is straightforward to describe the behavior of simple organisms using simple fuzzy rules (Schockaert et al. 2004; Rozin and Margaliot 2007).

Let us consider in detail the stigmergic paradigm, which is the basis of the first processing level. Stigmergy can be defined as an indirect communication mechanism that allows simple entities to structure their activities through the local *environment*. It is a primary ingredient in coordinating a complex behavior in social insects. In computer related problems, stigmergy is used by a number of biologically inspired methods and is also an appealing paradigm for pervasive computing (Ricci 2011; Cimino and

Marcelloni 2011). Here, stigmergy identifies a particular type of control: the control of the actions of a group of agents via a shared environment. The agents do not directly communicate amongst themselves, but only interact with and change the environment. In the literature, various types of stigmergy have been distinguished. *Sign-based stigmergy* occurs when markers are left in the environment to influence the subsequent behavior (choice and parameters) of entities. In *quantitative* stigmergy, the mark varies in a quantitative manner. In a stigmergic computing scheme, the environment acts as a shared medium through which agents communicate. Each agent is able to sense and to change the state of a part of the environment. These changes need to persist long enough to affect the subsequent behavior of other agents. Hence, the environment acts as a common shared service for all entities enabling a robust and self-coordinating mechanism.

Figure 2 represents an ontological view of the proposed approach. Here, base concepts are enclosed in grey oval shapes and are connected by properties, represented with directed edges in the figure. The core properties are *User moves into* the *Environment* and *User is in* a *Situation*. As these properties cannot be directly sensed (i.e., instantiated) by the system, they are shown with a dotted edge, as *abstract* properties. Indeed, the overall system is aimed at indirectly discovering them, by observing the collective behavior of the users starting from data provided by personal devices.

Let us consider a set of *U Users*. We assume that each user owns a *Device* able to provide current *Location* and *Time* (e.g., a smart phone equipped with clock and GPS reader), as well as a number of *Services*. A *User Agent* (UA)

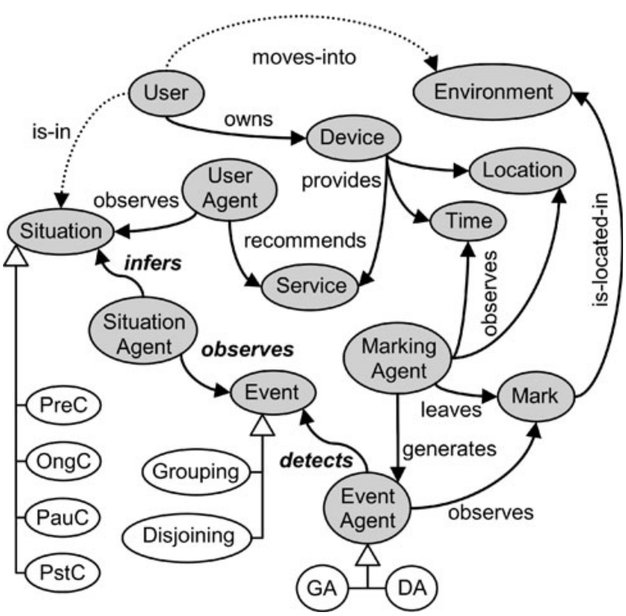


Fig. 2 An ontological view of the collaborative situation-aware scheme for mobile service recommendation

recommends a subset of such *Services observing* the current user *Situation* inferred by a *Situation Agent* (SA). The UA is based on an ontology which allows connecting situations to tasks, and then to specific services. This ontology was shown in one of our recent papers (Ciaramella et al. 2010a). We will not further discuss on how the UA works since the main aim of this paper is to show how a situation can be recognized by using an emergent paradigm rather than discussing an overall service recommender. The information that allows to identify the occurrence of a specific situation may be indirect (such as implicit inputs or context descriptions) and, in general, uncertain and imprecise. As a consequence, the situation occurrence is determined with a certainty degree. This inferential process is based on fuzzy logic, and is shown in italic bold style in figure. Due to the intrinsic vagueness of fuzzy inference, it is possible to recognize more than a current *Situation* with a related degree of certainty. As a set of specific situations we considered four key typical situations related to social events (collaboration in the following) namely, pre-collaboration (*PreC*), on-going collaboration (*OngC*), post-collaboration (*PstC*), and collaboration pause (*PauC*). In the figure, edges with white arrow head, and white oval shapes represent the classical inheritance and a specialized concept, respectively.

The *SA* infers situations by observing *Events*. The situation inference process exploits fuzzy *if–then* rules defined on the certainty degrees with which the events are detected. There are two types of events: *Grouping* and *Disjoining* events. The grouping event arises when two or more users tend to be close to each other. The disjoining event occurs when a user separates from a formed group of users. The *detection* of the two events is performed by, respectively, two types of *Event Agents* (EA): the *Grouping Agent* (GA) and the *Disjoining Agent* (DA). A unique GA is associated with the group, while a DA is connected to each user belonging to the group. The EAs *observe* the intensities of the *Mark*s and exploit these intensities for associating a certainty degree to the event by a fuzzy granulation process. *Marks* are *located in* the *Environment*, and are *produced* by *Marking Agents* (MAs). Each user is associated with an MA which observes *Time* and *Location* of her/his *Device* in order to produce marks. Whenever the MA leaves its mark in the environment, it receives from the *Environment* the information whether the mark is going to be superimposed on marks left by other MAs. If this occurs, the MA generates one GA and one DA. Possibly, GAs corresponding to the same group of users are fused.

The overall system architecture is shown in Fig. 3, by using a UML deployment diagram. More specifically there are four device categories, i.e., *Smart phone* on the client side, *Marking Server*, *Recommendation Server*, and *Situation Server* on the server side. The Smart phone provides the server side with the current user's position, generated

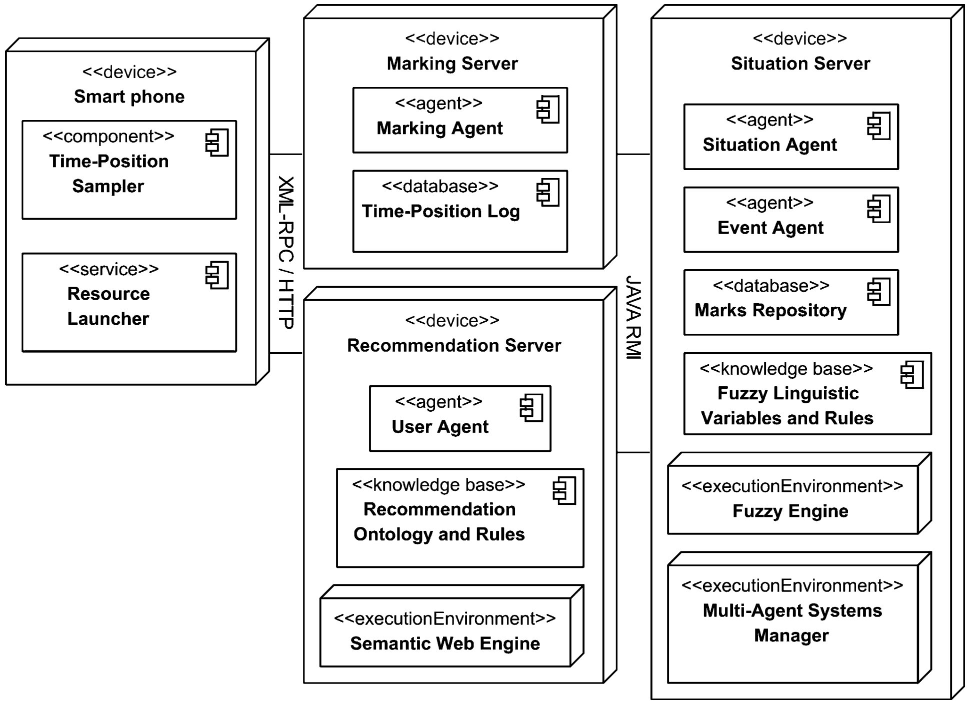


Fig. 3 A UML deployment diagram of the proposed collaborative situation-aware architecture

by its *Time-Position Sampler* module. The smart phone receives from the server side the resource recommendation, via its *Resource Launcher* module. The Marking Server manages the marking process, i.e., it hosts the MA and the *Time-Position Log* module, and delivers marks to the *Situation Server*. In the Recommendation Server, the UA steers the recommendation process, according to recommendation ontology and rules processed by means of a Semantic Web Engine (Cimino et al. 2012). Finally, the Situation Server manages the Environment (via a *Multi-Agent Systems Manager*), hosts the SA and EA instances, and supports both fuzzy granulation and situation fuzzy inference processes, according to linguistic variables and rules processed by means of the *Fuzzy Engine*. A single Marking Server and a single Recommendation Server can support many smart phone clients, via a lightweight and platform-independent communication protocol based on XML-RPC over HTTP. Thus, any client-side platform can be easily integrated with the System. A single Situation Server can support many Marking and Recommendation servers, via an efficient Java-RMI communication protocol. Indeed server-side subsystems are entirely Java-based. More specifically, the following environments have been employed to develop and execute the infrastructure. The Semantic Web Engine is based on Apache Jena,[1] a Java framework for building Semantic Web applications, used in conjunction with Pellet,[2] a Java based OWL DL reasoner. The Fuzzy Engine is based on jFuzzyLogic,[3] a Java package that implements a series of basic fuzzy operations as well as a fuzzy inference system. Finally, the Multi-Agent Systems Manager is based on Repast Simphony,[4] a Java-based modeling system supporting the development of interacting agents. It can be used as a GUI-based (user driven) simulation environment, as well as an execution engine run from another Java application.

In the next section, we will discuss in detail the marking process, the fuzzy granulation process and the situation inference process, which are the core processes of the MAs, the EAs and the SAs, respectively.

3 The three core processes

3.1 The marking process

In our architecture, an MA is associated with each user. The main responsibility of an MA is to periodically leave a mark where the user is currently located. Thus, while the user moves in the environment, the MA generates a marking path. Without loss of generality, we assume that our environment is constrained to a specific area. We superimpose to this area a grid consisting of L^2 squares,

[1] http://incubator.apache.org/jena.

[2] http://clarkparsia.com/pellet.

[3] http://jfuzzylogic.sourceforge.net.

[4] http://repast.sourceforge.net.

where each square $Q(x, y)$ is identified by a pair (x, y) of coordinates, with $x, y \in [1,\ldots, L]$. The actual size of the area and the number of squares depend on the specific application domain and contextual factors. Each mark covers a set of squares and is characterized by an intensity which has the highest value in correspondence to the square where the user is located and degrades with the increasing of the distance from this square. This spatial extension allows taking both the uncertainty of the localization and the movement of the user into consideration. Further, the intensity of the mark decays with the passage of time. This temporal decay gives us the possibility of monitoring the movement of the user. In particular, since we assume that the beginning of a collaboration occurs when at least half of users are in approximately the same position and are still, the combination of the spatial extension and the temporal decay allows us to recognize both the conditions.

Figure 4a shows a simple scenario of the marking process performed by three MAs. The levels of mark intensity are represented by different grey gradations: the darker the gradation is, the higher the intensity of the mark is. The highest intensity I_{MAX} of the mark left by a single MA is in correspondence to the position $Q(x_P, y_P)$ (the square with the darkest grey gradation in the figure) of the user when the mark is left. The mark intensity decreases with the number of squares from the position of the user of a percentage δ for each square. Further, the intensity left on each square has a temporal decay, and after a certain time the mark tends to dissolve. The decay time of the intensity is longer than the time period used by the MAs for leaving marks. Thus, if the user is still in a specific position, new marks at the end of each period will superimpose on the old marks and the intensity will reach a stationary level. On the contrary, if the MA moves to other locations, the mark intensities will decrease with the passage of time without being reinforced.

Figure 4b shows an example of this temporal decay: when the users move from one position to another, the intensity of the mark in the former position decreases. When the users are still and very close to each other the markers superimpose over one another and consequently the intensities sum up. The resulting intensities tend to be higher than the potential intensity of a single user. Figure 4c shows this scenario by associating a darker gradation with the squares where the marker superimposition occurs. Intuitively, this effect can be exploited to understand when two or more users are very close to each other and then probably have started a collaboration.

More formally, at each instant $\bar{t}$, $\bar{t} = 0, T_M, 2T_M, \ldots$, the MA i leaves in the squares $Q(x,y)$, $x, y \in [1,\ldots, L]$, a mark of intensity $I_i(x, y, \bar{t})$ defined as:

$$I_{i,\bar{t}}(x, y, \bar{t}) = \max(0, I_{MAX} \cdot [1 - \delta \cdot \max(|x - x_P|, |y - y_P|)]) \tag{1}$$

Every T_D seconds the intensity of the mark decays of a percentage α of its current value, that is,

$$I_{i,\bar{t}}(x, y, t) = \alpha \cdot I_{i,\bar{t}}(x, y, t - T_D) \quad \text{with } t = \bar{t} + T_D, \bar{t} + 2T_D, \ldots \tag{2}$$

For each square $Q(x, y)$, the actual value $I(x, y, t)$ of the intensity is obtained as the sum of the intensities of the marks left by each MA, that is,

$$I(x, y, t) = \sum_{\forall i, \forall \bar{t}: I_{i,\bar{t}}(x,y,t) > 0} I_{i,\bar{t}}(x, y, t) \tag{3}$$

Let us suppose that a user is still and alone. Then, from formulas (2) and (3) we can deduce that after $Z \cdot T_D$ seconds,

$$\begin{aligned} I(x, y, t) &= \alpha \cdot I_{i,\bar{t}}(x, y, \bar{t}) + \alpha^2 \cdot I_{i,\bar{t}}(x, y, \bar{t}) + \cdots + \alpha^Z \\ &\quad \cdot I_{i,\bar{t}}(x, y, \bar{t}) \\ &= I_{i,\bar{t}}(x, y, \bar{t}) \cdot \frac{1 - \alpha^Z}{1 - \alpha} \end{aligned} \tag{4}$$

(a) (b) (c)

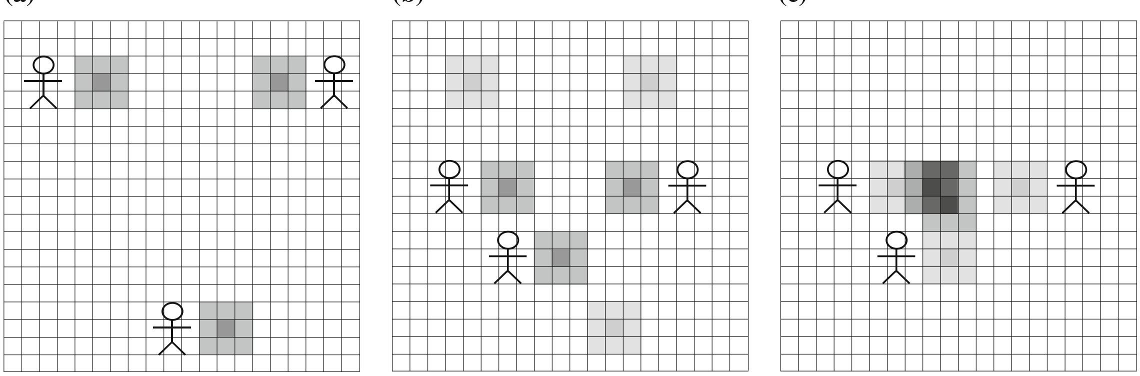


Fig. 4 Examples of scenarios for three MAs: **a** the three MAs are still and far from each other, **b** the three MAs are moving, and **c** the three MAs are still and close to each other

If Z ≫1, then

$$I(x,y,t) \rightarrow I_{i,\bar{t}}(x,y,\bar{t}) \cdot \frac{1}{1-\alpha}. \tag{5}$$

Obviously, when a number of users are still in the same location, we can easily deduce from formulas (3) and (5) that the intensity of square *Q(x,y)* grows up with the passage of time until achieving a stationary level. Exploiting this observation, in the following section, we will discuss how the four different situations can be recognized with different certainty degrees.

3.2 The fuzzy granulation process

The intensities left in the Environment from the different MAs are exploited by two different types of EAs, namely the GA and the DA. Both these agent types are generated by an MA whenever the *Mark* left by the MA itself is superimposed on at least one *Mark* left by other MAs. The GA characterizes the behavior of groups of MAs and is devoted to detect when a grouping event occurs. The rationale is that a grouping event occurs only if a number of users are close to each other. In this scenario, the intensity in the location where the users are still results from the superimposition of the intensities of the single MAs, thus making the grouping event detectable. Hence, a GA detects the presence of a group of users and provides a certainty degree of the grouping event for all the users belonging to the group.

Let (x_G, y_G) be the position of the GA created in the environment. Once instantiated, each GA observes a neighboring area, here denoted by $N(x_G, y_G)$, centered in (x_G, y_G). The center (x_G, y_G) coincides with the position (x_P, y_P) of the MA which generates the GA. As a consequence, the GA follows the same movements as the corresponding MA. We assume that the size of the area $N(x_G, y_G)$ is equal to the size of the area of a *Mark*. This area is fixed by the percentage δ in formula (1).

The intensity associated with the area $N(x_G, y_G)$ is computed as

$$I_{GA}(x_G,y_G,t) = \sum_{(x,y)\in N(x_G,y_G)} I(x,y,t) \tag{6}$$

Grouping Agents corresponding to the same group of users are fused in such a way that only one GA is associated with a group of users. Two GAs are fused when at least one square of the neighborhood of the former is superimposed on one square of the neighborhood of the latter. At each instant $\bar{t}$, the position (x_G, y_G) of the generated GA is computed as the center of gravity of the positions (x_P, y_P) of the MAs which have instanced the fused GAs.

The DA detects if a user, after having joined a group, separates from it. Thus, the DA characterizes the behavior of the single user after he/she has joined the group and provides a certainty degree of the disjoining event for that user: the disjoining event occurs when the user is alone and far from the group of users. The position (x_D, y_D) of a DA coincides at each time step with the position of the corresponding MA. A DA is removed by the Environment when the GA, which contains the user corresponding to the DA, is removed. Once instantiated, each DA observes a neighboring area, here denoted by $N(x_D, y_D)$, centered in (x_D, y_D). We assume that also the size of $N(x_D, y_D)$ is equal to the size of the area of a *Mark*. The intensity associated with the area $N(x_D, y_D)$ is computed as:

$$I_{DA}(x_D,y_D,t) = \sum_{(x,y)\in N(x_D,y_D)} I(x,y,t) \tag{7}$$

Both GAs and DAs are modeled by fuzzy granules. Fuzzy granules are conceptual entities that offer abstractions of the reality in the form of fuzzy concepts depending on the context (Bargiela and Pedrycz 2003). Therefore they represent a suitable formalism to model the behavior of agents working on contextual data characterized by uncertainty. The use of a fuzzy granulation approach allows us to manage the natural vagueness and imprecision of contextual data used for the detection of events. In our case, contextual data are represented by the intensities of the markers accumulated by the various MAs during time. Thus both the GA and the DA are designed to provide event degrees by exploiting only marking intensities deposited by the MAs.

Formally, an *s*-shape membership function is adopted for the GA:

$$\mu_{GA}(I_{GA}(x_G,y_G,t)) = \begin{cases} 0 & \text{if} \quad I_{GA}(x_G,y_G,t) \le a \\ 2\left(\frac{I_{GA}(x_G,y_G,t)-a}{b-a}\right)^2 & \text{if} \quad a \le I_{GA}(x_G,y_G,t) \le (a+b)/2 \\ 1-2\left(\frac{b-I_{GA}(x_G,y_G,t)}{b-a}\right)^2 & \text{if} \quad (a+b)/2 \le I_{GA}(x_G,y_G,t) \le b \\ 1 & \text{if} \quad I_{GA}(x_G,y_G,t) \ge b \end{cases} \tag{8}$$

where parameters a and b control the curve slope of the *s*-function. In choosing a and b, we have to consider the minimum and the maximum values which can be assumed by $I_{GA}(x_G,y_G,t)$. The minimum value $I_{GA}^{\min}(x_G,y_G,t)$ corresponds to the case in which a unique user has left a mark in the squares $N(x_G, y_G)$. If we assume that $\delta = 0.5$ (the value used in our experiments), then the minimum value is $I_{GA}^{\min}(x_G,y_G,t) = 5 \cdot I_{\mathrm{MAX}}$. The maximum value $I_{GA}^{\max}(x_G,y_G,t)$ corresponds to the case in which all the users are still and leave marks on the same squares. Then, from formulas (5) and (6), we conclude that the maximum value $I_{GA}^{\max}(x_G,y_G,t)$ is

$$
\begin{aligned}
I_{GA}^{\max}(x_G, y_G, t) &= \sum_{(x,y)\in N(x_G,y_G)} I(x,y,t) \\
&= \sum_{(x,y)\in N(x_G,y_G)} I_{i,\bar{t}}(x,y,\bar{t}) \cdot \frac{1}{1-\alpha} \\
&= U \cdot \left(I_{MAX} \cdot \frac{1}{1-\alpha} + 8 \cdot \frac{I_{MAX}}{2} \cdot \frac{1}{1-\alpha} \right) \\
&= 5 \cdot U \cdot I_{MAX} \cdot \frac{1}{1-\alpha}
\end{aligned}
$$

We set $a = I_{GA}^{\min}(x_G, y_G, t)$ and $b = \frac{2}{3} \cdot I_{GA}^{\max}(x_G, y_G, t)$. The choice of b is motivated by the following reasonable assumption: a grouping event occurs when at least half of the U users are close to each other. Thus, we consider that when a number of users higher than 2/3 U are close to each other, then the grouping event should have maximum degree. Figure 5 shows an example of a GA fuzzy granule.

As regards DA, the following z-shaped membership function is adopted as fuzzy granule:

$$
\mu_{DA}(I_{DA}(x_D, y_D, t)) = \begin{cases} 1 & \text{if} \quad I_{DA}(x_D, y_D, t) \le a \\ 1 - 2\left(\frac{I_{DA}(x_D,y_D,t)-a}{b-a}\right)^2 & \text{if} \quad a \le I_{DA}(x_D, y_D, t) \le (a+b)/2 \\ 2\left(\frac{b-I_{DA}(x_D,y_D,t)}{b-a}\right)^2 & \text{if} \quad (a+b)/2 \le I_{DA}(x_D, y_D, t) \le b \\ 0 & \text{if} \quad I_{DA}(x_D, y_D, t) \ge b \end{cases} \tag{9}
$$

where parameters a and b control the curve slope of the z-function. Also for DA, in choosing a and b, we have to consider the minimum and the maximum values which can be assumed by $I_{DA}(x_D, y_D, t)$. These values are equal to the ones already computed for $I_{GA}(x_G, y_G, t)$, that is, $I_{DA}^{\min}(x_D, y_D, t) = 5 \cdot I_{\mathrm{MAX}}$ and $I_{DA}^{\max}(x_D, y_D, t) = 5 \cdot U \cdot I_{\mathrm{MAX}} \cdot \frac{1}{1-\alpha}$. Unlike GA, which considers a group of users, DA takes only one user into consideration: a disjoining event occurs when a user is alone in the area of the Marker. Thus, we set $a = I_{DA}^{\min}(x_D, y_D, t)$ and $b = 2 \cdot I_{DA}^{\min}(x_D, y_D, t) \cdot \frac{1}{1-\alpha}$, where b coincides with the maximum value achievable in correspondence to two users still and alone. Obviously, for values higher than b, we can be sure that the user is not alone and therefore the disjoining event is recognized with minimum certainty degree. Figure 6 shows an example of a DA fuzzy granule.

Finally, the certainty degrees of the grouping event and the disjoining event for each user at time t are computed respectively as:

$$\mu_{grouping} = \mu_{GA}(I_{GA}(x_G, y_G, t))$$

$$\mu_{disjoining} = \mu_{DA}(I_{DA}(x_D, y_D, t))$$

3.3 The situation fuzzy inference process

The situation fuzzy inference process is in charge of assessing the current situation for each user. It is accomplished by an SA. In this paper we show the design of a particular SA, the Collaboration Agent (CA), which is aimed at recognizing four types of situations related to collaboration:

1. *PreC*, while the user is discussing with one or more other users about the coming collaboration;
2. *OngC*, while the user is attending the collaboration;
3. *PauC*, while the user is having a break during the collaboration;
4. *PstC*, while the user is discussing with one or more other users about the collaboration, once it has terminated.

The CA uses the certainty degrees of the grouping and disjoining events provided by the GAs and the DAs, respectively, to detect the situation in which each user is involved. Precisely, the CA detects for each user the beginning and the end of each situation by using a set of fuzzy rules. In this work, fuzzy rules were manually

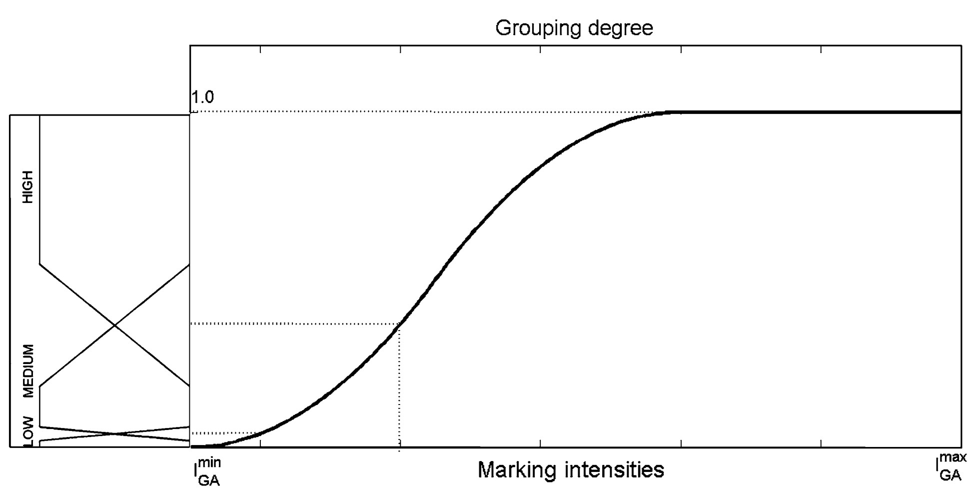


Fig. 5 Membership functions used to model the granulation process of a GA

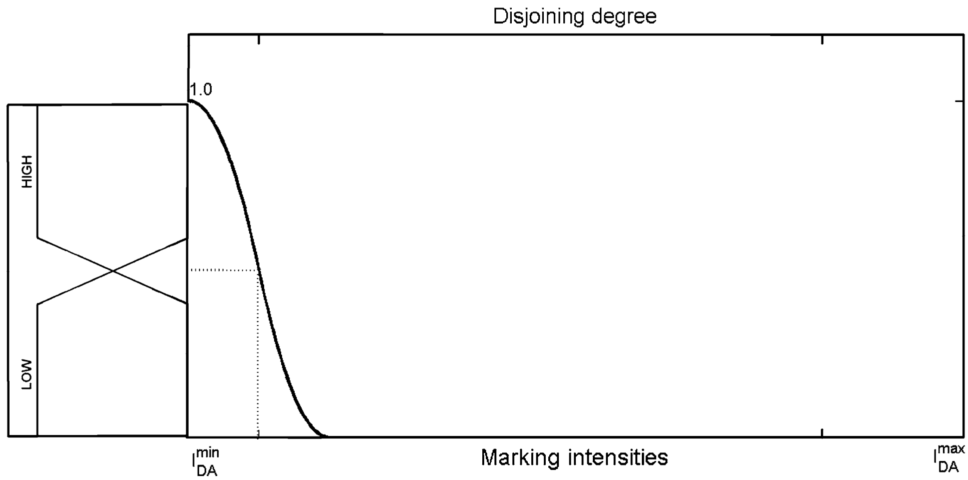


Fig. 6 Membership functions used to model the granulation process of a DA

Table 1 Fuzzy rules used by the CA for recognizing the situation of a user *i*

Rule 1	IF grouping degree is Medium and the agenda is empty THEN PreC **begins**
Rule 2	IF grouping degree is Medium and the agenda contains PreC THEN PreC **continues**
Rule 3	IF grouping degree is High and the agenda contains PreC THEN PreC **ends** and OngC **begins**
Rule 4	IF grouping degree is High and the agenda contains OngC THEN OngC **continues**
Rule 5	IF grouping degree is Medium and the agenda contains OngC THEN OngC **ends** and PstC **begins**
Rule 6	IF grouping degree is Medium and the agenda contains PstC THEN PstC **continues**
Rule 7	IF grouping degree is Low and the agenda contains PstC THEN PstC **ends**
Rule 8	IF grouping degree is Low and the agenda contains PauC THEN PstC **begins**
Rule 9	IF grouping degree is High and disjoining degree is High AND the agenda contains OngC THEN PauC **begins**
Rule 10	IF grouping degree is High AND disjoining degree is High AND the agenda contains PauC THEN PauC **continues**
Rule 11	IF grouping degree is High AND disjoining degree is Low AND the agenda contains PauC THEN PauC **ends** AND OngC **continues**

defined by observing the behavior of participants and by analyzing the situations that may occur from when a participant achieves the collaboration place until the collaboration ends. Specifically, fuzzy rules have been designed so as to describe the constraints characterizing the sequence of situations occurring during a collaboration.

For each user, the CA uses an *Agenda*, which is a small memory capable of storing the sequence of situations for the specific user. The agenda allows the CA to enforce constraints on the sequence of situations: for instance, the agenda avoids to recognize a *PauC* situation in place of a *PreC* situation. At the beginning, the agendas are empty for all users. Whenever the CA detects the beginning of a new situation for the *i*th user, the associated agenda is updated by adding the new situation. The agenda is reset for the *i*th user when the sequence $PreC \rightarrow OngC \rightarrow (PauC \rightarrow OngC) \rightarrow PstC$ is completed.

The fuzzy rules used by the CA to detect situations of the *i*th user are given in Table 1. The fuzzy rules are defined on three input variables: the value of the Agenda of the *i*th user, the grouping degree provided by the GA to which the *i*th user belongs and the disjoining degree supplied by the DA corresponding to the *i*th user. The certainty degree of the grouping event is described by the linguistic values LOW, MEDIUM and HIGH. These linguistic values are defined by trapezoidal fuzzy sets, as shown in Fig. 5. The parameters of these fuzzy sets have been defined by taking the following intuitive semantics of a grouping event into account (we assume that $U > 2$):

- a grouping event has LOW degree when two users are not very close to each other;
- a grouping event has MEDIUM degree when at least two and not more than $\left\lceil U/2 \right\rceil$ users are close to each other;
- a grouping event has HIGH degree when at least $\left\lceil U/2 \right\rceil$ users are close to each other.

Thus, the intersections between LOW and MEDIUM, and between MEDIUM and HIGH occur in correspondence to, respectively, the value $I_{GA}(x_G, y_G, t) = I_{GA}^{\min}(x_G, y_G, t) \cdot \frac{1}{1-\alpha}$ (maximum possible value of intensity generated by one user) and $I_{GA}(x_G, y_G, t) = \left(\left\lceil \frac{U}{2} \right\rceil - 1\right) \cdot I_{GA}^{\min}(x_G, y_G, t) \cdot \frac{1}{1-\alpha}$ (maximum possible value of intensity generated by $\left(\left\lceil \frac{U}{2} \right\rceil - 1\right)$ users). Since the intersections are adapted according to the number U

of users, the rules can be applied independently of the specific U.

Fuzzy rules devoted to detect the *PauC* situation for the ith user (rules 9, 10, 11) take into account also the certainty degree of the disjoining event for the ith user. The certainty degree is described by only two linguistic values LOW and HIGH. Similar to the grouping event, these linguistic values are defined by trapezoidal fuzzy sets, as shown in Fig. 6. The parameters of these fuzzy sets have been defined by taking the following intuitive semantics of a disjoining event into account:

- a disjoining event has LOW degree for a user when he/she is close to at least another user;
- a disjoining event has HIGH degree for a user when he/she is alone and far from a group of users.

Since the disjoining event is related to the behavior of a single user, the definition of the fuzzy sets does not depend on the number of users involved in the collaboration: thus it is defined regardless of U. In particular, we fixed the intersection between LOW and HIGH in correspondence to the value $\frac{a+b}{2}$, where $a = I_{DA}^{\min}(x_D, y_D, t)$ and $b = 2 \cdot I_{DA}^{\min}(x_D, y_D, t) \cdot \frac{1}{1-\alpha}$ are the values used in the definition of the z-function in formula (9). This value is slightly higher than $I_{DA}(x_D, y_D, t) = 5 \cdot I_{MAX} \cdot \frac{1}{1-\alpha}$, the maximum possible intensity value for a single user, so as to capture the disjoining event as soon as the user moves away from the group. Indeed, when the group is composed of at least three users certainly the intensity $I_{DA}(x_D, y_D, t)$ is higher than $\frac{a+b}{2}$.

In Table 1, two fuzzy rules (rules 5 and 8) are devoted to detect the beginning of situation *PstC*. The rule 8 has been added to model the case in which a user is in pause when the meeting ends. In such a case, the *PauC* situation should end and the *PstC* situation should start for that user.

By inferring the fuzzy rules in Table 1, the CA can provide a certainty degree for each situation and for each user at each time step. Of course, at each time step, only some situations will have a non-zero degree for a user. For example, in the preliminary phase of a meeting, a user may be in the *PreC* situation with high degree and in the *OngC* situation with low degree; likewise, during the ending phase of a meeting a user may be in the *OngC* situation with low degree and in the *PstC* situation with high degree. Given the certainty degrees of all situations for each user at a certain time step, the CA selects the situation with the highest degree as current situation to be included in the Agenda of the user.

4 Experimental results

In order to assess the effectiveness of the proposed multi-agent scheme in detecting collaboration situations, we have applied our model to three real scenarios involving a different number U of participants (P_1,…, P_U). In particular, the three scenarios, denoted as A, B and C, consider a meeting among 10, 7 and 4 participants, respectively, hold in Pisa (Italy). These scenarios are characterized as follows:

- Scenario A ($U = 10$). P_1 meets P_2 at a bar before arriving at the meeting place. P_8 reaches P_1 and P_2 at the bar and then together they go to the meeting place. During the meeting, P_3 leaves the meeting place for a short time to go to the bar. Further, P_4 and P_5 leave the meeting place for a longer time to go to the fast food. P_1, P_2, P_3 and P_4 leave the meeting place before the other participants.
- Scenario B ($U = 7$). This scenario was obtained by selecting participants P_1,…, P_7 from the Scenario A;
- Scenario C ($U = 4$). This scenario was obtained by selecting participants P_1,…, P_4 from the Scenario A.

As an example, Fig. 7 shows the GPS data generated by the mobile devices of each user in scenario B.

As a first step, continuous GPS data are discretized into a grid of square cells. The discretized tracks of the participants involved in the three scenarios are shown in Fig. 8a, b, c for scenarios A, B and C, respectively. Here, for the sake of clarity, we adopted a 10 × 10 grid, where each cell corresponds to ten cells of the real grid. For all the scenarios, the model parameters were set as follows: $L = 100$, $\delta = 50$ %, $\alpha = 0.5$, $T_D = T_M = T = 60$ s. We

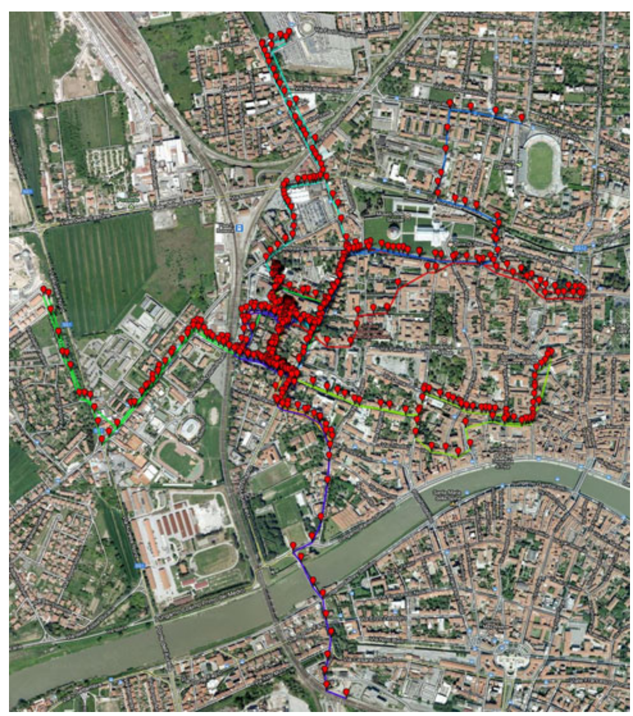
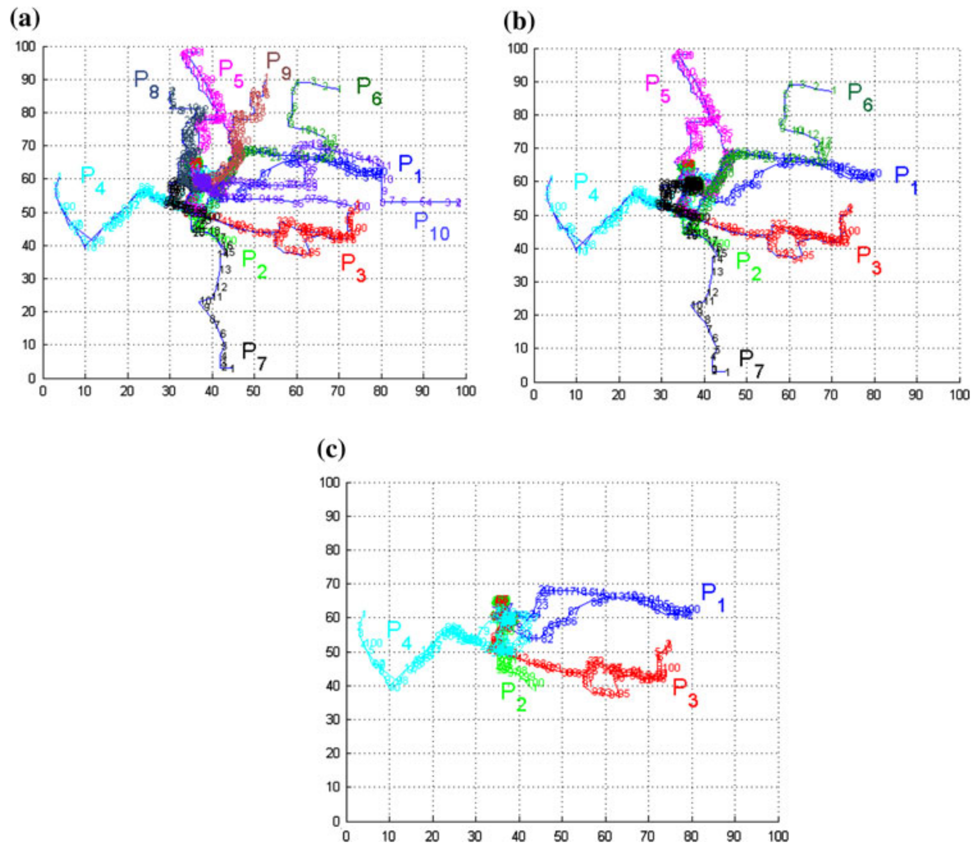


Fig. 7 GPS data for scenario B involving 7 participants to a meeting

Fig. 8 Tracks of the participants for scenario A (**a**), scenario B (**b**) and scenario C (**c**)



considered a time interval of 100 T_D. Fuzzy sets used to model the values LOW, MEDIUM and HIGH for the grouping degree are shown in Fig. 9. As explained in the previous section, the parameters of the fuzzy sets are automatically adapted to the number U of users.

As an example, in Fig. 10.a we show, for each participant in the scenario A, the certainty degree of the grouping event at instant $a = 49$: each degree is shown in correspondence to the position of the corresponding participant. At $\bar{t} = 49$, all participants are still at the meeting place (all GAs are fused in a single GA). We can observe that, for all participants, the certainty degree of the grouping event is maximum ($\mu_{GA} = 1.00$). In Fig. 10b, we show the certainty degree of the grouping event at instant $\bar{t} = 55$, when participants P_4 and P_5 leave the meeting place to go to the fast food. We can observe that the grouping event is still recognized with high degree by the GA which gathers all the remaining participants. Further, in the neighborhood of this GA, there is a peak indicating that a second GA has been created as soon as the two participants P_4 and P_5 have moved together away from the meeting place.

As an illustrative example of the situation inference process performed by the CA using the fuzzy rules in Table 1, Fig. 11a, b, c show for participant P_3 the sequences of situations and the corresponding certainty degrees in the three scenarios, respectively. According to the description of the scenarios given above, participant P_3 leaves first the group for a short time to go to the bar and then leaves definitively the group before the end of the meeting. It can be clearly seen that in each scenario the CA successfully recognizes the *PauC* situation during the *OngC* situation. It should be noted that, in the scenario A, the CA detects the *PauC* situation two times for user P_3. The first time corresponds to the actual pause. The second time corresponds to the case in which the user leaves the meeting before the other participants. This is recognized by the CA as a *PauC* situation as long as at least half of the participants are grouped (the meeting is going on), while it is recognized as a *PostC* situation as soon as the group is composed by a number of users lower than $\left\lceil U/2 \right\rceil$. Since the number of participants is high in the scenario A, the situation is initially recognized as a pause, while it is recognized as a *PostC* situation only when another participant leaves the group.

To assess the goodness of our approach, we have compared the instants when the CA recognizes the beginning and the end of each situation for the three scenarios with the instants when the beginning and the end occur really. Tables 2, 3 and 4 show these instants for the three scenarios, respectively. In each table, the actual instants are represented between parentheses.

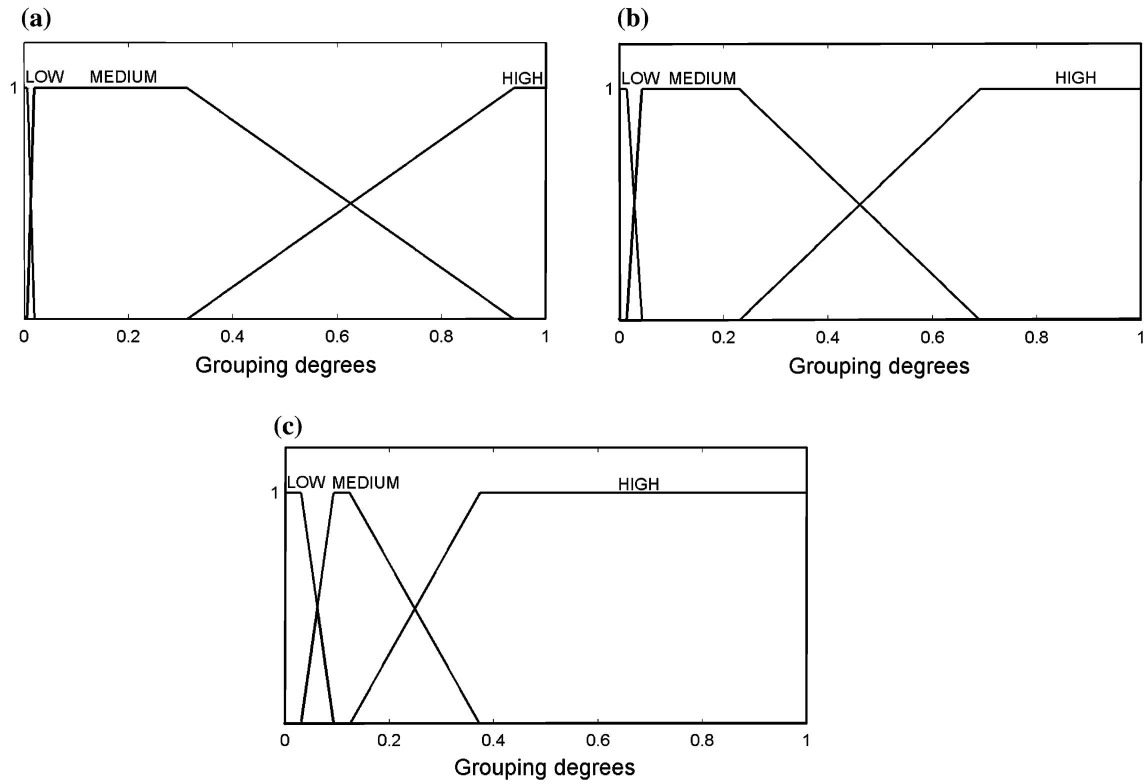


Fig. 9 Fuzzy sets used to model the grouping degree for scenario A ($U = 10$) (**a**), scenario B ($U = 7$) (**b**) and scenario C ($U = 4$) (**c**)

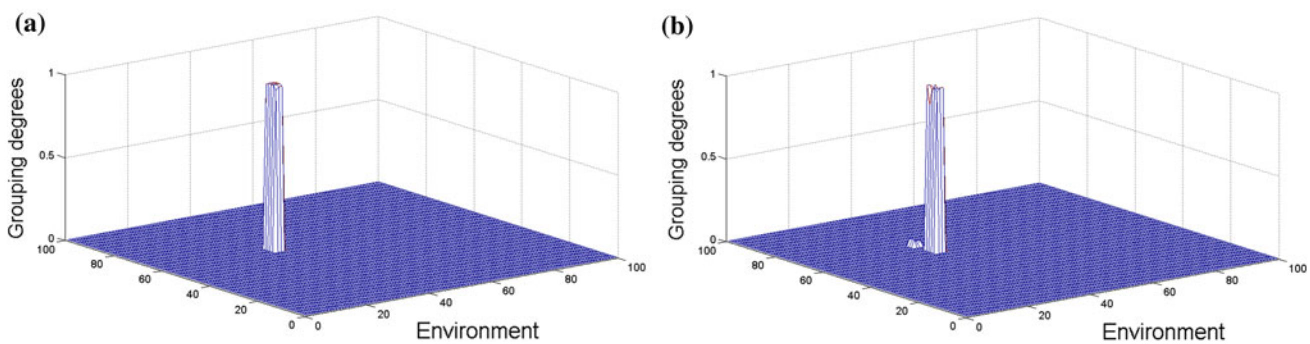


Fig. 10 Certainty degrees of the grouping event in the scenario A when **a** all participants are still at the meeting place and when **b** two participants leave together the meeting place for a pause

From Table 2, we can observe that, in scenario A, the CA recognizes correctly that P_1 meets P_2 at a bar before arriving at the meeting place (step $t = 28$) and that P_8 reaches P_1 and P_2 at the bar (step $t = 29$) before going to the meeting place. The beginning of the meeting is correctly recognized for almost all the participants. Also, the CA recognizes the beginning (step $t = 61$) and the end (step $t = 67$) of the pause situation for P_3. Further, the CA detects that P_4 and P_5 begin a pause almost together (steps $t = 53$ and $t = 54$, respectively) and end the pause together (step $t = 71$). As we have already discussed, the CA detects the *PauC* situation two times for user P_3. The first time corresponds to the actual pause (from step $t = 61$ to step $t = 67$), while the second coincides with the early disjoining of P_3 from the group. Until the CA does not recognize the *PostC* situation (when the group is composed by a number of users lower than $\lceil U/2 \rceil$), then the disjoining is considered as a pause. The same observations can be made for P_4. The CA recognizes the beginning of the *PstC* situation at step $t = 82$ for all participants. In particular, at the same step, the CA correctly recognizes the end of the meeting and, for participants P_1, P_2, P_3 and P_4, who were in the *PauC* situation, determines the beginning of the *PstC*

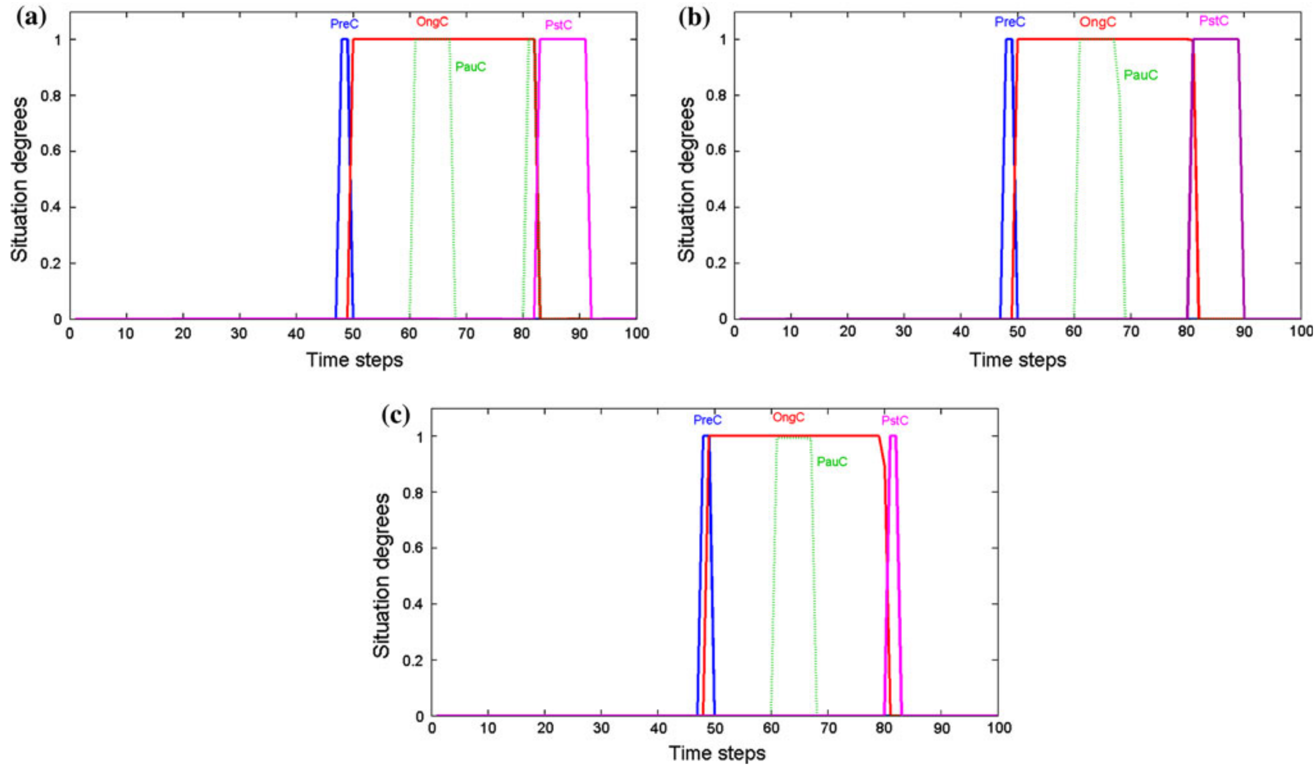


Fig. 11 Sequences of situations and corresponding certainty degrees for participant P_3 in scenarios A (**a**), scenario B (**b**) and scenario C (**c**), respectively

Table 2 Results of the situation inference process in scenario A

	PreC begins	PreC ends/ OngC begins	PauC begins	PauC ends	OngC ends/ PstC begins	PstC ends
P_1	28 (28)	46 (46)	78 (78)		82 (82)	90 (90)
P_2	28 (28)	46 (46)	78 (78)		82 (82)	90 (90)
P_3	48 (47)	49 (48)	61 (61)	68 (67)	82 (82)	90 (90)
			81 (80)			
P_4	41 (41)	46 (46)	53 (53)	71 (71)	82 (82)	90 (90)
			78 (78)			
P_5	44 (44)	46 (46)	54 (54)	71 (71)	82 (82)	90 (90)
P_6	44 (44)	46 (46)			82 (82)	90 (90)
P_7	38 (38)	46 (46)			82 (82)	90 (90)
P_8	29 (29)	47 (47)			82 (82)	90 (90)
P_9	45 (45)	47 (47)			82 (82)	90 (90)
P_{10}	46 (46)	48 (48)			82 (82)	90 (90)

situation. Finally, the CA detects that no participant is close to another participant in the same place and at step $t = 90$ recognizes the end of the *PstC* situation for all participants.

Similar observations can be made by examining the results for scenario B in Table 3. In this case, the CA correctly determines the beginning of the *PstC* situation at step $t = 81$ when only three users (a number lower than $\lceil U/2 \rceil$) are grouped. The end of the *PstC* situation is recognized by the CA at step $t = 89$ with one only step in advance with respect to the target step.

From Table 4 it can be seen that at step $t = 28$, P_1 meets P_2 at a bar and the CA correctly recognizes the beginning of the *PreC* situation. In scenario C, however, we are considering only four users. Thus, the meeting of P_1 with P_2 at the bar also determines the beginning of the *OngC* situation. Indeed, we recall that, referring to our semantics, the *OngC* situation starts when half of the users are

Table 3 Results of the situation inference process in scenario B

	PreC begins	PreC ends/ OngC begins	PauC begins	PauC ends	OngC ends/ PstC begins	PstC ends
P_1	28 (28)	45 (46)	78 (78)		81 (81)	89 (90)
P_2	28 (28)	45 (46)	78 (78)		81 (81)	89 (90)
P_3	48 (47)	49 (48)	61 (61)	69 (67)	81 (81)	89 (90)
P_4	41 (41)	45 (46)	53 (53) 78 (78)	71 (71)	81 (81)	89 (90)
P_5	44 (44)	46 (46)	54 (54)	71 (71)	81 (81)	89 (90)
P_6	45 (44)	46 (46)			81 (81)	89 (90)
P_7	44 (38)	45 (46)			81 (81)	89 (90)

Table 4 Results of the situation inference process in scenario C

	PreC begins	PreC ends/ OngC begins	PauC begins	PauC ends	OngC ends/ PstC begins	PstC ends
P_1	28 (28)	29 (28)	**39 (–)** 80 (80)	**40 (–)**	81 (81)	82 (81)
P_2	28 (28)	29 (28)	78 (78)		81 (81)	82 (81)
P_3	48 (47)	49 (48)	61 (61)	67 (67)	81 (81)	82 (81)
P_4	41 (41)	42 (42)	44 (44) 53 (53) 78 (78)	45 (45) 70 (70)	81 (81)	82 situations, we computed (81)

involved in the meeting. The CA recognizes the beginning of the *OngC* situation at step $t = 29$, with a delay of one step. This delay is due to the low number of participants which does not allow the intensity to increase very much. At step $t = 39$, although P_1 and P_2 are close to each other, the disjoining intensity for P_1 decreases and the CA recognizes the beginning of a pause, which however terminates at the subsequent instant. This pause is the only error made by our system in the three scenarios. In the table, we have highlighted the error by representing the instants in bold and by using a hyphen in place of the actual time. At step $t = 41$, P_4 reaches P_1 and P_2 at the meeting point. At step $t = 44$, P_4 goes away from P_1 and P_2. The CA correctly recognizes a *PauC* situation for P_4. This situation ends in the subsequent time step when P_1, P_2 and P_4 are again together. After step $t = 49$, also P_3 achieves the meeting point. Both for P_3 and for P_4 the CA correctly recognizes the beginning of a *PauC* situation at steps $t = 61$ and $t = 53$, respectively, and the end of these situations at steps $t = 67$ and $t = 70$, respectively. Both P_2 and P_4 go away from the meeting point before the other participants ($t = 78$). For both P_2 and P_4 a *PauC* situation is recognized. When the meeting ends at step $t = 81$, the CA determines the beginning of the *PstC* situation for all participants. The *PstC* situation terminates for all the participants at step $t = 82$.

To provide a measure of the effectiveness of the CA agent in recognizing situations, we computed the responsiveness index defined as:

$$R(S_s) = \frac{\sum_{i=1}^{U} \left| t_{i,s} - t'_{i,s} \right|}{U}$$

where $t_{i,s}$ represents the time step at which the sth situation begins/ends for each ith user and $t'_{i,s}$ is the time step at which the CA agent recognizes the beginning/end of this situation. Thus $R(S_s)$ is computed as the average of the differences between the step in which a situation begins/ends for a user and the step in which the CA automatically recognizes the beginning/end of the same situation for the same user. Table 5 shows the responsiveness values obtained for each situation recognized during the test of the model in the three scenarios. We observe that on average the value of the responsiveness is close to 0. Further, for all the situations, the responsiveness is lower than one time step (except for the end of the *PstC* situation, where its

Table 5 Responsiveness values obtained in the three scenarios

	Scenario A	Scenario B	Scenario C
PreC begin	0.1	0.28	0.25
PreC end/OngC begin	0.1	0.72	0.75
PauC begin	0.1	0	0
PauC end	0.1	0.28	0
OngC end/PstC begin	0	0	0
PstC end	0	1	1
Average	0.06	0.38	0.33

value is 1), thus pointing out the good performance of the CA in detecting situations.

5 Conclusions

A collaborative multi-agent scheme based on the idea of emergent collective behavior has been presented. The proposed scheme, implemented for detecting situations of users involved in social events, is structured into three processing levels managed by different agents that are modeled using a fuzzy granulation approach. The effectiveness of the situation-aware scheme has been shown on three real scenarios involving a different number of users participating to a meeting. The obtained results in terms of situation recognition and responsiveness show that the scheme can be successfully applied to any scenario, regardless the number of users involved in the collaboration. Situations detected by the proposed scheme can be exploited to recommend personalized information and services to users during a social event.

With respect to the approach used in our previous work on situation-aware resource recommender, the context knowledge injected in the current system has been reduced, by removing the user calendar. In the new proposed scheme, the behavior of the agent which recognizes the social events is entirely determined by the human designer via linguistic rules. A challenging problem to be investigated as a future work is the possibility of modeling situation-specific agents as an outcome of a machine learning technique embodied by a situation-independent agent.

References

Adomavicius G, Tuzhilin A (2010) Context-aware recommender systems. In: Ricci F, Rokach L, Shapira B, Kantor PB (eds) Recommender systems handbook. Springer, US, pp 217–253

Arabo A, Shi Q, Merabti M (2009) A framework for user-centred and context-aware identity management in mobile ad hoc networks (UCIM). Ubiquitous Comput Commun J Spec Issue New Technol Mobil Secur 1–11

Arabo A, Shi Q, Merabti M (2011) ContextRank: begetting order to usage of context information and identity management in pervasive ad-hoc environments. In J. Symonds (ed), Emerging pervasive and ubiquitous aspects of information systems: cross-disciplinary advancements IGI global, pp 275–297. doi: 10.4018/978-1-60960-487-5.ch016

Bargiela A, Pedrycz W (2003) Granular computing. An introduction. Kluwer Academic Publishers, USA

Barron P (2005) Using stigmergy to build pervasive computing environments. PhD Thesis in Computer Science, University of Dublin, Trinity College

Brueckner SA, Van Dyke Parunak H (2005) Swarming distributed pattern detection and classification. In: Weyns D et al. (eds) Proceedings of the first international workshop on environments for multi-agent systems (E4MAS 2004), Lecture notes in artificial intelligence 3374, Springer-Verlag, Berlin Heidelberg, pp 232–245

Burke R (2002) Hybrid recommender systems: survey and experiments. User Model User-Adap Inter 12(4):331–370. doi: 10.1023/A:1021240730564

Cena F, Console L, Gena C, Goy A, Levi G, Modeo S, Torre I (2006) Integrating heterogeneous adaptation techniques to build a flexible and usable mobile tourist guide. AI Communications 19(4):369–384

Ciaramella A, Cimino MGCA, Lazzerini B, Marcelloni F (2010a) A situation-aware resource recommender based on fuzzy and semantic web rules. Inter J Uncertain Fuzziness Knowl-Based Syst 18(4):411–430. doi:10.1142/S0218488510006623

Ciaramella A, Cimino MGCA, Lazzerini B, Marcelloni F (2010b) Using context history to personalize a resource recommender via a genetic algorithm. In: Proceedings of IEEE international conference on intelligent systems design and applications (ISDA'10). Cairo, pp 965–970

Cimino MGCA, Marcelloni F (2011) Autonomic tracing of production processes with mobile and agent-based computing. Inf Sci 181(5):935–953. doi:10.1016/j.ins.2010.11.015

Cimino MGCA, Lazzerini B, Marcelloni F, Ciaramella A (2012) An adaptive rule-based approach for managing situation-awareness, expert systems with applications, Elsevier Science. doi: 10.1016/j.eswa.2012.03.014 (in press)

De Maio C, Fenza G, Gaeta M, Loia V, Orciuoli F (2011) A knowledge-based framework for emergency DSS. Knowl-Based Syst 24(8):1372–1379. doi:10.1016/j.knosys.2011.06.011

Herlocker JL, Konstan JA (2001) Content-independent task-focused recommendation. IEEE Internet Comput 5(6):40–47. doi:10.1109/4236.968830

Heylighen F, Gershenson C (2003) The meaning of self-organization in computing. IEEE Intell Syst Sect Trends Controv Self-Organ Inf Syst 18(4):72–75

Holland O, Melhuish C (1999) Stigmergy, self-organization, and sorting in collective robotics. Artif Life 5(2):173–202. doi:10.1162/106454699568737

Jiang K, Wang P, Yu N (2011) ContextRank: personalized tourism recommendation by exploiting context information of geotagged web photos. In: Proceeding of sixth international conference on image and graphics (ICIG). Hefei, Anhui, pp 931–937

Luther M, Fukazawa Y, Wagner M, Kurakake A (2008) Situational reasoning for task-oriented mobile service recommendation. Knowl Eng Rev 23:7–19. doi:10.1017/S0269888907001300

Margaliot M (2008) Biomimicry and fuzzy modeling: a match made in heaven. IEEE Comput Intell Mag 3:28–48. doi:10.1109/MCI.2008.926602

Naganuma T, Kurakake S (2005) A task oriented approach to service retrieval in mobile computing environment. In: Proceedings of IASTED international conference on artificial intelligence and applications, Innsbruck (14-16/2/2005), pp 527–532

Park HS, Yoo JO, Cho SB (2006) A context-aware music recommendation system using fuzzy bayesian networks with utility theory. In: Wang L, Jiao L, Shi G, Li X, Liu J (eds) Fuzzy systems and knowledge discovery. Lecture notes in computer science. Springer, Heidelberg, pp 970–979

Petry H, Tedesco P, Vieira V, Salgado AC (2008) ICARE: A context-sensitive expert recommendation system. In: Proceedings of workshop on recommender systems (ECAI'08), Patras, pp 53–58

Rao VS (2010) Multi-agent distributed data mining: an overview. Inter J Rev Comput 3(30):83–92

Resnick P, Iacovou N, Suchak M, Bergstrom P, Riedl J (1994) Grouplens: an open architecture for collaborative filtering on etnews. In: Proceedings of the 1994 ACM conference on computer supported collaborative work, Chapel Hill, pp 175–186

Ricci F (2011) Mobile recommender systems. Inter J Inf Technol Tour 12(3):205–231. doi:10.3727/109830511X12978702284390
Rozin V, Margaliot M (2007) The fuzzy ant. IEEE Comput Intell Mag 2:18–28. doi:10.1109/FUZZY.2006.1681932
Sarwar B, Karypis G, Konstan J, Riedl J (2001) Item-based collaborative filtering recommendation algorithms. In: Proceedings of the 10th international world wide web conference, Hong Kong, pp 285–295
Schockaert S, De Cock M, Cornelis C, Kerre EE (2004) Fuzzy ant based clustering. In: Dorigo M, Birattari M, Blum C, Gambardella LM, Mondada F, Stutzle T (eds) Ant colony, optimization and swarm intelligence. Lecture notes in computer science. Springer, Heidelberg, pp 11–17
Sipper M (2002) Machine Nature: the coming age of bio-inspired computing. McGraw-Hill, New York
Terveen L, Hill W (2001) Beyond recommender systems: helping people help each other. In: Carroll JM (ed) Human–computer interaction in the new millennium. Addison Wesley, New York, pp 487–509
Vernon D, Metta G, Sandini G (2007) A survey of artificial cognitive systems: implications for the autonomous development of mental capabilities in computational agents. IEEE Trans Evol Comput 11(2):151–180. doi:10.1109/TEVC.2006.890274
Weißenberg N (2006) An ontology-based approach to personalized situation-aware mobile service supply. GeoInformatica 10(1):55–90. doi:10.1007/s10707-005-4886-9