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A Collaborative Situation-Aware Scheme for Mobile Service Recommendation

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***Abstract*—Situation-aware service recommendation for mobile devices is aimed at proactively pushing personalized suggestions to users, presenting them unseen or unknown services. A challenging area in the field is that of recommendation schemes emerging from users' collective behavior. When we consider a mobile user, for instance, the recommendation process can be based on social events that can arise from collective positioning information. In this scenario, we discuss a collaborative multi-agent scheme for event detection, in which fuzzy representations are employed to cope with the approximation typical of implicit and aggregated information. More specifically, the first level of information processing is managed by marking agents leaving marks in the environment which are associated with users' positioning. The accumulation of marks enables a fuzzy information granulation process, managed by event agents, in which relevant events can emerge. Finally, a fuzzy inference level, managed by situation agents, deduces user situations from the underlying events.**

Keywords-collaborative context awareness; multi-agent system; emergent paradigm; context awareness; fuzzy information granule; mobile resource recommender.*

I. INTRODUCTION

Mobile Recommendation is a new paradigm that sensibly increases the usability of mobile systems, by proactively providing personalized and focused access [1]. In some recent papers [2][3], we have proposed a situation-aware resource recommender (SARR) for mobile users. *Situation-awareness* is a computing paradigm in which applications can sense and explore user situation, in order to identify his demand at a certain time. The fundamental vehicle to gain the user situation 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 characters of cognitive systems [4], as well as dealing with an intrinsic uncertainty in data [3]. SARR is based on a *cognitivist* approach [4], 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 which 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. In SARR, users' situations are modeled with a rule-based paradigm, via fuzzy and crisp logic. Indeed, context sources include vague information. As an example, let us consider location and time of meetings. The structure of rules has been designed according to a upper situation ontology which is domain independent. The user calendar acts as a reference for the parameterization of such fuzzy rules for each user. Hence, the current user situation is inferred via (i) the *dynamic instantiation* of abstract fuzzy rules over concrete location and time references coming from user agenda; (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 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, a higher uncertainty in fuzzy linguistic variables determines a lower responsiveness of the system. To cope with this problem, in [2] context history is employed as a training set for a genetic algorithm which aims to adapt fuzzy sets to the actual behavior and habit 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 this paper we propose and design an approach based on the *emergent* paradigm [4] for detecting events. Emergent paradigms are based on the principle of self-organization [5], 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 [6]. The fact that simple individual behaviors can lead to a complex emergent behavior has been known for centuries. More recently, it has been noted that this type of emergent collective behavior is a desirable property in pervasive computing [6][7][8].

In this paper we started to design this form of collaborative situation awareness considering an important class of events: social events (e.g., meetings, conferences, festivals, entertainment, and so on). In this scenario, we discuss in the following 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 that are associated to users' positioning. The accumulation of such marks enables the second level, a fuzzy information granulation process, in which relevant events can emerge by means of event agents. Finally, in the third level a fuzzy inference level, managed by situation agents, deduces user situations from the underlying events. The system is tested considering a representative scenario.

II. The Proposed Approach

The basic idea comes from the thought that social events are natively based on self-organizing processes. The collective positioning information that arises from people can enact spontaneously some type of *stigmergic* information process [6]. 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 [9]. Indeed, many animal and human actions are intrinsically "fuzzy", hence fuzzy modeling seems an appropriate tool for studying such behaviors [10]. Moreover, it is straightforward to describe the behavior of simple organisms using simple fuzzy rules [11],[12].

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, a number of biologically-inspired methods use stigmergy, and it is also an appealing paradigm for pervasive computing [1][8].

In the literature, a variety of types of stigmergy have been distinguished. In the following we briefly describe the main aspects of our stigmergic model. *Sign-based stigmergy* occurs when marker deposits are released into 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.

Fig.1 represents an ontological view of the proposed system, designed using the textual analysis process described in [3]. 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 users' behavior starting from data provided by personal devices.

Let us consider a set of *U Users*, each of which 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) *recommends* a subset of such *Services observing* the current user *Situation* inferred by a *Situation Agent* (SA). 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 have 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.

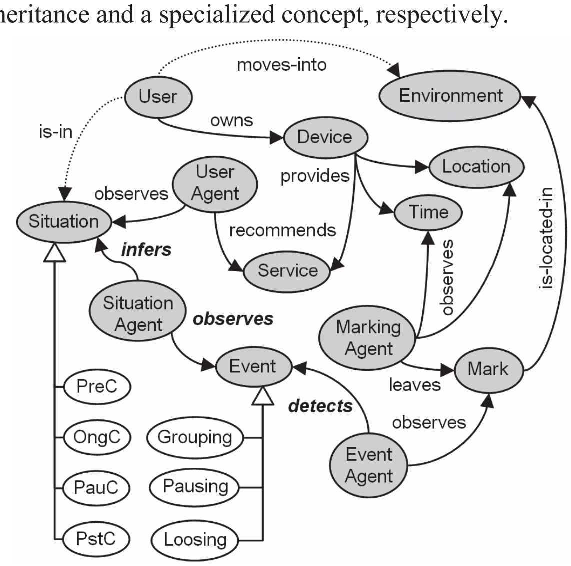

Figure 1. An ontological view of the collaborative situation-aware scheme for mobile service recommendation.

The *Situation Agent* infers Situations by *observing Events*. This is the third processing level, implemented via fuzzy *if-then* rules. There are three types of events: *Grouping*, *Loosing* and *Pausing*. The *detection* of events is made by the *Event Agent* (EA). To this aim, EAs *observe*

*Mark*s and create proper fuzzy granules. This is the second level of processing and will be detailed in the next subsection. *Mark*s are *located in* the *Environment*, and are *produced* by *Marking Agent*s (MA). For each user there is an MA who observes *Time* and *Location* of his *Device* in order to produce marks. In the next section, the design of each of the three processing levels is covered.

III. THE DESIGN OF THE THREE PROCESSING LEVELS

A. *The marking processing level*

Each user is associated with an MA, which periodically leaves a mark on the space where the user is currently located. While a user moves in the environment, the MA of each user deposits a marking, thus forming a marking path. We consider the spatial area under observation normalized in $[0,1]\times[0,1]$. We superimpose to the area a grid consisting of L^2 squares, where each square Q is identified by a pair of coordinate (x, y), with $x, y \in [1,\ldots, L]$. The size of the area and the number of squares depend on the specific application domain. Each mark is specific to an MA and is characterized by an intensity with a spatial and a temporal decay. Fig. 2 shows a simple scenario of marking process performed by two MAs, located in the black squares. Here, the intensity is represented by a grey level.

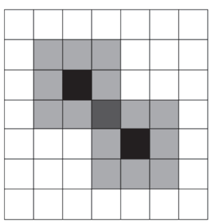

Figure 2. A simple scenario of marking.

The released mark has a central (maximum) intensity where the corresponding MA is located. Also, the mark has a spatial extension, defined by the number of vertical or horizontal steps (squares) from the MA position itself. In the figure, the spatial extension is exactly two. The mark intensity decreases with the number of steps (squares) from the MA position, of a percentage δ per step. Further, the intensity released on each square has a temporal decay, and after a certain time the mark disappears. 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 location, 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 marks intensities will decrease with the time without being reinforced.

More formally, every T_M seconds the MA leaves a mark of intensity $I(x,y)$ in the square $Q(x,y)$, which is equal to I_{MAX} where the MA is positioned, and leaves also a mark of intensity $(1\text{-}\delta)\cdot I_{MAX}$ in all the neighboring squares $Q(h,k)$, with $h\in\{x\text{-}1, x, x\text{+}1\}$, $k\in\{y\text{-}1, y, y\text{+}1\}$, and $(h,k)\neq(x, y)$. Every T_D seconds the intensity of each mark decays of a percentage α of its current value.

For each square, the value of the intensity is obtained as the sum of the intensities of the marks left by each MA. Hence, marks of different MAs can overlap and different interaction patterns can arise, as will be discussed in the next subsection.

B. *The fuzzy granulation processing level*

In the Environment, there are three types of EA, related to corresponding events, i.e., the Grouping Agent (GA), the Pausing Agent (PA), and the Loosing Agent (LA).

The GA characterizes the behaviors of groups of MAs by analyzing intensities higher than the maximum intensity that can be produced by a single MA. The rationale is that a grouping event occurs only if a number of users are still and 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, 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.

The LA detects the absence of interaction of a user and provides a certainty degree of the loosing event for that user; the loosing event involves individually each single user; it occurs when the user is alone and far from any group of users. The PA detects the temporary absence of a user from the collaboration. The logic of a PA can be easily derived from the logic of GA and LA. Hence, in the following we focus on GA and LA, to detail the design of this level.

We use a fuzzy granulation approach where both GAs and LAs are modeled by fuzzy granules so that we can manage the natural vagueness and imprecision of contextual data used for the detection of events. Fuzzy granules are conceptual entities that offer abstractions of the reality in the form of fuzzy concepts depending on the context [13]. Therefore they represent a suitable formalism to model the behavior of agents working on contextual data characterized by uncertainty.

In our case, contextual data are represented by intensities of markings accumulated by the various MAs during time, thus we model fuzzy granules as fuzzy sets defined on the domain of marking intensities. For each type of agent a fuzzy granule is defined, whose membership function is designed so as to mimic the task of that agent. Thus both the GA and the LA are designed to provide event degrees by exploiting only marking intensities deposited by the MAs.

An instance of a GA is required as soon as an MA detects that the intensity of the marking in its position is higher than a threshold. A GA is effectively instantiated if it does not already exist for the MAs that released such marking intensity. We denote by (x_G,y_G) the position of the GA created in the environment. Once instantiated, each GA creates a two-dimensional fuzzy granule that is centered in (x_G,y_G) and covers a neighboring area[1], here denoted by $N(x_G,y_G)$. The membership function of the GA is defined so as to model the following concept: the higher the intensity of a square in $N(x_G,y_G)$ the higher its contribution to the creation

[1] In our simulations we consider a neighborhood of 3×3 squares.

of a group. Formally, an *s*-shape membership function (Fig. 3) is adopted for the GA:

$$\mu_{GA}\left(I\left(x,y\right)\right)=\begin{cases} 0 & \text{if } I(x,y)\le a \\ 2\left(\dfrac{I(x,y)-a}{b-a}\right)^2 & \text{if } a\le I(x,y)\le (a+b)/2 \\ 1-2\left(\dfrac{b-I(x,y)}{b-a}\right)^2 & \text{if } (a+b)/2\le I(x,y)\le b \\ 1 & \text{if } I(x,y)\ge b \end{cases}$$

where parameters *a* and *b* control the curve slope of the *s*-function.

Finally, the certainty degree of the grouping event is computed by the GA as:

$$\mu_{grouping}=\frac{1}{\left|N\left(x_G,y_G\right)\right|}\sum_{(x,y)\in N(x_G,y_G)}\mu_{GA}\left(I\left(x,y\right)\right).$$

As soon as a GA detects a grouping event, an LA is created for each user belonging to the group. For each user, the position of an LA in the environment, denoted by (x_L,y_L), coincides at each time step with the position of the corresponding MA. Each LA is modeled as a fuzzy granule whose membership function is defined so as to express the following concept: the lower the intensity of square (x_L,y_L), the higher its contribution to the loosing of the user from the group. Formally, a *z*-shaped membership function (Fig. 3) is adopted for the LA:

$$\mu_{LA}\left(I\left(x,y\right)\right)=\begin{cases} 1 & \text{if } I(x,y)\le a \\ 1-2\left(\dfrac{I(x,y)-a}{b-a}\right)^2 & \text{if } a\le I(x,y)\le (a+b)/2 \\ 2\left(\dfrac{b-I(x,y)}{b-a}\right)^2 & \text{if } (a+b)/2\le I(x,y)\le b \\ 0 & \text{if } I(x,y)\ge b \end{cases}$$

where parameters *a* and *b* control the curve slope of the *z*-function.

Summarizing, both the GA and the LA are modeled as fuzzy granules in order to detect events emerging from the collective behavior of users participating to the meeting.

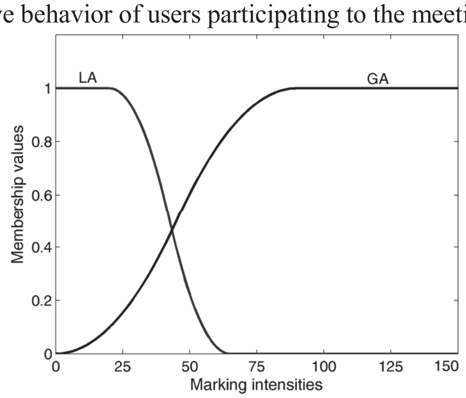

Figure 3. Membership functions used to model the granulation process of the GA and the LA.

C. *The fuzzy inference processing level*

This level is in charge of assessing the current users' situations. 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: (i) PreC, while the user is preparing to the collaboration; (ii) OngC, while the user is attending the collaboration; (iii) PauC, while the user is having a break during the collaboration; (iv) PstC, while the user is thinking about the collaboration, once it has concluded.

The CA uses certainty degrees of the events provided by GA, LA, and PA. Precisely, the CA detects the beginning and the end of each situation through the inference of a set of fuzzy rules. In this work, fuzzy rules were manually defined by observing the behavior of participants and by analyzing the situations that may occur from the time a participant achieves the meeting place until the meeting ends. Specifically, fuzzy rules have been designed so as to describe the constraints characterizing the sequence of situations occurring during a meeting. In order to better control the sequence of situations for each user, the CA makes use of an *Agenda*, representing a small memory capable of storing the sequence of situations for a specific user. At the beginning, the agenda is empty for all users. Then, each time the CA detects the beginning of a new situation for a user, the associated agenda is updated by adding the new situation. The agenda is reset when the sequence *PreC* → *OngC* → (*PauC* → *OngC*) → *PstC* is completed by a user.

TABLE I. Fuzzy Rules Used for Situation Detection

IF grouping event has low degree and agenda is empty THEN PreC **begins**
IF grouping event has high degree and the agenda contains PreC THEN PreC **ends** and OngC **begins**
IF grouping event has high degree and the agenda contains OngC THEN OngC continues
IF loosing event has low degree and the agenda contains OngC THEN OngC **ends** and PstC **begins**
IF grouping event has high degree AND loosing event has low degree AND the agenda contains OngC THEN PauC **begins**
IF loosing event has high degree and the agenda contains PstC THEN PstC **ends**
IF grouping event has degree high AND loosing event has degree low AND the agenda contains PauC THEN PauC **ends** AND OngC continues

The fuzzy rules used by the CA are given in Tab. I. The fuzzy terms *begins*, *ends* and *continues* are modeled by means of fuzzy sets with membership functions depicted in Fig. 4. The use of such fuzzy terms enables to express the gradual progression that characterizes the beginning and the end of each situation. By inference of such rules, the CA can provide for each user the certainty degree of being in each situation. 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 *PreC* with high degree and in *OngC* with low degree; likewise, during the ending phase of a meeting a user may be in *OngC* with low degree and in *PstC* with high degree. Given the certainty degrees of all situations for each user, the CA selects the situation with higher degree as current situation to be included in the user Agenda.

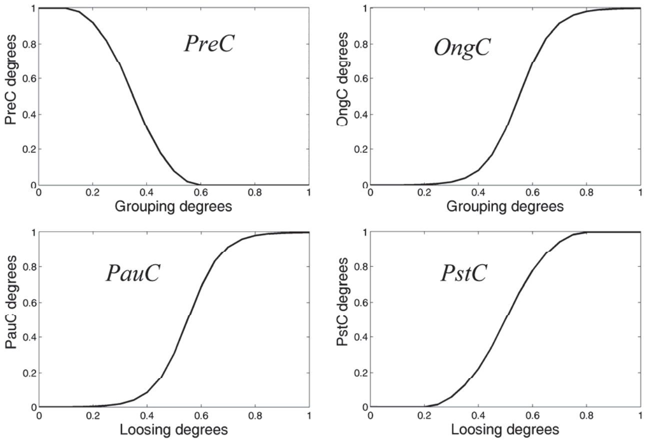

Figure 4. Membership functions used by the CA to derive certainty degree of situations.

IV. EVALUATION CASE STUDY

In order to verify the suitability of the proposed approach for situation assessment, we preliminarily applied our model to a case study that was designed to simulate in a realistic manner the behavior of some participants to a meeting. In particular, the considered scenario (depicted in Fig. 5) involves 7 people (P_1,…,P_7) that are going to attend a meeting. More specifically: P_1 and P_2 meet at midway, P_3, P_4 and P_5 arrive at the meeting place in advance, whereas P_6 and P_7 directly meet near the meeting place. During the meeting, P_5 receives a phone call and leaves the group for a short time while P_2 leaves the group for some time to go to the bathroom. When the meeting ends, P_1 and P_2 are the first participants to go away from the place, followed by P_6 and P_7. Finally, P_3, P_4 and P_5 leave the meeting place.

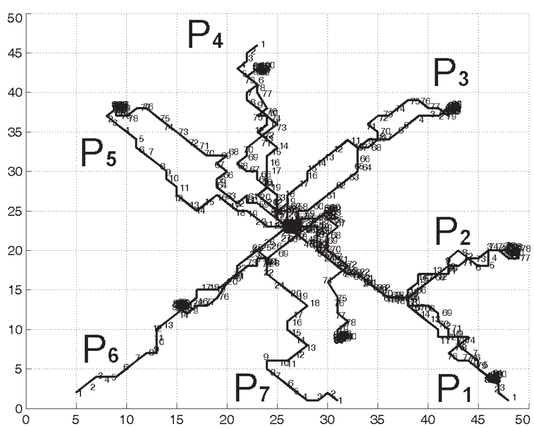

Figure 5. The considered scenario.

In the model, we used the following parameters: L=50, 80 time steps, δ = *50%,* α=10%, $T_D = T_M = T = 60$ *sec*.

As an example, in Fig. 6.a, we show the certainty degree calculated for the grouping event in correspondence of *t=40*, when all participants reach the meeting place. In this step, for all participants, the grouping event degree is maximum (μ_{GA}=1.00) and the loosing event is minimum (μ_{LA}=0.00). In Fig. 6.b, the grouping event degree obtained at *t=46* is shown. It can be observed that the grouping event takes high degrees (most of participants are at the meeting place) and that, in the neighbourhood, there is a peak indicating the leaving of participant P_2 from the group. In this step, the loosing event for P_2 has high degree (about 1.00).

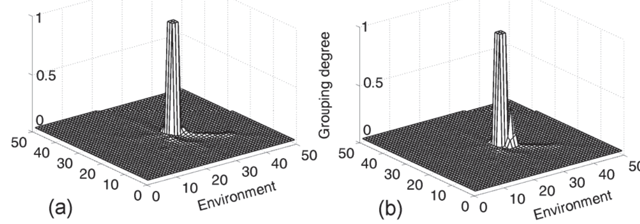

Figure 6. Degrees of the grouping event when the group is formed (a) and when participant P_2 leaves the group for a pause (b).

Next, by exploiting the certainty degrees of the grouping and loosing events, the CA recognized the situations through the inference of the fuzzy rules listed in Tab. I. As a demonstrative example, in Fig. 7, we show the sequence of situations recognized by CA for participant P_2 and the trend of the computed certainty degrees. It can be clearly seen the detection of the *PauC* situation during the *OngC* situation.

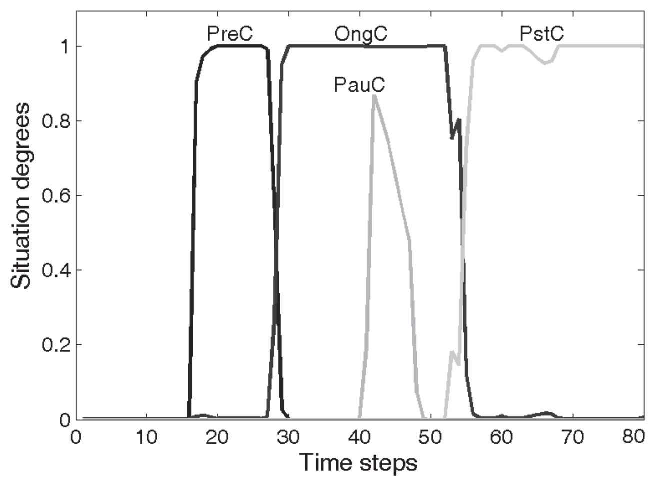

Figure 7. Degrees of situations provided by the CA for participant P_2.

In Tab. II, we indicate the time steps at which the CA recognized the beginning and the end of the identified situations for each participant. Values in brackets refer to the target time steps in which situations begin or end in the considered scenario. We can observe that CA recognized correctly that P_1 and P_2 meet at midway at the time step 17 and that P_3, P_4 and P_5 arrive at the meeting place in advance with respect to the other participants. Moreover, for P_2, CA perfectly recognizes the beginning and the end of the pause situation while it does not detect that P_5 leaves for short time the meeting to answer the phone call. This is due to the fact that P_5 during his pause moves to positions very close to the meeting place, where marking intensity values are quite high, thus the GA detects a grouping event for P_5. As concerns the

PstC situation, CA detects that P_1 and P_2 are the first participants to leave the meeting and it correctly recognizes the time step at which P_4 and P_5 moves from the meeting place. However, for P_3, P_6 and P_7, the CA determines the beginning of the *PstC* situation in steps that are successive compared with the target steps. This is essentially due to the fact that these participants remain in positions very close to the meeting place also after the target steps (referring to the beginning of the *PstC* situation).

TABLE II. RESULTS OF SITUATION DETECTION

	P_1	P_2	P_3	P_4	P_5	P_6	P_7
PreC begin	17 (17)	17 (17)	22 (17)	22 (17)	22 (17)	25 (17)	25 (17)
PreC end/ OngC begin	29 (32)	29 (32)	26 (24)	26 (24)	26 (24)	28 (28)	28 (28)
PauC begin	- -	41 (41)	- -	- -	- (36)	- -	- -
PauC end	- -	49 (49)	- -	- -	- (41)	- -	- -
OngC end/ PstC begin	53 (51)	53 (51)	60 (57)	57 (57)	57 (57)	59 (51)	59 (51)

To assess the effectiveness of the CA agent to recognize situations, we employed the responsiveness as performance index. Such index is defined as the average of the differences between the step in which a situation starts/ends for a user and the step in which the CA automatically detects the beginning/end of the same situation for the same user. Formally, the average responsiveness can be expressed as follows:

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

Where, for each p-th user, $t_{i,p}$ represents the time step at which the i-th situation begins/ends and $t'_{i,p}$ is the time step at which the CA agent recognizes the beginning/end of the considered situation. Tab. III shows the responsiveness obtained for each situation recognized during the test of the system. On the overall, it can be seen that the average value of responsiveness is less than two steps, thus indicating a good performance of the system.

TABLE III. THE OBTAINED RESPONSIVENESS VALUES

	R
PreC begin	4.43
PreC end/OngC begin	1.71
PauC begin	0
PauC end	0
OngC end/PstC begin	3.28
Average	**1.89**

V. CONCLUSIONS

In this paper, we presented a collaborative multi agent scheme for the detection of situations related to social events. The proposed approach is based on an emergent paradigm, and it is structured into three processing levels managed by a number of different agents: the marking, the fuzzy granulation and the fuzzy inference levels.

The effectiveness of the proposed approach was shown by testing the system on a representative scenario. The obtained results in terms of situation detection encourage the application of the proposed model to more complex case studies. Future works will be addressed to apply the developed system on a real scenario.

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