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A multi-agent system for enabling collaborative situation awareness via position-based stigmergy and neuro-fuzzy learning

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ABSTRACT

Situation awareness is a computing paradigm which allows applications to sense parameters in the environment, comprehend their meaning and project their status in the next future. In collaborative situation awareness, a challenging area in the field of Ambient Intelligence applications, situation patterns emerge from users′ collective behavior. In this paper we introduce a multi-agent system that exploits positioning information coming from mobile devices to detect the occurrence of user′s situations related to social events. In the functional view of the system, the first level of information processing is managed by marking agents which leave marks in the environment in correspondence to the users′ positions. The accumulation of marks enables a stigmergic cooperation mechanism, generating short-term memory structures in the local environment. Information provided by such structures is granulated by event agents which associate a certainty degree with each event. Finally, an inference level, managed by situation agents, deduces user situations from the underlying events by exploiting fuzzy rules whose parameters are generated automatically by a neuro-fuzzy approach. Fuzziness allows the system to cope with the uncertainty of the events. In the architectural view of the system, we adopt semantic web standards to guarantee structural interoperability in an open application environment. The system has been tested on different real-world scenarios to show the effectiveness of the proposed approach.

1. Introduction

Situation awareness is a computing paradigm that enables applications to sense and explore situations in which the users are, with the aim of predicting their demands at a certain time [1]. The paradigm relies on the *context*, that is, all the relevant data and information (e.g., the user′s position in space and time, the surrounding things and events) which can help comprehending what is happening in the environment [2–4]. This form of autonomous perception implies reasoning, decision, adaptation, and other characters of cognitive systems [5], as well as dealing with an intrinsic uncertainty in data [6,7].

To this aim, Korpipää et al. [8] have proposed a framework for managing uncertainty in raw data and inferring higher-level context abstractions with a related probability. Fuzzy sets are employed to convert unstructured raw data into a representation defined in a context ontology through predefined fuzzy labels. Situations are recognized by means of a basic Bayes classifier, which learns conditional probabilities from training data for each situation. In [9] fuzzy quantization is used to convert raw sensor data into context information. Such information is exploited by fuzzy controllers for adapting applications to the specific context. However, no semantic description of context is considered. Ranganathan et al. [10] have modeled uncertainty in situation awareness by associating a confidence value with all pieces of contextual information. The authors adopt three methods to infer the user′s situation: (i) probabilistic logic, (ii) fuzzy logic, and (iii) Bayesian networks.

In [11] uncertainty is managed by first extending the context ontology so as to allow additional probabilistic markups and then by adopting Bayesian networks to infer the current situation of the user. In [12] contextual information is codified in the antecedent part of linguistic rules whose consequent parts express the degree of confidence in the occurrence of a situation. Weights can be specified to represent the relative importance of each contextual condition for inferring a situation. In [13] a neuro-fuzzy classification system is trained to map sets of contextual information to particular situations by fuzzy rules.

In [7,14] we have proposed a design method for managing situation awareness. This method is based on the concurrent use

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of a semantic and a fuzzy engine. The semantic engine can infer one or more situations exploiting symbolic information. When multiple 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.

The structure of rules has been designed according to an upper situation ontology which is domain independent. The user calendar acts as a reference for the parameterization of such fuzzy rules for each user. The use of a calendar is however an *explicit* input required to the user. On the contrary, context information should be collected in terms of collaborative *implicit* input, coming from changes in the environment.

To avoid using explicit inputs as context sources, in [15,16] we have proposed an approach based on the *emergent* paradigm [5] for automatically detecting social events (e.g., meetings, conferences, festivals, entertainment, and so on) by exploiting a position-based stigmergy paradigm. Stigmergy can be defined as an indirect communication mechanism that allows simple entities to structure their activities through the local *environment* [17]. The approach has been referred to as collaborative situation awareness (CSA). In particular, each user is associated with one marking agent which leaves periodically marks in the environment in correspondence to his position. In a stigmergic computing scheme, the environment acts as a common shared service for all entities enabling a robust and self-coordinating mechanism. The accumulation of these marks is monitored by an event agent which detects events based on a fuzzy information granulation process. Finally, situation agents infer user situations from the underlying events. The inference process is performed by fuzzy rules generated by an expert taking some mathematical constraints into consideration.

In this paper, we extend our approach by focusing on a multi-agent architecture. Further, in order to make the approach completely independent of the user's inputs, we generate the fuzzy rules by exploiting a neuro-fuzzy system. We adopt Gaussian membership functions and train the neuro-fuzzy system by tracing a number of users involved in a social event. We need only to know the number of users who participate in the event. The proposed scheme is tested on four 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. In Section 2, we introduce the functional view of the system. Section 3 shows the architecture of the system, by focusing on the knowledge representation. In Section 4, we discuss some experimental results. Section 5 draws some final conclusion.

2. The functional view of the system

Situation awareness is achieved in our multi-agent system by exploiting three processing levels: the marking, the fuzzy granulation and the inference processing levels. In this section, we will describe how the three levels work and interact with each other. The first two levels will be discussed shortly. The interested reader can refer to our previous paper [16] for details. The third level will be analyzed in depth. Indeed, unlike in [16], where fuzzy partitions were generated heuristically, here we adopt a neuro-fuzzy approach. Further, we employ slightly different fuzzy rules which determine the situation at a certain instant by considering the certainty degrees of the situations at the previous time step.

2.1. The marking processing level

We consider the spatial area under observation normalized in $[0,1]\times[0,1]$ and superimpose on this area a grid consisting of L^2 squares, where each square Q is identified by a pair of coordinates (x,y), with $x,y\in[1,\dots,L]$. The size of the area and the number of squares depend on the specific application domain. Each user is associated with a *Marking Agent* (MA), which periodically leaves a mark at the position where the user is currently located. Each mark is specific to an MA and is characterized by an intensity with a spatial and a temporal decay. In particular, the intensity decreases with the increase of the distance from the position of the user and with the passing of the time. The time period of the intensity decay 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 the time without being reinforced.

Formally, at each instant $\bar{t}$, $\bar{t}=0,T_M,2T_M,\dots$, the MA_i leaves in the squares $Q(x,y), x,y\in[1,\dots,L]$, 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,

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

with $t=\bar{t}+T_D,\bar{t}+2T_D,\dots$

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,

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

The intensities of the marks are granulated in the second processing level by two event agents (EAs), namely the Grouping Agent (GA) and the Disjoining Agent (DA). Both the GA and the DA agents 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 control logic of a generic marking agent MA_i can be summarized as follows:

Loop
  Wait for T_M seconds;
  Leave a mark of Intensity $I_i(x,y)$ in the squares $Q(x,y)$;
  Ask the Environment whether, in at least one square
    with $I_i(x,y)>0$, there exists another mark left by
    another MA_j with intensity $I_j(x,y)>0$;
  If there exists such mark
  Then Generate a *GA* and a *DA*;
End loop

2.2. The fuzzy granulation processing level

The GA characterizes the behavior of groups of MAs and is devoted to detect when a grouping event occurs. Once instantiated, each GA observes a neighboring area, here denoted by $N(x_G,y_G)$, centered in the position (x_G,y_G) of the GA. The position (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. The intensity associated with the area $N(x_G,y_G)$ is computed as

$$I_{GA}(x_G,y_G,t)=\sum_{(x,y)\in N(x_G,y_G)} I(x,y,t) \tag{4}$$

GAs 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