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Abstract: Agent-based recommender systems have been exploited in the last years to provide informative suggestions to users, showing the advantage of exploiting components like beliefs, goals and trust in the recommendations' computation. However, many real-world scenarios, like the traffic one, require the additional feature of representing and reasoning about spatial and temporal knowledge, considering also their vague connotation. This paper tackles this challenge and introduces CARS, a spatio-temporal agent-based recommender system based on the Belief-Desire-Intention (BDI) architecture. Our approach extends the BDI model with spatial and temporal information to represent and reason about fuzzy beliefs and desires dynamics. An experimental evaluation about spatio-temporal reasoning in the traffic domain is carried out using the NetLogo platform, showing the improvements our recommender system introduces to support agents in achieving their goals.

1 INTRODUCTION

Agent-based recommender systems (Casali et al., 2008a; Chen and Cheng, 2010; Batet et al., 2012; Othmane et al., 2016b) have been proposed in the last years in different scenarios, like tourism, health-care, and traffic, to provide suggestions and support users to achieve their goals. The advantage of such systems is that of encoding users' beliefs and goals in the system to return a recommendation which is as close as possible to their needs, with the possibility to include additional information like the confidence in the source. In addition, several application scenarios require to formalize knowledge about the time and the location in which the action is taking place. This information often needs to be considered as a whole, as in the case of the traffic scenario, where a traffic jam is identified by its location and the time it is occurring during the day, and require to encode a certain degree of vagueness as well.

In this paper, we answer the following research question:

- *how to represent and reason about fuzzy spatial-temporal knowledge to provide useful recommendations?*

To answer this question, we introduce CARS, a spatio-temporal Cognitive Agent-based Recommender System, extending with spatio-temporal information the system proposed by (Othmane et al., 2016b). Based on the extension principle of fuzzy set theory (Zadeh, 1975), we define a fuzzy counterpart of Allen's intervals (Allen, 1983) to model temporal knowledge, while fuzzy topological relations are defined in terms of a fuzzy extension of the region connection calculus (Randell et al., 1992), whereby regions are represented as fuzzy sets. These two components, namely spatial and temporal information, are combined together based on the assumption that the degree to which a spatio-temporal belief is true is the minimum between the confidence degrees of the spatial belief and temporal one, respectively. Spatio-temporal knowledge is thus exploited by agents to update their beliefs following the other agents' recommendations, with the aim to reach their goals. To show the advantages of the proposed agent-based recommender system, we address an empirical evaluation in a simulated environment using the NetLogo platform. In particular, we consider the traffic scenario, where the goal of the agents is to reach a certain point of interest in the fastest way as possible. The results of the simulations show that CARS allows agents to faster reach their own destinations with respect to the baseline, where no recommendation to the agents is provided.

To the best of our knowledge, CARS is the first agent-based recommender system taking into account at the some time *i)* spatial and temporal knowledge, and *ii)* the vagueness and incompleteness typical of these components. Related work considers either spatial or temporal knowledge without providing a unique reasoning model (Jarvis et al., 2005), or does not take into account the fuzzy connotation of spatio-temporal knowledge (Schuele and Karaenke, 2010; Behzadi and Alesheikh, 2013).

The rest of the paper is organized as follows. After some preliminaries, Section 3 formally introduces the spatio-temporal fuzzy representation of the agents' beliefs as well as their update mechanism. Section 4 describes the experimental setting and discusses the results. The discussion of the related work and conclusions end the paper.

2 PRELIMINARIES

In this section, we provide some background about the formalisms we adopt to introduce our spatio-temporal fuzzy representation of beliefs and goals.

2.1 Region Connection Calculus

One of the most important formalisms for topological relationships is the Region Connection Calculus (RCC) (Randell et al., 1992). The RCC is an axiomatization in first order logic of certain spatial concepts and relations. The basic theory assumes just one primitive dyadic relation: $C(x,y)$, to be read as "x connects with y". RCC has eight basic relations (illustrated in Figure 1): DC (DisConnected), EC (Externally Connected), PO (Partial Overlap), EQ (EQual), TPP (Tangential Proper Part), NTPP (Non Tangential Proper Part) and their converse relations TPPi (TPP inverse) and NTPPi (NTPP inverse). The formal definition of the spatial relation entailed in the RCC is given in Table 1 for reference. For further details about RCC, we refer the reader to (Randell et al., 1992).

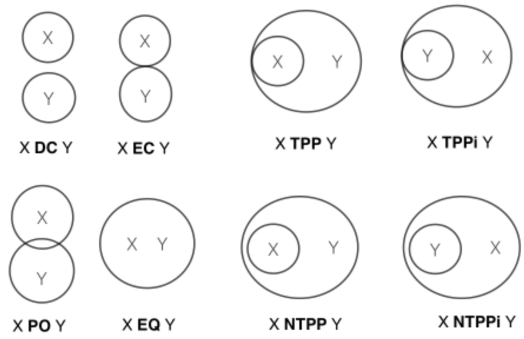


Figure 1: The main RCC-8 relations.

2.2 Allen's Intervals Algebra

Allen's Interval Algebra (Allen, 1983) is an algebra of binary relations on intervals for representing and reasoning about qualitative temporal information. Allen's approach is based on the notion of time intervals and binary relations among them. A time interval X is an ordered pair $\langle X^-, X^+\rangle$ such that $X^- < X^+$, where X^- and X^+ are interpreted respectively as the starting and ending points of the interval. Allen introduces thirteen basic interval relations, illustrated in Table 2: $\prec$ (before), m (meets), o (overlaps), d (during), s (starts), f (finishes), their converse relations ($\succ$, m_i, o_i, d_i, s_i, f_i), and $=$ (equal), where each basic relation can be defined in terms of relations involving its endpoints. For example, the interval relationship $X\, d\, Y$ (interval X occurs during interval Y) can be expressed as $(X^- > Y^-) \wedge (X^+ < Y^+)$. We refer the reader to (Allen, 1983) for a more detailed discussion.

2.3 Fuzzy set theory

Fuzzy set theory (Zadeh, 1965) deals with sets or categories whose boundaries are blurred or gradual. A fuzzy set is a set of objects whose membership to the set takes a value between zero and one. Each fuzzy object can have partial or multiple memberships. A fuzzy set A in universe of discourse $\mathcal{X}$ is mathematically characterized by a membership function $\mu_A(x)$, which associates with each x in X a real number in the interval $[0,1]$, with the membership value at x representing the "degree of membership" of x in A.

Let $\mathcal{X}$ be a set of objects, called the *the universe*, whose elements are denoted x. A membership in a fuzzy subset $\mathcal{A}$ of $\mathcal{X}$ is defined by the membership function $\mu_{\mathcal{A}}$ from $\mathcal{A}$ to $\{0,1\}$ such that

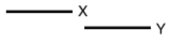
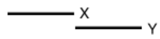
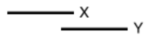
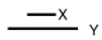
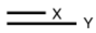
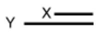
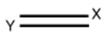
$$\mu_{\mathcal{A}}(x) = \begin{cases} 1 & \text{iff} \quad x \in \mathcal{A} \\ 0 & \text{iff} \quad x \notin \mathcal{A} \end{cases}$$

The closer the value of $\mu_{\mathcal{A}}(x)$ is to 1, the more x belongs to $\mathcal{A}$. $\mathcal{A}$ is a subset of $\mathcal{X}$ that has no sharp boundary and is characterized by a set of pairs $\mathcal{A} = \{(x, \mu_{\mathcal{A}}(x)), x \in \mathcal{X}\}$. When X is a finite set $\{x_1, \ldots, x_n\}$, a fuzzy set is expressed as $\mathcal{A} = \sum_{i=1}^{n} \mu_{\mathcal{A}}(x_i)/x_i$; when x is not finite, we write $\mathcal{A} = \int_{\mathcal{X}} \mu_{\mathcal{A}}(x)/x$.

Table 1: Definition of spatial relations entailed in the RCC. U is the universe of all regions; x and y are variables denoting arbitrary elements of U, i.e. regions.

Name	**Relation**	**Definition**
Disconnected	$DC(x,y)$	$\neg C(x,y)$
Part	$P(x,y)$	$\forall z \in U, C(z,x) \rightarrow C(z,y)$
Proper Part	$PP(x,y)$	$P(x,y) \wedge \neg P(y,x)$
Equals	$EQ(x,y)$	$P(x,y) \wedge P(y,x)$
Overlaps	$O(x,y)$	$\exists z \in U, P(z,x) \wedge P(z,y)$
Discrete	$DR(x,y)$	$\neg O(x,y)$
Partially Overlaps	$PO(x,y)$	$O(x,y) \wedge \neg P(x,y) \wedge \neg P(y,x)$
Externally connects	$EC(x,y)$	$C(x,y) \wedge \neg O(x,y)$
Tangential Proper Part	TPP	$PP(x,y) \wedge (\exists z \in U, EC(z,x) \wedge EC(z,y))$
Non-Tangential Proper Part	$NTPP(x,y)$	$PP(x,y) \wedge \neg(\exists z \in U, EC(z,x) \wedge EC(z,y))$

Table 2: Allen's thirteen time relations.

Relation	**Converse**	**Pictorial Example**	Endpoint Relations
$X \prec Y$	$X \succ Y$		$X^+ < Y^-$
XmY	Xm_iY		$X^+ = Y^-$
XoY	Xo_iY		$X^- < Y^-, X^+ > Y^-, X^+ < Y^+$
XdY	Xd_iY		$X^- > Y^-, X^+ < Y^+$
XsY	Xs_iY		$X^- = Y^-, X^+ < Y^+$
XfY	Xf_iY		$X^- < Y^-, X^+ = Y^+$
$X = Y$	$X = Y$		$X^- = Y^-, X^+ = Y^+$

2.4 The Extension Principle

The extension principle (Zadeh, 1975) provides a way to extend non-fuzzy mathematical concepts to deal with fuzzy quantities. It is defined by the following equation:

$$\mu_{A*B}(z) = sup_{z=x*y} \min\{\mu_A(x), \mu_B(y)\} \quad (1)$$

where $\forall x, y \in \mathcal{X}$, $\mu_A(x) \in [0,1]$ and $\mu_B(y) \in [0,1]$ are membership functions defining the degree of membership of the elements of $\mathcal{X}$ to the fuzzy subsets A and B, respectively. Symbol $*$ denotes any crisp operator. Some of the consequences of applying a fuzzy function to logical operators are the following:

$$\mu_{X \wedge Y} = \min(\mu_X, \mu_Y)$$
$$\mu_{X \vee Y} = \max(\mu_X, \mu_Y)$$
$$\mu_{\neg X} = 1 - \mu_X$$

The union $\cup$ and the intersection $\cap$ of ordinary subsets of $\mathcal{X}$ can be extended such that:

$$\forall x \in \mathcal{X}, \mu_{A \cup B} = \max(\mu_A(x), \mu_B(x)) \quad (2)$$

$$\forall x \in \mathcal{X}, \mu_{A \cap B} = \min(\mu_A(x), \mu_B(x)) \quad (3)$$

where $\mu_{A \cup B}$ and $\mu_{A \cap B}$ are respectively the membership functions of $A \cup B$ and $A \cap B$.

2.5 T-Norms and T-Conorms

T-norms and T-conorms (Deschrijver et al., 2004) are used to calculate the membership values of intersection and union of fuzzy sets, respectively. A T-norm is a binary operation $T : [0,1]^2 \rightarrow [0,1]$ satisfying the following axioms for all $x, y, z \in [0,1]$:

(i) $T(x,y) = T(y,x)$ (commutativity),

(ii) $T(x,y) \leq T(x,z), if\ y \leq z$ (monotonicity),

(iii) $T(x,T(y,z)) = T(T(x,y),z)$ (associativity),

(iv) $T(x,1) = x$

Some common T-norms (and respectively, their corresponding T-conorms) are the minimum $T_M(S_M)$, the product $T_P(S_P)$ and Łukasiewicz $T_W(S_W)$, defined as follows:

- $T_M(x,y) = \min(x,y)$, $S_M(x,y) = \max(x,y)$;
- $T_P(x,y) = x.y$, $S_M(x,y) = x + y + xy$;
- $T_W(x,y) = \max(0, x + y - 1)$, $S_W(x,y) = \min(1, x + y)$.

Implicators generalize the logical implication to the unit interval and are defined by $I_S(x,y) = S(1-x,y)$ for x and y in $[0,1]$, e.g., the implicator for S_M is defined by $I_{S_M}(x,y) = \max(1-x,y)$. For more details, we refer the reader to (Schweizer and Sklar, 1960; Schweizer and Sklar, 1983).

3 SPATIO-TEMPORAL BELIEF REPRESENTATION AND REASONING

In this section, we describe the the main features of our formal representation of fuzzy spatio-temporal beliefs. Since we extend the multi-agent BDI recommender systems proposed by (Othmane et al., 2016b; Othmane et al., 2016a) with the formal representation of fuzzy spatio-temporal information, we begin by recalling our multi-context framework, which handles information uncertainty using possibility theory.

3.1 A Multi-Context Recommender Agent

Using cognitive agents architecture such as the belief-desire-intention model as a base of a recommender system is relevant especially in real-world applications (Casali et al., 2008b). Casali *et al.* (Casali et al., 2008a) and (Othmane et al., 2016b) proposed similar multi-agent BDI recommender systems that handles information uncertainty using possibility theory. We decided to extend the approach proposed in (Othmane et al., 2016b) because it proposes already a mechanism for beliefs and intentions update compared to (Casali et al., 2008a). In (Othmane et al., 2016b), a BDI agent visualized in Figure 2 is defined using multi-context systems (Parsons et al., 2002) as follows:

$$Ag = (\{BC, DC, GC, SC, PC, IC, CC\}, \Delta_{br})$$

where BC, DC, GC represent respectively the Belief Context, the Desire Context and the Goal Context which model an agent mental attitude. PC, IC and CC are functional contexts that represent respectively the Planning Context, the Intention Context and the Communication Context. SC is for the Social Context, and it models social influence between agents. Authors of (Othmane et al., 2016b) assume a trust relationship between agents and trustworthiness of an agent a_i towards agent a_j about an information ϕ is interpreted as a necessity measure $\tau \in [0,1]$. The behavior of these contexts is handled by means of internal deduction rules Δ_i and axioms L_i. The overall behavior of the system is handled by bridge rules like Rule (2) (shown in Figure 2) linking GC to DC, and expressed as follows:

$$(2) GC : G(a_i, \phi) = \delta_\phi \rightarrow DC : D^+(a_i, \phi) = \delta_\phi$$

It can be read as follows: if an agent a_i has as goal ϕ with a satisfaction degree δ_ϕ in a GC then it positively desires ϕ with the same degree δ_ϕ in a DC.

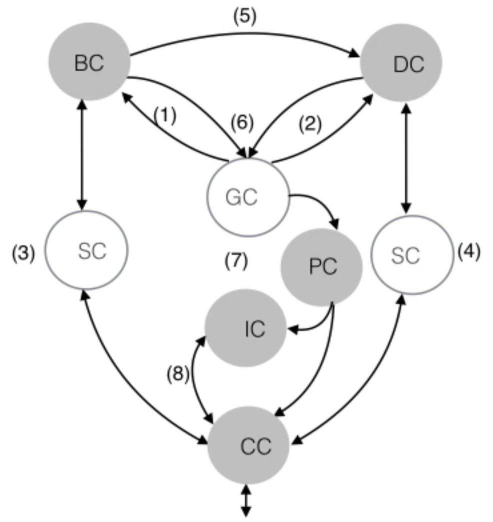


Figure 2: A global view of the multi-context agent components

For more details about this agent model, we refer the reader to (Othmane et al., 2016b).

Indeed, the work of (Othmane et al., 2016b) has shown how autonomous BDI agents (Othmane et al., 2016a) can evolve and move within a dynamic environment, this work lacks from a spatial and temporal reasoning in order to match the needs of a real-world application.

A spatio-temporal belief is an event defined as a spatial relation holding in a temporal interval. A spatio-temporal belief consists then of a sequence of snapshots of an entity taken at specific time points: b_1 at t_1, b_2 at t_2,..., b_n at t_n where $t_1, t_2, ..., t_n \in T$ and $b_1, b_2, ..., b_n$ are spatio-temporal beliefs concerning a moving spatial object (e.g. car, moving person, etc..).

3.2 Fuzzy Sets for Representing Imprecise Spatio-Temporal Beliefs

Spatio-temporal data are often affected by imprecision and uncertainty (Galton, 2009) due to several reasons. Spatial uncertainty refers to positional accuracy (e.g., location of an individual or a car). Temporal uncertainty states whether temporal information describes well a spatial phenomena. A fuzzy set, because of its ability to represent degrees of membership, is more suitable for modeling geographical entities. In a GIS database, real world objects can be represented by the degrees of membership to multiple classes or objects.

Representing only the spatial or the temporal dimension is not sufficient to model and analyze such phenomena. Modeling change involves incorporating both dimensions simultaneously. In this work,

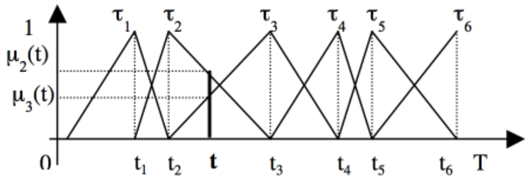


Figure 3: Fuzzy time membership function.

we adopt a dual representation of dynamic spatial information proposed by Bordogna *et al.* (Bordogna et al., 2003). In this approach, they introduce two representations: *i)* a precise spatial reference and indeterminate or vague time reference (e.g., if I leave home now, I should be at work around 8 pm), and *ii)* a precise time reference and a fuzzy spatial one (e.g., an accident has just occurred in between Route A and Route B). According to (Bordogna et al., 2003), a spatial dynamic object can be represented in the first case as a set of pairs (τ_i, o_i): $o_d := \{(\tau_1, o_1), .., (\tau_i, o_i), ..., (\tau_n, o_n)\}$, where τ_i is the time fuzzy validity range associated with the spatial object o_i. The semantics of τ_i is defined by a triangular membership function centred in t_i (see Figure 3). In the same way, a spatial object with precise time reference is defined by a set of pairs (t_i, σ_i), where σ_i stands for the spatial validity of the observed phenomenon at time instant t_i represented as a triangular membership function. In order to reason about such information, we need a mechanism to represent also qualitative relationships between spatio-temporal entities. For this reason, we propose a fuzzy RCC-8 and an extension to Allen's intervals to support fuzziness.

3.3 Fuzzy Allen's Intervals

The twelve relations defined by Allen for simple time intervals presented in Section 2.2 are generalized for modeling fuzzy time relations. Each basic relation can be defined in terms of endpoint relations defined in Table 2. Using the extension principle, a fuzzy temporal relation is defined. For example, the fuzzy relation d_f is introduced for the simple temporal relation d (during), as follows: $X d_f Y \Leftrightarrow (X^- >_f Y^-) \wedge (X^+ <_f Y^+)$, and the corresponding degree of confidence, using the extension principle, can be expressed as: $\mu_{X d_f Y} = \min(\mu_{X^- >_f Y^-}, \mu_{X^+ <_f Y^+})$.

All the values X and Y can be generalized to fuzzy values and represented by fuzzy triangular numbers. Based on the extension principle, we define first the confidence degrees of the fuzzy relations $\geq_f$ and $\leq_f$, in order to deduce respectively the one of $>_f$, $<_f$ and $=_f$. Suppose we have two fuzzy intervals A and B defined by triangular fuzzy functions as follows: $A = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$. By applying the extension principle, we can deduce the following fuzzy relations:

$$\mu_{A \leq_f B} = \begin{cases} 0 & \text{if} \quad a_1 > b_3 \\ \frac{b_3 - a_1}{b_3 - a_1 + a_2 - b_2} & \text{if} \quad a_1 \leq b_3, b_2 < a_2 \\ 1 & \text{if} \quad a_2 \leq b_2 \end{cases} \tag{4}$$

$$\mu_{A \geq_f B} = \begin{cases} 0 & \text{if} \quad b_1 > a_3 \\ \frac{a_3 - b_1}{a_3 - b_1 + b_2 - a_2} & \text{if} \quad b_1 \leq a_3, b_2 > a_2 \\ 1 & \text{if} \quad b_2 \leq a_2 \end{cases} \tag{5}$$

From Equations 4 and 5, we can deduce the confidence degree of relations $>_f$, $<_f$ and $=_f$ as follows:

$$\begin{aligned} A <_f B &= A \leq_f B \wedge \neg(A =_f B) \\ A >_f B &= A \geq_f B \wedge \neg(A =_f B) \\ (A =_f B) &= A \leq_f B \wedge A \geq_f B \end{aligned}$$

Let us consider, for instance, $A = (8, 9, 10)$ and $B = (8.5, 9.5, 10.5)$ representing two fuzzy time-points. We can compute the degree of confidence of this fuzzy temporal relation "*A* occurs at approximately the same time as *B*" using Equation 4 and Equation 5 as follows: $\mu_{A =_f B} = \mu_{A \leq_f B \wedge A \geq_f B} = \min(\mu_{A \leq_f B}, \mu_{A \geq_f B}) = \min(1, 0.75) = 0.75$.

3.4 Fuzzy Topological Relations

The eight binary topological predicates for simple regions (Section 2.1) are generalized for modeling fuzzy topological relations. Based on the approach proposed by Schockaert *et al.* (Schockaert et al., 2009) and the definition of the RCC relations in Table 2, we present here an approach for modelling imprecise spatial information when regions are represented as fuzzy sets. Let U be a nonempty set (representing regions), and **C** a reflexive and symmetric binary fuzzy relation on it modeling connection. Several other topological relations can be defined based on this relation. These include the RCC8 basic relations DC, EC, PO, EQ, TPP, NTPP, and the converses of TPP and NTPP (see Table 3 for their definitions).

Note that we adopt, following (Schockaert et al., 2006), the Łukasiewicz-norm T_w and its corresponding implicator I_{T_w} to generalize the standard logical conjunction and implication. In addition, we chose this logic for its convenience, especially regarding the implication function. The implicator corresponding to the Łukasiewicz t-norm is defined by: $I_{T_W} = \min(1, 1 - x + y)$. In fact, the minimum operator does not eliminate values arbitrarily, leaving thus more uncertainty. For simplicity, we write I_W instead of I_{T_W} in the remainder of the paper.

Table 3: Fuzzy RCC definitions

Name	Definition	Fuzzy Definition
$DC(x,y)$	$\neg C(x,y)$	$1 - C(x,y)$
$P(x,y)$	$\forall z \in U, C(z,x) \to C(z,y)$	$\inf_{z \in U} I_W(C(z,x), C(z,y))$
$PP(x,y)$	$P(x,y) \wedge \neg P(y,x)$	$\min(P(x,y), 1 - P(y,x))$
$EQ(x,y)$	$P(x,y) \wedge P(y,x)$	$\min((P(x,y), P(y,x))$
$O(x,y)$	$\exists z \in U, P(z,x) \wedge P(z,y)$	$sup_{z \in C} T_W(P(z,x), P(z,y))$
$DR(x,y)$	$\neg O(x,y)$	$1 - O(x,y)$
$PO(x,y)$	$O(x,y) \wedge \neg P(x,y) \wedge \neg P(y,x)$	$\min(O(x,y), 1 - P(x,y), 1 - P(y,x)))$
$EC(x,y)$	$C(x,y) \wedge \neg O(x,y)$	$\min(C(x,y), 1 - O(x,y))$
$NTP(x,y)$	$\forall z \in U, C(z,x) \to O(z,y)$	$\inf_{t \in U} I_W(C(z,x), O(z,y))$
$TPP(x,y)$	$PP(x,y) \wedge \neg NTP(x,y)$	$\min(PP(x,y), 1 - NTP(x,y))$
$NTPP(x,y)$	$PP(x,y) \wedge NTP(x,y)$	$\min(1 - P(x,y), NTP(x,y))$

Using this formalism, we can, for example, calculate a fuzzy spatial relation "p is precisely located far from q". Knowing the location of p and q, we can calculate their fuzzy position using Equation 6. We can then calculate the degree to which those two locations are connected, and consequently, their degree of disconnection: $DC(p,q) = 1 - C(p,q)$.

3.5 Fuzzy Spatio-Temporal Belief Representation and Reasoning

In order to represent an imprecise spatio-temporal belief or desire such as "An accident occurred around 8 PM between road A and road B" or "I want to be at work before 9 AM", we combine the RCC spatial relations with Allen's temporal relations. The degree to which this belief is true is computed using the minimum between the degrees of confidence of the spatial belief and the temporal one, respectively. For representing a spatio-temporal belief, we annotate spatial formulas with temporal information, meaning that a spatial formula is true during a time interval or at a specific time point. In other words, it can be written as follows: $X\ DC_I\ Y$, $Y\ PO_J\ Z$, where X and Y represent two different regions or moving objects, and I and J are time intervals. This formula means that X is disconnected from Y during time interval I, and Y is part of Z during time interval J.

Let us consider again the belief "An accident (A) occurred around 8 PM (t_1) between road A (R_A) and road B (R_B)". This can be formalized as follows:

$$(A\ PO_{t_1} R_A) \wedge (A\ PO_{t_1} R_B).$$

Its degree of belief is:

$$B((A\ PO_{t_1} R_A) \wedge (A\ PO_{t_1} R_B)) = \\ = \min\{B(A\ PO_{t_1} R_A), B(A\ PO_{t_1} R_B)\}.$$

Later, one can reason about temporal intervals or time-points to infer relevant information such as being at the same time nearby the accident place. This spatio-temporal belief is essential for an agent to decide or not to reconsider its intention in case the degree of confidence of this belief is high. However, this belief is no longer useful after a certain time period, or if the accident is not placed on the agent's route (i.e., intentions).

4 EVALUATION

In this section, we present the evaluation of the CARS recommendation system equipped with the fuzzy spatio-temporal belief representation. The purpose of the evaluation is to quantify the gain of agents, in terms of execution and limited waiting time, to reach their goals, by exchanging spatio-temporal beliefs and desires. To this aim, we propose to test the proposed model in a real-world scenario where spatio-temporal knowledge represents a crucial factor in the user decision making process. In this evaluation, different agent's strategies are considered, following the ideas proposed by (Othmane et al., 2016a):

- *individual agent strategy*: agents behave individually without taking into account any information coming from other agents. Only information from external resources are considered in this case, e.g., data from the Traffic Message Channel (TMC).
- *social agent strategy*: agents are part of a social network and communicate with the other agents in the network by exchanging their own beliefs and desires. Agents fully trust all other agents in the network.
- *social distrustful agent strategy*: agents are part of a social network, but they consider also the trustworthiness degree of the other agents, when they exchange messages. Agents accept information only from trustworthy agents. An agent is considered as deceitful if the information it provides is repeatedly proven to be false.

4.1 Scenario

In order to evaluate the applicability of the proposed model in a real-world application, we propose the following scenario. Agent a_1 uses an electric car, and needs to reach an electric public charging point. Like most road users, a_1 usually consults web-based or mobile mapping services before the trip to determine the nearest charging station and to avoid possible traffic jams. Knowing where to get to and estimating the time needed for the journey, a_1 can plan its trip. Thus, it selects a course of actions that will result in reaching its destination before the battery of its car goes out of charge. It chooses a route to follow and a time to leave so that it can arrive by a desired arrival time. Once the trip is planned, it can be executed. As long as a_1 has not found any obstacle within the journey, it can keep executing its original plan. However, it just found that a certain road on its route is closed due to an accident (other city events such as soccer games or music concerts can be considered as well). As a_1 is not able to drive through that road anymore, it has to reconsider its options and find an alternative route to reach its destination while taking into account its battery life (hence its arrival time).

4.2 Implementation

In agent-based systems with spatial reasoning and social behavior, a visual output is needed to display the agents' movements and interactions in two- or three-dimensional spaces. NetLogo[1] is a multi-agent programming language and modeling environment for simulating natural and social phenomena particularly suited for modeling complex systems evolving over time.

To implement our scenario, we decided to use NetLogo, as it also provides support for the BDI architecture and the FIPA Agent Communication Language. The spatial module is implemented using the Geographic Information Systems (GIS) extension for Netlogo[2]. We used data about the road network and Electric Vehicle (EV) charging points from the Nice city open geographical database[3] in shapefile format (i.e., the format supported by the GIS Netlogo extension). The resulting environment of agents is shown in Figure 4.

In order to adapt a fuzzy topological relation to a GIS vector data model, we assume that crisp regions are a set of trapezoidal shapes containing a finite sequence of line segments. To simplify the representation, we use a Gaussian function distribution as an approximation of the trapezoidal distribution. Then, the membership function $\mu(x,y)$ of a spatial object with coordinates (x,y) is defined by the following equation:

$$\mu_{x,y} = e^{-k_d|(x-x_R)+(y-y_R|^2}, \tag{6}$$

where x_R and y_R are the coordinates of a landmark point, and k_d corresponds to a flattening coefficient defined according to the user description (d) of a belief. We define then different coefficients for $k_{\text{precisely}}$, $k_{\text{approximately}}$, k_{near}, k_{around}. An example of this distribution run is visualized in Figure 5.

Agents in this simulation are spatial entities (moving cars) in an environment (the road network of the Nice city) which may change their location and attributes as time goes by[4]. At the beginning of the simulation, each agent has a desire. As defined in our scenario, the desire of an agent is to go to the nearest EV recharge point. A recommended plan is proposed to the agent following the multi-context approach to the deliberation of agent behavior proposed by (Othmane et al., 2016b; Othmane et al., 2016a). Once the agent starts executing its plan, we trigger at different random times in different random places spatio-temporal events, i.e., accidents. If the agent receives information, it adds it to its belief base and, if the accident is on its route, it updates its intentions, if possible. Agents applying the *individual strategy* have no knowledge from the other agents, thus they update their route only when they encounter a closed route in their plan.

4.3 Results and discussion

The experiments were conducted as a version of the scenario proposed in Section 4.1, with the adoption of the three different strategies described in Section 4. The scenario is executed with 10, 50, 100, and 150 agents as part of the environment in three different experiments. We measured the time it took an agent to reach its destination. Results of the average time for agents to reach their destination for the different cases are reported in Figure 6-[a]. The average time for all agents to reach their destination increases as the number of agents increases. This can be explained by the traffic overload, which cannot be avoided due the number of cars on the road network. However, it is worth noticing that the time decreases when the two social agent strategies are exploited, in contrast

[1] https://ccl.northwestern.edu/netlogo/

[2] https://ccl.northwestern.edu/netlogo/docs/gis.html

[3] http://opendata.nicecotedazur.org/data/

[4] The simulation code is available at this link: http://modelingcommons.org/browse/one_model/4832#model_tabs_browse_info.

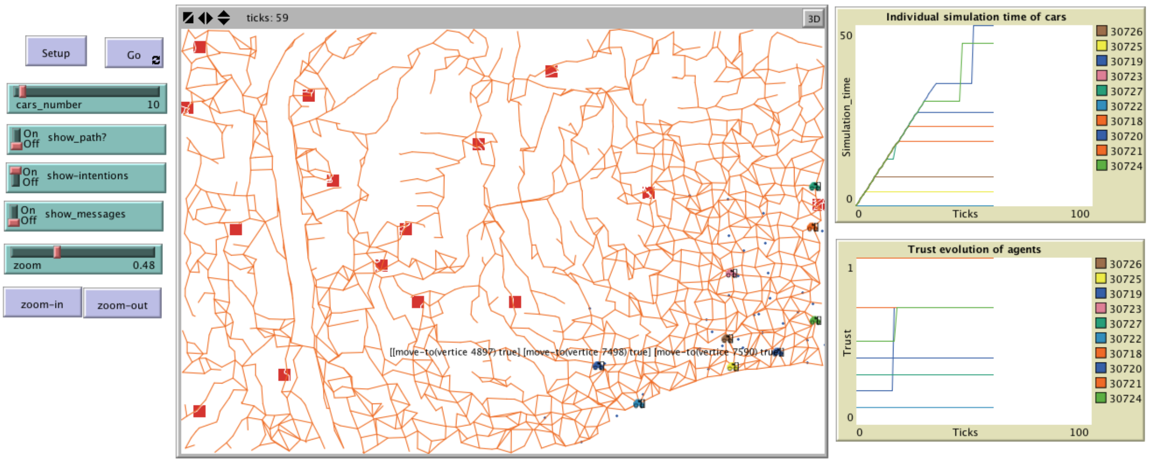


Figure 4: The user interface of the agent-based simulation in NetLogo. The central part shows the agent's environment constituted of roads. Blue points represent Electric Vehicle charging stations. An agent is represented by a car. Red squares represent accidents. Labels represent an agent intention, which consists of two elements: the name, mapped to a NetLogo command, and a done-condition, mapped to a NetLogo reporter. Intentions are stored in a stack, and are popped out when they are to be executed. If the done-condition is satisfied, the intention is removed and the next intention is popped out consecutively. The figure shows also, on the right-hand side, how the graphs are updated dynamically as the program runs. The left-hand pane shows some setup parameters.

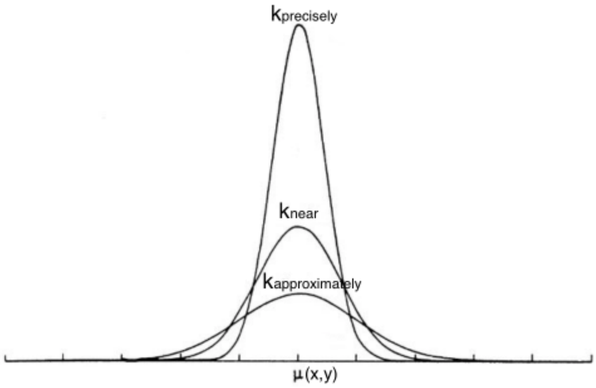


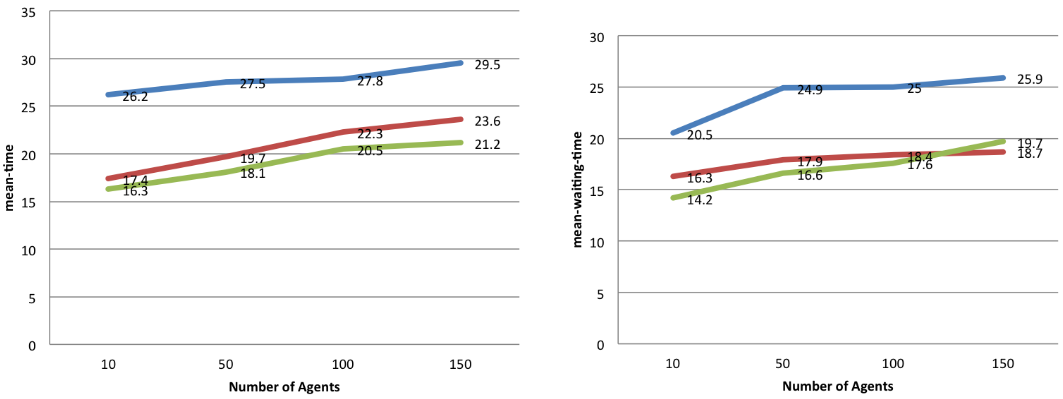
Figure 5: Example of the Gaussian distribution

to the individual agent strategy. Notice also that social agents using trust-based information to judge the reliability of the recommendations they receive have better performance than purely social ones. As a conclusion, the results show that exchanging spatio-temporal beliefs among agents enhances the overall performance of the agent network.

It is worth observing that some agents adopting the individual strategy do not even reach their destination (i.e., they cannot satisfy their goals). Therefore, the average time reported in the diagrams keeps rising indefinitely. In contrast, social agents always achieve their goals and reach their destination, with an even more limited time interval observed for those agents exploiting trust-based information. These results show that exchanging fuzzy spatio-temporal beliefs helps agents to achieve their goals by anticipating the consequences of their intentions. In other words, agents can anticipate and change their intentions to avoid huge waiting time. Taking into account spatio-temporal beliefs coming only from trustworthy agents avoids agents to be mislead and hence to waste time. Figure 6-[b] reports the average waiting time of agents. Within social agents, results are slightly better for those exploiting trust-based information, except when the number of agents is 150. This is due to the time required to process such information for the whole agent network, as more processing time is needed to verify agents' reliability.

5 RELATED WORK

Few approaches exist to represent and reason about spatio-temporal beliefs, desires and intentions' dynamics. Jonker *et al.* (Jonker et al., 2003) propose a formal spatio-temporal state language to define the spatio-temporal behavior of an agent in a dynamic environment. Although their approach provides an interesting formalism for predicting agent spatial behavior, many questions concerning beliefs, desires and intentions dynamics are left open. For example, no mechanism for updating beliefs, desires and intentions in this formalism is presented. Maleš and colleagues (Maleš and Žarnić, 2011) use modal logic to define an agent capable of updating its mental attitude according to spatio-temporal relations consid-



(a) (b)

Figure 6: Experimental results (selfish agents: blue, social agents: red, social distrustful agents: green): (a) average time required by the agents to reach a destination, and (b) average waiting time for the agents.

ered as events. They define a language for events in which spatio-temporal knowledge is defined under the form of predicates, with an example in the traffic scenario. Nevertheless, the proposed framework is still in a preliminary stage and presents some drawbacks, e.g., lack of a mechanism to update such spatio-temporal beliefs and desires. Schuele *et al.* (Schuele and Karaenke, 2010) propose a spatial model to enable BDI agents to move autonomously and collision-free in a spatial environment. Authors assume that in a spatial context, the agents' knowledge about their environment is uncertain. However, this problem is not handled through a qualitative approach for spatial reasoning. Time reasoning is not handled neither. Other relevant approaches for spatial reasoning in BDI models are discussed in (Vahidnia et al., 2015). However, none of them consider the imprecision and vagueness that characterise spatial knowledge. So far, to the best of our knowledge, many approaches to reason about time in the BDI agent model are proposed in the literature (among them, see (Jarvis et al., 2005; Fisher, 2005; Sierra and Sonenberg, 2005) but none of them deals with time information imprecision. Unlike the aforementioned approaches, our approach besides combining spatial and temporal reasoning within the BDI model, it addresses the open challenge of spatio-temporal information vagueness and fuzziness that strongly characterizes such a kind of knowledge.

6 CONCLUSIONS

In this paper, we have introduced and evaluated the CARS agent-based recommender system, where fuzzy spatio-temporal beliefs are formally represented and updated. Answering the need to represent spatio-temporal information to provide recommendations in the traffic scenario, we define spatio-temporal knowledge annotating spatial formulae (formalized through fuzzy RCC) with temporal information (formalized through fuzzy Allen's time intervals). The goodness of the proposed formal framework is validated through an empirical evaluation simulating the agents' behaviour in the traffic scenario. Results show that the time required by the agents to reach a certain point of interest sensibly decreases when the CARS model is applied.

Several open challenges have to be tackled as future research. First of all, further qualitative relations about directions should be introduced concerning spatial reasoning to allow the representation of a model closer to reality. Second, on the simulation side, extending the evaluation introducing new metrics to further reduce the processing time is also part of our future research.

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