An intelligent fuzzy agent for spatial reasoning in GIS

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Abstract. In this paper, an intelligent fuzzy agent can identify the values of risks and the environmental damages of the smoke plumes. When smoke plumes move: data extractor extracts the fuzzy areas form NOAA satellite images, spatial decision support system updates information from data base, and topological simulator computes the strength and type of topological relationships and sends the extracted information to a designed knowledge based system. A fuzzy inference subagent infers the information provided by data extractor subagent, topological simulator subagent and knowledge base, and sends the results back to the spatial decision support subsystem. The risk amounts for pixel elements of the forest area are computed and dangerous sites are specified based on the spatial decision support system in GIS environment. Then, a genetic learning agent tries to generate and tune the spatial knowledge bases for the next risk calculation. By the experimental results, the designed system provides flexibility, efficiency and robustness for air pollution monitoring.

Keywords Spatial reasoning, Agent, Fuzzy, GIS

1 Introduction

Agents are one of the most popular objects for searching solutions to realistic computational problems characterized by incomplete information and autonomy in dynamic and distributed spaces. Different definitions for an agent presented by researchers; for example Ferber said "An agent is a program or spatial package that is capable for acting in an environment and can communicate with other agents" [1]. Generally, we can say an intelligent agent should behave in a SMART (Specific, Measurable, Attainable, Realistic, Time bound) manner and generate different judgment results by using various parameter settings and training sets. These agents have several characteristics such as Autonomy, Mobility, Social ability, Reactivity and Proactiveness [2; 3] and typically deals with dynamic, incomplete and uncertain domains of decision making problems where mathematical methods can not perform well, because of ill-structured forms. Ill-structured forms are complex and dynamic decision making problems which included incomplete or indefinite goals, objectives, criteria and alternatives. Wide ranges of these problems are appeared in the spatial applications such as environmental modeling, ecological management, land use planning and etc [4; 5; 6].

[7; 8; 9] seem to be first spatial systems, employing agent technology for spatial applications. They used agents for fast creation of robust, scalable and seamless access to nomadic services. In [10], an automated generalized agent-based system has been developed for a digital personal mobile tourist guide using GIS, databases, natural language processing, intelligent user interfaces and knowledge representation parts. Also, [11] has implemented an agent-based architecture providing adaptive services using intelligent agents that learns the key characteristics quite quickly, including spatio-temporal variations for wireless networks. In another research area, [12] presents the IMA architecture which is aimed at replacing the monolithic approach to spatial systems with a dynamic, lean, and customizable system supporting spatially-oriented applications.

But, the mentioned systems proposed by authors in above, have the lacks of flexible uncertain spatial behavior learning and reasoning mechanism. Our intelligent agent based system is more powerful, because of uncertain spatial reasoning and learning capabilities. This system makes use of a spatial knowledge base and uncertain algorithms to carry out goals defined by human developers or runtime users in a GIS. Geographic information system (GIS) provides the prospect of monitoring dynamic variations in the phenomena with indefinite boundaries by different criteria and factors. Also, our system presents a new way for analyzing topological relations between uncertain spatial phenomena in an online environmental alarm system. The necessity of this subject is stated by the fact that environmental pollution, as a result of oil wells, adversely affects forest areas.

To satisfy the needs of quick response, this study presents an intelligent fuzzy agent system using real-time information to enhance production decisions. For this purpose the designed intelligent spatial fuzzy agent system (ISFA) contains: a data extractor subagent (DEA), fuzzy topological simulator subagent (FTSA), fuzzy inference subagent (FIA) and a genetic learning subagent (GLA), to carry out the risk values. Moreover, the spatial decision support subsystem (SDSS) will process the information and order the risk areas for final decisions in overall snapshots. In addition, spatial data base (SDB) and knowledge base (KB) will store the extracted and predefined information and rules for mentioned application.

2 Intelligent spatial fuzzy agent architecture

Our system contains a sophisticate user interface, a spatial data base, different active agents, a knowledge base, a spatial decision support and a GIS. Designing this system would not be possible if integration of each component required extensive programming. Then, we decided to build an intelligent agent in object oriented programming language. In this kind of programming, an object can respond to the request of any other objects that knows how to address it. Figure 1 shows the general architecture of this system.

In Figure 1, While satellite images (NOAA-AVHRR) and different spatial data (Iran political boundary, Forest areas, DTM, Soil types, Synoptic stations and etc) are stored in the SDB, the DEA starts extracting fuzzy boundaries of smoke plumes and target forest area based on different sample points and spatial images, then, immediately sends them to FTSA for simulating the topological relations based on fuzzy topological matrixes. The derived linguistic terms extracted by FTSA are sent to the KB and FIA to save as fuzzy rules and infer by the other experts predefined rules for the application. This mean, the parameters of the fuzzy variables that represent the behavior of smoke plumes and forest area will be stored in the KB for FIA. FIA retrieves the KB to get the fuzzy risk values of all the forest area for computing the risk and possibility and sends the computing results to SDSS. Also, SDB sends the required information including Soil types and Vegetation Species to the SDSS for ranking and ordering alternatives. Finally, SDSS will refer to the FIA and SDB to get the dangerous risk area and announce the GIS using sound. Furthermore, the actual decisions of the risk area will be stored into KB for genetic learning behavior. To solve the contradictory problem, the GLA will judge the consistency of the training data set retrieved from the KB first. If there is a case with different output for the same inputs then GLA will discard the contradictory information.

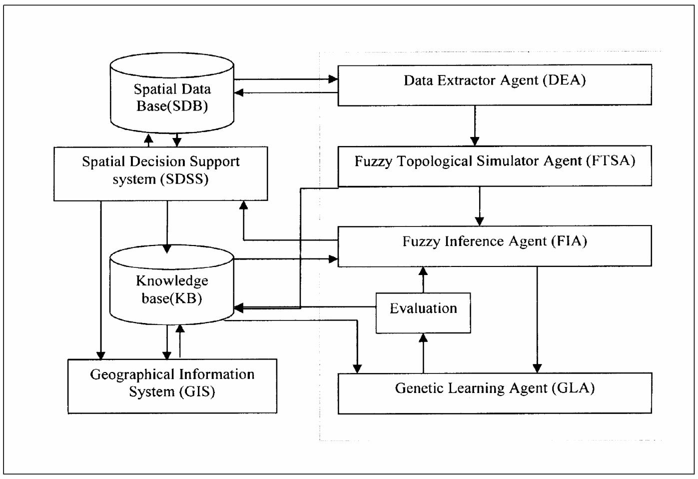

Fig. 1. The ISFA architecture

3 Case study and related data

Our case study is located at 32˚ N, 53˚ E in the Middle East, between Kuwait and Iran territory and support the assumption that smoke plumes from Kuwait reached the territory of Iran during 1991 Persian Gulf War. It has been reported that nearly 700 oil wells were set on fire starting on 19 February 1991 for which the last fir extinguished on 2nd November 1991. During the peak period of the fires, the wells were emitting about 5000 tones of smoke per day [13]. Oil pollution movement via south west of Iran could be confirmed using NOAA-AVHRR midday images. The polluted inland areas can be outline as natural resources such as forest lands. This pollutant impacts on the: biological, physical and chemical characteristics of soil, the amount of acid rain falls and increasing heavy metals through the forest lands. The main objective of our study is to track, estimate and evaluate the risk values in terms of natural forest cover due to the mentioned atmospheric pollution quickly. This purpose would be possible if an integrated intelligent system designed using a variety of tools for making decision available. Thus, using GIS and Remote sensing data are essential for the identification of dangerous sites prior to undertaking further analyses or field investigations. GIS spatio-temporal data sets of Forest area, Political boundary, Synoptic stations (for Wind direction and climate), Soil types, Forest species, Digital elevation models (DEMs) and satellite NOAA-AVHRR daily data were collected for the southwest of Iran from different sources, such as Iranian Natural Resources Organization (INRO), Iranian National Centre for Oceanography (INCO), National Cartographic Center (NCC), and Soil Conservation and Watershed Management Research Center (SCWMRR) during 1991. They were summarized as shown in Table 1.

Table1. Spatial data used in the study

Data	Scale	Data Source
Forest area	1:250000	INRO
Synoptic stations	1:250000	INCO
Soil types	1:250000	INRO
Forest species	1:250000	INRO
DEM	1:250000	NCC
NOAA-AVHRR	1:1000000	SCWMRR

These features required for the inferring in FIA and decision making in SDSS and they are stored into SDB using designed sophisticated interface. For example, to obtain the spatial data sets of the fuzzy forest area, the forest land was classified by DEA around features to be used in FTSA. Monthly meteorological and oceanography information, which are essential to support the movement of smoke plumes and estimating risk values, are extracted by synoptic stations through the global telecommunication system (GTS). Forest species and Soil types are used in SDSS for ranking final risk area and determining dangerous sites. The AHRR (1.1 km at nadir) sensors aboard four satellites transmitting data during 1991 (NOAA-9, 10, 11 and 12) were capable of providing at least four images every 24th. In this way, they provided a better opportunity to follow the dynamics of smoke plumes than satellite with longer intervals. The available spectral channels have simply demonstrated in Table 2.

Table 2. Characteristics of NOAA Images

Spectral Bands	NOAA-10	NOAA-9,11,12
Band-1	0.58-0.68(visible)	0.58-0.68(visible)
Band-2	0.725-1.10(near-infrared)	0.725-1.10(near-infrared)
Band-3	3.55-3.93(thermal-infrared)	3.55-3.93(thermal-infrared)
Band-4	10.50-11.50(thermal-infrared)	10.3-11.3(thermal-infrared)
Band-5	10.50-11.50(thermal-infrared)	11.50-12.50(thermal-infrared)

For the purpose of detection and estimation of smokes and reducing the time of processing, we used channel 2 midday images with minimum shadow and shading. In addition, persistency and accumulated smoke density which are two important parameters for risk estimation derived by DEA using NOAA series images and saved in SDB for further analysis.

4 Implementation results

The intelligent spatial fuzzy agent (ISFA) user interface contains four subagents including data extractor subagent (DEA), fuzzy topological simulator subagent (FTSA), fuzzy inference subagent (FIA) and genetic learning subagent (GLA) to assist the SDSS including spatial decision subagent (SDA). Each subagent in the proposed system possesses both the extracted and the predefined knowledge to perform a particular step in decision making process. The designed ISFA user interface, consisted of control codes written in Mathlab and a large set of VB.NET modules, allows users to choose the required functions to be used in the system.The extracted knowledge for a task is captured in procedural codes written in VB.NET. Often these are procedures for executing a piece of software developed by a simulation subsystem, a geographical information subsystem, a knowledge based subsystem, or spatial decision support subsystem. In some cases, some of designed subagents know how to operate class of models (for example, spatial data extractor and fuzzy topological simulator have this capability). DEA and FTSA gather the spatial information and fuzzy topological relations from spatial data and satellite images and send them to FIA and SDSS. Also, DEA receives the computed results of SDSS and sends them to FIA. Data extractor subagent can extract the required data for FTSA, FIA and SDSS based on various smoke plumes and environmental treatments. The DEA responds to the stored and portal received data by the interface and helps users set up their preference and required parameters in different snapshots. While a snapshot is started, DEA connected to the SDB and uses preference module to identify the fuzzy spatial regions of forest area and smoke plumes. These computed regions are sent to FSTA for deriving topological linguistic terms between regions which are used in FIA for inferring. Also, DEA determines fuzzy values of persistency, wind direction, amount of smoke, distance, and inclusion index in each snapshot for every pixel of the classified regions and updates knowledge base by derived data. Moreover, it can connect to user preference module for determining fuzzy weights of Soil types and Forest species layers semantically for ranking risk areas in SDSS. Users can recall and revise this treatment knowledge base later and reuse it for other risk units. FTSA is responsible for constructing Fuzzy topological relations between fuzzy smoke plumes and forest areas by simulating the Fuzzy 9-intersection matrixes [14]. Therefore, the relations can be described using the terms of 'Disjoint', 'Touch', 'Equal', 'Contain', 'Cover' and 'Overlap'. The FTSA is responsive to change in the values of these variables with respect to the conditions in the real world and try to update knowledge base using simulation results. Moreover, this subagent can compute the inclusion index parameter to add more quantitative information to the topological descriptions [15]. The overall architecture of Fuzzy Inference Agent (FIA) in the ISFA is consisted of three layers. There are three kinds of nodes in this model: input linguistic term nodes, rule nodes, and output linguistic term nodes. In layer1, a fuzzy linguistic term node represents a fuzzy variable and the mapping degree of it. The nodes in the first layer just directly transmit input values to next layer to constitute a condition specified in some rules.

In layer2, a rule node represents a rule and decides the final firing strength of that rule during inferring. In our model, 22rules are de fined by domain expert's knowledge previously (Figure 2). Hence, the rule nodes perform the fuzzy AND operation.

In layer3, an output linguistic term node shows a fuzzy output variables resulted by inferring. In this layer the output fuzzy variable for FIA is denoted the risk values for each smoke plume at the forest area. The output term node performs the fuzzy OR operation to integrate the fired rules which have the same consequence and then uses the Centroid operators for defuzzyfication.

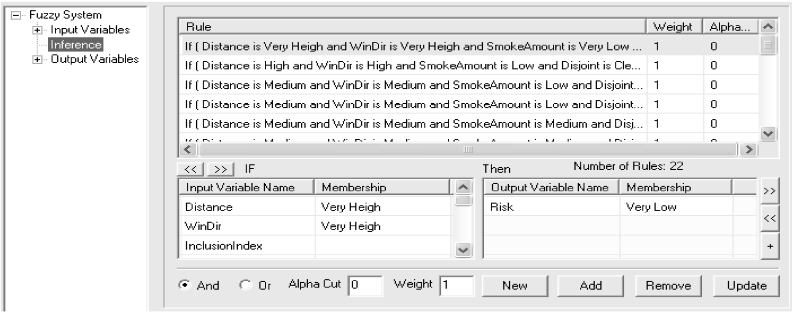

Fig.2. Designed FIA rules

After each snapshot, the solution result is stored in the KB and SDB. GLA retrieves the recorded data to encode each solution and evaluate them for creating next new solutions. In here, we used the approach proposed by [16] to learn the solutions and rules for every snapshot. In KB and SDB, fuzzy variables and linguistic modifiers are coded, then, each chromosome is composed of these two parts for each smoke plume i. After that, dynamic restrictions which are used to preserve meaningful fuzzy sets and improve learning efficiency are applied. The initial population for the gene pool is composed of four groups considering the randomized and original fuzzy variables and linguistic modifiers chromosomes (two-by two). The chromosome in the current population is evaluated by the fitness function. If the evaluation does not satisfy the fitness function, then elitism is used in GLA. In the beginning of selection, the best chromosomes in the current population are selected to the new population without crossover and mutation. The remaining chromosomes in the new population are selected by the Roulette Wheel Selection mechanism [17]. After the elitism selection, the one-point crossover method is adopted and a crossover point is randomly set. The portions of the two chromosomes beyond this cut-off point to the right are to be exchanged to form the offspring. An operation rate with a typical value between 0.7 and 1.0 is normally used as the probability of crossover. The mutation process is applied to each offspring individually after the crossover exercise. It alters each gene randomly with a typical probability value of less than 0.1. The probability parameters of crossover and mutation are critically dependent upon the nature of the objective function. An objective function is a measuring mechanism that is used to evaluate the status of chromosome. The objective (fitness) function used here is to minimize the mean square error (MSE) as follows:

$$\text{MSE}=\frac{1}{2n}\sum_{t=1}^{n}(O_{in}-O_{ind})^2 \tag{1}$$

Where n denotes the number of the training data for smoke plume i, O_{in} denotes the output of FIA for the nth training data, and O_{ind} denotes the desired output of the nth training data for smoke plume i. It is necessary to note that computational value in each snapshot is introduced as input fuzzy variable in next snapshot. Thus, it can be said that computational results in various periods will be dependent on each other through entering the results obtained from inference to the knowledge base. MSEs indicate that performance of GL is better than Cordon, with GL (0.9, 0.05) having better performance than others.

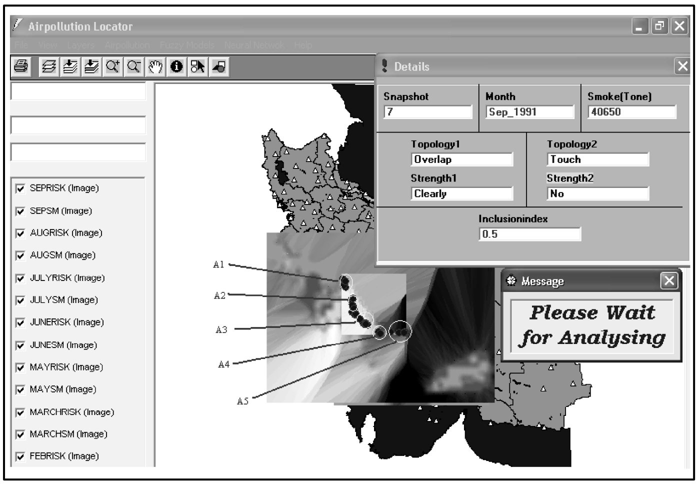

Fig. 3. Final risk assessment unites for the forest area during Persian Gulf War

Spatial decision making agent uses user preference module and fuzzy rule sets to estimate and judge how well a final risk unit satisfies expert's goals. Final risk unites are achieved by accumulating different snapshots and learning results during a period of time (in here 1991). For example, daily snapshots of smoke plumes give a risk area on the forest region where accumulated monthly and monthly results accumulated yearly. Four fuzzy categories: fails, nearly passes, barely passes, and passes indicate how well a goal is met in every set of snapshots. Spatial decision analysis subagent can perform goal satisfaction analysis on any sets of snapshots representing the risk areas at every pixels of forest in time. SDB and KB provide fuzzy risk units, soil types and forest species for the used application. DEA, user preference module and FIA provide the required information for fuzzy ranking of alternatives.

Final assessments are presented as fuzzy set values or intervals, then, probabilistic method which is more attractive and considers minimum sets of preliminarily assumptions [18] is applied for final fuzzy ranking. Figure 3 demonstrates the final risk assessment unites during 1991 for 5 classified risk areas (A1, A2, A3, A4, A5) during 1991.

5 Conclusion and Remarks

The designed intelligent fuzzy agent system includes online uncertain analysis of air pollution and its impacts on the environmental phenomena, then, is tested for the southwest of Iran during Persian Gulf (1991). This system contains five subagents including DEA, FTSA, FIA, GLA, and SDA to perform the intelligent air pollution support task. Moreover, a spatial user interface to evaluate the spatial results of proposed system is also constructed. Case studies using the ISFA decision process on the ranging of south west of Iran have been initiated and provide agents by flexible manner for inferring and making decision based on fuzzy values. The proposed intelligent system has the ability of monitoring dynamic variations in the phenomena with indefinite boundaries, analyzing spatial treatments, uncertain spatial reasoning and learning and expert's goal satisfaction. Therefore, by using this intelligent agent, the users will be able to extract the decision rules automatically and equipped them by learning algorithms.

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