A Multi-Agent Simulator for Teaching Police Allocation

Vasco Furtado, Eurico Vasconcelos

University of Fortaleza – UNIFOR, Mestrado em Informática Aplicada - MIA
vasco@unifor.br, jose_eurico@yahoo.com

Abstract

This article describes the ExpertCop tutorial system, a simulator of the crime in an urban region. In ExpertCop, the students (police officers) configure and allocate an available police force according to a selected geographic region and then interact with the simulation. The student interprets the results with the help of an intelligent tutor, the Pedagogical Agent, observing how the crime behaves in the presence of the allocated preventive policing. The interaction between domain agents representing social entities as criminals and police teams drives the simulation. ExpertCop induces students to reflect on resource allocation. The pedagogical agent implements interaction strategies between the student and the geosimulator, designed to make simulated phenomena better understood. In particular, the agent uses a machine learning algorithm to identify patterns on simulation data and to formulate questions to the student about these patterns. Moreover, it explores the reasoning process of the domain agents by providing explanations that help the student to understand simulation events.

Introduction

Simulation aims to represent a phenomenon via another one and it is useful to measure, demonstrate, test, evaluate, foresee, and decrease risks and costs. Practical application can be seen in various areas, such as, in the aeronautical industry, nuclear industry and military. In educational terms, simulation is important because it allows learning through the possibility of doing. Simulation has been shown to be a good teaching tool, especially for complex situations, with high cost and risk.

Multi-Agent Systems (MAS) have been widely adopted in the development of complex systems. One of the most important reasons to use a MAS paradigm is to handle the interaction of different entities or organizations with different (possibly conflicting) goals and proprietary information. A MAS is also appropriate when there is a need for representing individually each entity of the modeled domain or if these entities have an intelligent behavior to be modeled.

Social or urban environments are dynamic, non linear, and made of a great number of variables, characterizing a complex system. The use of MAS to simulate social environments has become broadly used (Khuwaja *et al.* 1996). Aggregating a Geographical Information Systems (GIS) to a MAS in the simulation of social or urban environments characterize the geosimulation (Benenson and Torrens 2004). Despite recent proposals on new models and implementation of instructional layers in simulators (Gibbons *et al.* 2001), few tools have been created specifically for geosimulation. These applications involve particular features as the geographic ones, which must be exploited by intelligent tutorial systems in order to enrich learning.

This article describes the educational tutorial system ExpertCop that considers the main characteristics, which we claim to be essential to a general architecture of an educational geosimulation. ExpertCop aims to enable police officers to better allocate the preventive police force in the urban areas. This software produces, based on a police resource allocation plan, simulations of how the crime behaves in a certain period of time based on the defined allocation. The goal is to allow a critical analysis by police officers who uses the system, making them to understand the cause-and-effect relation of their decisions.

Geosimulation generates a great amount of data deriving from the occurred interactions in the simulation process, and it is necessary to make chronological, geographical and statistical associations among these data to understand the cause and effect of the simulated events. Thus, we propose the use of an intelligent tutor agent as data analysis supporting tool, the Pedagogical Agent. This agent uses a machine learning concept formation algorithm to identify patterns on simulation data, to create concepts representing these patterns and to elaborate questions to the student about the learned concepts. Moreover, it explores the reasoning process of the domain agents for providing explanations, which help the student to understand simulation events.

Urban Simulation and Intelligent Tutoring

The simulation based on MAS is a live simulation that differs from other types of computational simulations because simulated entities are individually modeled with the use of agents. Social or urban environments are dynamic and non-linear, with a great number of variables. MAS are also appropriate when the environments are composed by a great amount of entities whose individual behaviors are relevant in the simulation general context.

A particular kind of simulation, called geosimulation, treats an urban phenomena simulation model with a multi-agent approach to simulate discrete, dynamic, and event-oriented systems (Benenson and Torrens 2004). In geosimulated models, simulated urban phenomena are considered a result of the collective dynamic interaction among animate and inanimate entities that compose the environment.

Simulation is widely used as an educational tool because the computerized simulation of the activity studied allows the student to learn by doing (Piaget 1976) and to understand the cause and effect relationship of his/her actions. The simulation *per se* isn't a sufficient tool for education. It lacks a conceptual form (both graphic and interactive) for the student to understand the simulation model. Therefore, some works have tried to integrate the notions of intelligent tutoring system (ITS) and simulation in order to better guide learning and to improve understanding of the simulation process. The idea aims at emulating the work of a human teacher that has knowledge of the content to be taught, and how and to whom it should be taught.

The ExpertCop System

Motivation

The police resource allocation in urban areas to perform a preventive policing is one of more important tactical management activities that usually is decentralized by subsectors in police departments of the area. Tactical managers analyze the disposition of crime in their region and accordingly allocate the police force. We adopt the principle that by knowing where the crime is happening and the reasons associated to this crime, it is possible to make a optimized allocation and consequently, to decrease the crime rate.

The volume of information that police departments have to analyze is one of the main factors to provide the society with efficient answers. Tactical managers who perform police allocations, for instance, lack ability for decision-making based on information analysis. In reality, understanding criminal mapping activities, even using GIS, is a non-trivial task. In addition to that, experiments in this domain cannot be performed without high risks because they result on loss of human lives. In this context, simulation systems for teaching and decision support provide a fundamental tool.

Goals

The ExpertCop system aims to support education through the induction of reflection on simulated phenomena of crime in an urban area. The system receives as input a police resource allocation plan, and it makes simulations of how the crime rate would behave in a certain period of time. The goal is to lead the student to understand the consequences of the allocation as well as understanding the cause-and-effect relations.

In the ExpertCop system, the simulations occur in a learning environment along with graphical visualizations that help the student's learning. The system allows the student to manipulate parameters dynamically and analyze the results.

ExpertCop Architecture

ExpertCop Architecture is composed of a MAS system, a GIS, a database and an interface as shown in Figure 1. The interface in ExpertCop allows the student to move among the functionalities and processes of the system in a logical, ergonomic and organized way. The GIS is responsible for generate, manipulate and update a map of the city to be studied in a small scale. The system database contains i) the information about each student and about his/her simulations, ii) the configuration data, iii) the real data on crime and statistics on crime yielded for the department of state police and iv) the domain ontology. The most important component is the MAS platform and it will be discussed in detail next.

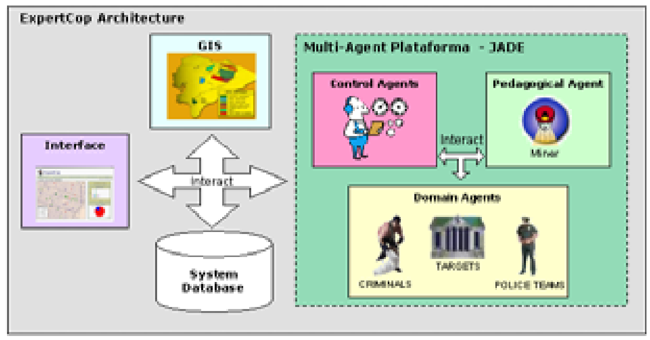

Figure 1: ExpertCop system architecture.

The MAS Platform

- The structure, communication, administration and agents' distribution is provided by the framework Java Agent Develop Framework - JADE (TILab 2003). The multi-agent platform in ExpertCop is made up of three groups of agents: Control agents, domain agents and the pedagogic agent. The control agents are responsible for the control, communication and flow in the system. The most important control agents are the *GIS agent* that is responsible for answering requests from the graphical interface, domains and control agents; the *manager agents* which are responsible for the coordination and interaction with domain agents and control pre-programmed activities as activation and deactivation and the *Log agent* that is responsible for recording all interactions among system agents. Other important control agent is the Pedagogical Agent (PA). It is endowed with pedagogical strategies, and aims to help the user in the understanding of the simulation process and results. PA will be discussed in details in the pedagogical proposal session of this work.

The *domain agents* are the actors of the domain. They are:

- ***Notable Points:*** Notable points are buildings relevant to the objective of our simulation, such as shopping, banks, parks and drugstores. They are located in the simulation map having the same characteristics of the buildings they represent.

- **Police teams:** The mission of the police teams is to patrol the areas selected by the student during the work period and work shifts scheduled for the team. A software agent represents each team and has a group of characteristics defined by the student, such as means of locomotion, type of service and work shift that will influence the patrol. The team works based on its work period and work shift. The work period determines the beginning and end of work, and the work shift determines the work and rest periods. Consider a team that works a shift of 8 hours and then rests for 16, working from 8 a.m. to 4 p.m. The team would work a first shift from 8 a.m. to 4 p.m., and then rest for 16 hours, returning to work the following day at 8 a.m. The patrol areas are composed of one or more connected points. The patrol areas are given to the police team as a mission. These areas are associated to intervals of time so as to fill out the work period of the team. A team with a work shift of 8x16 should patrol an area (or areas) for repetitive periods of eight hours every twenty-four hours. Suppose a police team called Beta who has 2 areas to patrol in its shift. The user/student should define the intervals of each area as follows.

Beta police team;
Work shift: 8 x 16; Work period: 8 a.m. to 4 p.m.
Area of patrol 1(4hs): start 8 a.m. end 12 a.m.
Area of patrol 2(4hs): start 12 a.m. end 4 p.m.
The total work load is eigth hours.

Each team organizes its patrol areas in a list according to the chronological order of the work period associated to each area. One or more points that determine the area make up each patrol area in its turn. Initially, the police teams begin their activities at a common initial geographical point (the neighborhood police station). From that point onwards, the working police teams (during their work period) verify the schedule that their areas must be patrolled. After identifying the area that must be patrolled at that time, the police team places in order the points that form that area in a list and utilizes the first point of as the *Objective Point*. With the objective defined the team should move towards it. To obtain the next position at each moment of the simulation, the team asks the GIS Agent for the next point between the current position and the objective point according to the speed of the manner of locomotion used.

The calculation of walking time of the agent takes into account the time elapsed between the last point request and the current time. When arriving at his Objective Point, the team places it at the end of the list and considers the new initial point of the list as his objective. Following this flow the team moves along the points that make up the patrol area. This process of going to different patrol area and different patrol points is repeated until the end of the work shift of the team.

- **Criminals*:*** The Criminal Manager creates each criminal agent in the simulation, with the mission of committing a specific crime. After the selection of the area and simulation period by the student, the criminal manager loads from the database of the system all the crimes pertaining to the area and period selected and places the crimes in chronological order. When beginning the simulation, observing the chronological order of the events, it creates for each crime a criminal agent. The criminal's task is to evaluate the viability of committing the crime. The evaluation is based on risk, benefit and personality factors, defined on the bases of a set of interviews with specialists in crime of the Public Safety Secretariat and on research in the area of criminal psychology.
  - ***The risk*** is defined starting from the variables: *Type of crime*: Each type of crime is associated to a risk level, which is based on the type of punishment for the crime, on the level of experience and on the apparatus of the criminal. ExpertCop works only with robberies, thefts and burglary, which are the types of crime influenced directly by preventive policing. *Type of target*: The type of target indicates the resistance capacity against a crime. These targets are associated with the types of crime mentioned previously. Table 1 associates the risk value of the type of crime to the type of target.

TARGET/CRIME	Robbery	Theft	Burglary
PERSON	Low	Very Low	**x**
VEHICLE	Average	Very Low	**x**
DRUGSTORE	Average	Very Low	**x**
LOTTERY HOUSE	High	**x**	**x**
GAS STATION	Average	**x**	**x**
COMMERCIAL ESTAB.	High	Low	Low
BANK	Very High	**x**	**x**
RESIDENCE	Average	Low	Low

Table 1: Table of risks per type of crime and target.

Police Presence: Police presence (distance in relation to the place of the crime) is the main factor that influences risk. The greater the distance between the closest team and the place of the crime, the smaller the risk is. We considered three categories for the evaluation of the criminal as for the distance from policing. Any distance between 0 and 200 meters is considered close, between 200 and 500 meters is considered as average distance and above 500 meters is considered far. An expert policeman based on the visual reach of a person and the extension of a block defined these categories.

Public illumination: When the crime occurs at night, public illumination in the area is a factor of evaluation. Areas with deficient illumination facilitate criminal action influencing the risk directly. The areas can be classified as badly or well illuminated.

Existence of escape routes: The existence of places such as slums, woods or deserted areas close to the place of the crime facilitates escape, augmenting the risk of committing the crime. The classification as to the proximity of escape routes follows the same parameters of the distances of police teams. These areas may be close (0 to 200m), at average distance (200 to 500m) or far away (above 500m) from the place of the crime.

- ***Benefit*** is defined starting at the type and amount of spoils that the target can offer. For example, person is low while bank is very high.
- ***Personality*** defines criminal "courage" level in the face of crime. When being created, a type of personality is associated to the criminal (apprehensive, careful, fearless and bold) chosen randomly by the criminal manager and giving random airs to the criminal. A "bold" criminal evaluates risk with fewer criterions, giving more weight to the benefit. But an “apprehensive" criminal does the opposite, giving much more weight to risk.

The values of the variables regarding crime (type of crime, type of target, geographical location of crime, date and time) are sent to the criminal by the criminal manager. But to obtain the data on the environment (geographical factors) the criminal exchanges messages with the GIS Agent, who furnishes the geographical location, date and time of the crime.

Having collected all the necessary information for the decision support process of the crime to be executed, the agent uses set of production rules for evaluation the viability of committing the crime. The inference rules containing the structure of the decision support process and an inference machine is represented in the JAVA-based JEOPS shell (Figueira and Ramalho 2000). This process results in the decision of committing or not the crime. In the sequence we demonstrate an example of rules.

IF **distance_police** = *close* AND **type_crime** = *robbery* AND **type_victim** = *bank* THEN **risk** = *high*

IF **type_victim** = *bank* THEN **benefit** = *high*

IF **benefit** = *high* AND **risk** = *high* AND **personality** = *bold* THEN **decision** = *commit_crime*

Capital letters denote the logical structure of the rule; bold, the variables that make up the agent's internal state; italic, the values of the variables coming from the data of the crime and the exchange of messages with the GIS Agent.

After deciding whether to commit a crime, the criminal sends a message to the GIS Agent, which then marks the decision on the map exhibited for the user (red if the crime is committed; green if not).

The Pedagogical Proposal of the System

The pedagogical model of the system is based on the concept of Intelligent Tutoring Simulation System, which includes the simulation plus an agent that provides adaptive explanations for a student.

The Simulation as a Pedagogical Tool

ExpertCop simulation is designed to be part of a pedagogical tool. The student can learn by doing. He/she initially interacts with the system allocating the police, which exposes his/her beliefs about the allocation of resources. A simulation of the agents' interaction is then done and the student beliefs can be validated by means of a phase of result analyses. This cycle can be repeated as many times as the student finds necessary.

The pedagogic agent uses two distinct forms to explain the events of the system, the explanation at a micro level and at a macro level.

Micro-level explanation

To explain the simulation events (crimes), the system uses a tree of proofs describing the steps of reasoning of the criminal agent responsible for the event. This tree is generated from the process of the agent's decision making. The agent's evaluation of a crime is represented by a set of production rules explored by an inference engine. The student can obtain the information on the crime and the process that led the agent to commit it or not, by just clicking with the mouse on the point that represents the crime on the map. Each crime, represented by a point on the screen, is associated with a proof tree.

Macro-level Explanation

In ExpertCop, we understand as emerging behavior, the effects of individual events in crime, its increase or reduction, criminal tendencies and seasonableness. For the explanation of the emerging behavior of the system, the pedagogic agent tries to identify patterns of behavior from the database generated in the simulation.

First, the agent, takes (requesting the LOG agent) the simulation data, (events generated for the interaction of the agents as crimes (date, hour, motive, type) and patrols (start time, final time, stretch)), and pre-processes it, adding geographic information as escape routes, notable place coordinates, distance between events, agents and notable places and social and economical data associated to geographic areas. After pre-processing, in the mining phase, PA identifies patterns by means of the probabilistic concept formation algorithm COBWEB (Fisher 1987). This algorithm generates a hierarchy of probabilistic concepts. Probabilistic concepts have attributes and values with an associated conditional probability of an entity having a attribute a with a value v given the fact that this entity is covered by the concept C, $P(a=v|C)$. The generated concepts are characterized according to their attribute/value conditional probabilities. That is to say, a conceptual description is made of attribute/values with high probability. Having the probabilistic concept formation hierarchy constructed, the agent identifies and filters the adequate concepts for being transformed in questions to the student. The heuristics used to filter which concepts will generate questions to the student and which features will compose these questions follow the steps below. The root of the hierarchy is ignored (not appraised), because it aggregates all the concepts and is thus too general. The hierarchy is read in a bottom-up fashion from the most specific to the most generic concepts. The criteria used in the analysis of the concepts for selection are:

- A concept must cover at least 10% of the total of examples. We assume that fewer than 10% of the examples would make the concept poorly representative.
- An attribute value is only exhibited in the question when it is present in at least 70% of the total of the observations covered by an example.
- A question must contain at least three attributes.

When going through a branch of the tree considering the previous items, in case a concept is evaluated and selected, the nodes superior to this concept (parent, grandparent...) will no longer be appraised to avoid redundant information. This doesn't exclude the nodes in the same level of the hierarchy of this node that may be appraised in the future.

An example of COBWEB result is the concept exposed in Figure 2. That concept is displayed to the user/student as the following question: **"**Did you realize that *crime*: theft, *victim*: vehicle, *week day*: Saturday, *period*: night, *local*: residential street, *neighborhood*: Aldeota frequently occur together?**"** Having this kind of information, the user/student can reflect on changes in the allocation, aiming to avoid this situation.

System Functioning

Initially, the student must register with the system and configure the simulation parameters using a specific interface. After that the student determines the number of police teams to be allocated and the characteristics of these teams. Based on the geographic and statistical data available in the map about the area and on their knowledge about police patrol, the student determines the areas to be patrolled and allocates the police teams available on the geoprocessed map. To realize the allocation process, the student selects the patrol areas in the map for each team. After that he/she defines the piece of time that the police team will be in each patrol area. The sum of each piece of time must be equal to the team's workload. Figure 3 shows the interface for the allocation process.

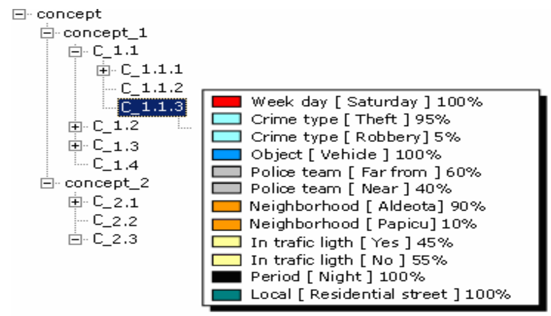

Figure 2: Example of ExpertCop concept tree formed by PA

Agents representing the police teams monitor the patrol areas defined by the user following the programmed schedule. The patrol function is to inhibit possible crimes that could happen in the neighborhood. We presume that the police presence is able to inhibit crimes in a certain area size. The goal of the student is to provide a good allocation, which avoids the most the occurrence of crimes.

After the configuration and allocation process, the user can follow the simulation process in the simulation interface. At the end of the simulation process, the user accesses the pedagogical tools of the system. Figure 4 shows the functionalities for visualization.

Besides the visualization functionalities, the student can access the explanation capabilities (described before). A micro-level explanation can be obtained from the click of the mouse in any red or green point at the screen that indicates occurred or avoided crimes, respectively. The student can request a macro-level explanation pushing the hint bottom represented at the screen. A set of questions is shown to the student in order to make him/her to reflect about possible patterns of crimes.

At each new allocation performed, the system will comparatively evaluate the simulated moments, showing to

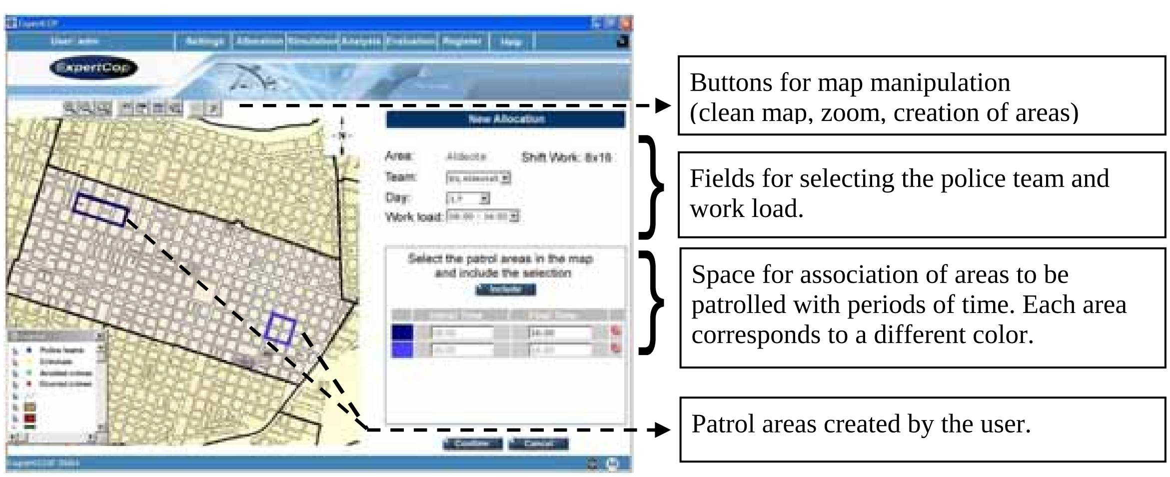

Figure 3: ExpetCop's police allocation interface.

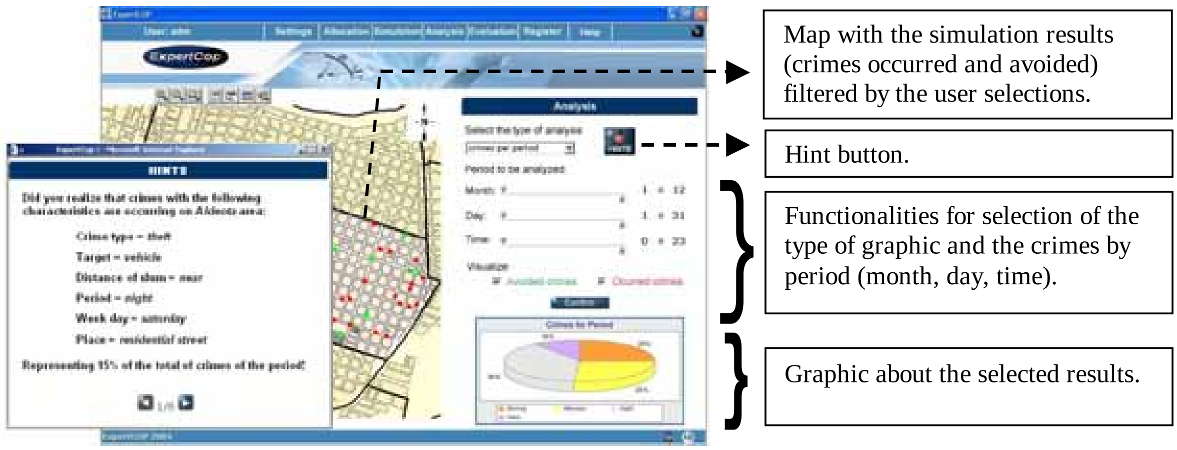

Figure 4: Visualization Functionalities

the student whether the modification brought a better effect to the crime rate or not. PA makes also comparisons among results obtained in each simulation tour for evaluating learning improvements done by the student. The student can also evaluate the results among a series of simulation at evaluation screen. In this screen the results of all simulations made by the student are shown in a bar graphic.

Evaluation of the system

ExpertCop was used to support a course at the Ministry of the Justice and the National Secretariat of Public Safety - SENASP. This course had the objective of emphasizing the importance of information technologies in public safety. ExpertCop was intended to help policemen reflect on the forms of treatment and analysis of information and how this influences the understanding of crime. The audience was made up of three groups of thirty professionals in the area of public safety: civil police officers, chiefs of police, and military police (which are the majority).

Methodology

The Expert Cop's workflow tries to improve the learning process following three successive steps, concrete experience, reflexive observation and abstract conceptualization, described by Kolb (1984). In the course, the use of ExpertCop occurred in two distinct stages, one explanatory and the other evaluative.

In the first stage, the participants were instructed on the process of allocation of police resources, what it is all about, how it occurs in practice, and the factors involved in this process. After this contextualization, ExpertCop was presented, with its objectives and functionalities. Concluding this stage, the participants made use of the tool in an illustrative simulation to familiarize themselves with the functionalities.

In the second stage, training was carried out by a set of three simulations in city areas with different characteristics. In the first simulation, the participants had to create and configure a certain number of teams (according to the size of the area), allocate them on the map and activate the simulation. At the end of the first simulation we asked the participants to identify, according to their beliefs, five factors that influenced the occurrence of the crimes. They did that by observing on the map of the crimes that occurred and those avoided. We requested that the participants not mention complex factors of political or socioeconomic order, such as unemployment or taxes because we focused on geographical and/or visual factors that affect directly the crime rates. After collecting the participants' beliefs, we allowed them to use the pedagogic support of the system (clues, explanations and evaluations). After the use of the pedagogic support tools, the collection of beliefs about the crimes was carried out again. In the subsequent simulations (city areas 2 and 3), we allowed them to make their allocations and use the pedagogic support of the tool according to their needs. During the simulations, the time needed to accomplish the allocation process in the training simulations was measured for a sample of the participants (two of each different group, civil policemen, chiefs of police, and military policemen).

We hypothesized that:

- The use of the pedagogic support of the system would help the students in the understanding and identification of new beliefs regarding crime and the allocation process.
- The identification of new beliefs would be reflected in the second data collection.
- The acquisition of new concepts and beliefs would make the student improve his allocation and consequently obtain better results in the simulations.
- The student will notice that the more careful the analysis of the information previously available is made, the better his decision making process will be.

Analyses and Results

Protocol Analysis

We observed that the participants in general familiarized themselves with the functionalities of the tool after the first phase of the training. The patrol areas they created in the first simulation aimed only at covering a larger inclusion area. The issue of schedule working hours or a more careful analysis of the areas themselves was ignored. In the subsequent simulations the patrol areas were defined as smaller areas and were placed in specific areas and time. We also observed that in spite of the participants demonstrating more ability in handling the tool at the end of each simulation, a greater expense of time was verified during the allocation process. This increase in time occurred due to the fact that the participants spent more time analyzing the geographical and social data before the allocation. Another observation is that among the participants an atmosphere of cooperation was generated, where they compared results and patrol routes seeking to identify similar strategies among themselves. However, in some of them the fact that the outcome of the simulations was worse caused a loss of self-esteem, while in others, it increased the analysis time in search of the reasons for the worsening of the results. Teacher intervention was necessary to handle lack of motivation. This was done by means of a face-to-face tutorial, where the teacher tries together with the participant to solve the problems faced.

Analysis of the beliefs collected

Evaluating the beliefs collected in the two phases, we observed that:

- Most of the participants altered their initial beliefs on the reasons that favored crimes.
- More specific and practical beliefs replaced those initially observed, which were more generic.
- Time factors, such as the relationship between the day and the periods of the day, with the number of crimes occurred, began to be taken into consideration.
- A large number of beliefs were mentioned related to the importance of the analysis of the characteristics of the area for good policing.
- The military Policemen that worked in the allocation process indicated a low alteration in their beliefs, mentioning relevant factors at once in the first collection. They included factors that were until then unknown to the system. We consider this to be important because it enables improving the system, and because we see that the goal of reflection on factors that influence the crime was obtained even in this situation.

Analysis of the results obtained in the simulation

Analyzing the results of the simulations, we observed that the participants could be categorized according to their experience and the type of activity they exercise:

- Among the participants that exercised the activity of military policemen (40% of the total of students), it was verified that those that had already worked in police allocation had better results than the others. They had homogeneous results in the three simulations (the standard deviation of the results is 3%).
- Knowing the activity facilitated the understanding and analysis of the factors approached, and had a direct affect on the results. We verified that the results of participants who work daily with computers and those who had little or no contact were similar.
- Of the total number of participants, 69% had positively growing or homogeneous results and 31% had results that varied negatively.
- The average growth (in terms of reducing crime rates) was 2% between the first and last simulation of training.
- Of the total number of participants, 36% obtained a general average considered very good (above 30% of the crimes were avoided), higher than the participants' general average.

Conclusions

Evaluating these results we conclude that the pedagogic support offered by the system helps the participant understand and better identify the factors that affect crime, allowing thus for better performance in their allocations and consequently a reduction in crime levels. The students were capable of noticing the importance of the analysis of the data in the allocation process. The tool revealed easy to use and attractive to the students. They continue using the system even after the end of the course.

Based on the results, we conclude that the learning level is higher in participants with little or no experience in the domain or in the treatment of information.

Related Work

Previous use of MAS simulation in education (Khuwaja *et al*. 1996), (Querec *et al*. 2003), (Gibbons *et al*. 2001), ITS (Johnson *et al*. 2000), social simulation to support decision-making, and GIS tools (Gimblett 2002) strongly influenced this research work. Our proposal is an intersection among these areas. There are many projects that describe solutions with parts of our system design. Virtual environments for training, such as Securevi proposed by Querec (2003), is a system based on Mascaret model that uses multi-agents systems to simulate realistic, collaborative and adaptive environments for training simulation. Intelligent GIS, such as the proposed system by Djordjevic (1995), intends to provide computer support in fire rescue. The system has a “Fire Trainer”, an intelligent agent that covers the activities connected to education. Phoenix system (Cohen *et al*. 1989) is a discrete event simulator based on an agent architecture. The system is a real time, adaptive planner that simulates the problem of forest fires.

Intelligent Tutoring Systems like built by Wisher (2001) describes an intelligent tutoring for field artillery training or Sherlock system by Lesgold (1992) that provides advice for impasses while using a simulated system. The architecture proposed by Atolagbe (1996) and Draman (1991) for educational simulation has also similar points with this work although they don't emphasize the power of simulation in GIS or the use of KDD to improve student learning. Several works in games and entertainment (Galvão *et al.* 2000) (Leemkuil *et al*. 2003) use simulation with an educational propose. Even though they present some similarities with our approach, game simulators have a different pedagogical strategy. They focus on the results of the simulation while we believe that the most important is the process itself. Another differential is that few games are adapted to the student level. In order to diminish this, we have proposed to put ITS features in games as in (Angelides and Siemer 1995).

Conclusion and Future Work

This paper described the ExpertCop system, a pedagogical geosimulator of crime in urban areas. The ExpertCop architecture is based on the existence of MAS with a GIS to perform geosimulations and of a pedagogical agent that follows the simulation process; the agent can define learning strategies as well as use a conceptual clustering algorithm to search relations in the facts generated in the simulation. ExpertCop is focused on police officers' education, related to resources allocation.

Initial trainings with police officers interacting with the system were performed aiming to evaluate learning by using this tool. As complement to the use of the system, a course was made where ExpertCop was used as a tool for analysis and reflection of practical situations. The methodology adopted to analyze the learning of students in ExpertCop has shown a significant improvement in the students' data analysis abilities, in the process of resource allocation with ExpertCop and in the identification of factors that influence the crime.

We intend to continue this research on the ExpertCop system, enhancing its functionalities, and increasing the training support, aiming to make it not only an educational tool but a decision-making support tool as well. The next steps are to render ExpertCop multi-user and to put it available on the Web. Two sets of new courses will be done in the near future and new evaluations can be done from these.

Acknowledgement

This work is partially supported by the CNPQ (552009/2002-4), FUNCAP and Motorola. The authors thank Bill Clancey for the insightful comments.

References

Angelides, M.C.; Siemer J. 1995. Evaluating Intelligent Tutoring with Gaming-Simulations. In *Proceedings of 1995 Winter Simulation Conference*, 1376-1383. Arlington, VA, USA: ACM.

Atolagbe, T.; Hlupic, V. 1996. A Generic Architecture for Intelligent Instruction for Simulation Modelling. In *Proceedings of the 1996 Winter Simulation Conference*, 856-863. San Diego, USA: Ed. by Charnes J.M., Morrice D.J., Brunner D.T.

Benenson, I. & Torrens, P.M. (2004). Geosimulation: object-based modeling of urban phenomena. *Computers, Environment and Urban Systems* 28 (1/2): 1-8.

Cohen, P. R.; Michael L. G.; David M. H.; Adele E. H. 1989. Trial by fire: Understanding the design requirements for agents in complex environments. *AI Magazine.*10(3): 32-48.

Djordjevic-Kajan, S.; Mitrovic, D.; Mitrovic, A.; Stoimenov, L. Stanic, Z. 1995. Intelligent GIS for Fire Department Services, In *Proceedings of Eurocarto XIII*, 185-196. Ispra, Italy

Draman, Murat. 1991. A generic architecture for intelligent simulation training systems. In *Proceedings of the 24th annual symposium on Simulation*, 30-38. New Orleans, Loisiana: IEEE Computer Society.

Figueira, F. C.; Ramalho, G. 2000. Jeops – The Java Embedded Object Production System. In *Advances in Artificial Intelligence*, 52-61. London: Springer-Verlag.

Fisher, D. 1987. Knowledge Acquisition via Incremental Conceptual Clustering. *Machine Learning* 2:139-172.

Galvão, J.R.; Martins, P.G.; Gomes, M.R. 2000. Modeling Reality with Simulation Games for a Cooperative Learning. In *Proceedings of the 2000 Winter Simulation Conference*, 1692-1698. Orlando, FL: Society for Computer Simulation.

Gibbons, A. S.; Lawless, K. A.; Anderson, T. A.; Duffin, J. 2001. The web and model-centered instruction. In BH Khan (Ed.), Web-based training, 137-146. Englewood Cliffs, NJ.

Gimblett, H. R. eds. 2002. *Integrating Geographic Information Systems and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes*. University of Arizona & Santa Fe Institute: Oxford University Press.

Johnson, W.L.; Rickel, J.W.; Lester, J.C. 2000. Animated Pedagogical Agents : Face-to-Face Interaction in Interactive learning Environments. *Intern. Journal of AI in Education* 11.

TILab S.p.A. Java Agent Development Framework -JADE. 2003. At ttp://sharon.cselt.it/projects/jade.

Khuwaja, R.; Desmarais, M.; Cheng, R. 1996. Intelligent Guide: Combining User Knowledge Assessment with pedagogical Guidance. In *Proceedings of International Conference on Intelligent Tutoring Systems*. Berlim: Springer Verlag.

Kolb, D. A. 1984. Experiential learning: experience as the source of learning and development. Englewood Cliffs, Prentice Hall.

Leemkuil, H.H.; Jong, T. de; Hoog, R. de; Christoph, N. 2003. KM Quest: a collaborative internet-based simulation game. *Simulation & gaming* 34: 89-111.

Lesgold, S.; Lajoie, M.; Bunzo; G. Eggan, 1992. SHERLOCK: A coached practice environment for an electronics troubleshooting job. In *Computer Assisted Instruction and Intelligent Tutoring Systems*. Hillsdale, N.J.: Lawrence Erlbaum Associates.

Piaget, J. 1976. Le comportement, moteur de l'évolution. Paris: Ed. Gallimard.

Querrec R.; Buche C.; Maffre E. Chevaillier, P 2004. SecuReVi: Virtual environments for fire fighting training. In *Proc. of Conf. Internationale sur la Réalité Virtuelle*, 169-175, Laval, France.

Wisher, R. A.; MacPherson, D. H.; Abramson, L. J.; Thorndon, D. M.; Dees, J. J. 2001. The virtual sand table: Intelligent tutoring for field artillery training. Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.