

A Multiagent Simulator for Teaching Police Allocation

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■ This article describes the ExpertCop tutorial system, a simulator of 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 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 in simulation data and to formulate questions to the student about these patterns.

Simulation aims to represent one phenomenon by means of another and it is useful to measure, demonstrate, test, evaluate, predict, and decrease risks and costs. Practical application can be seen in various areas, such as in the aeronautical industry, nuclear industry, and the 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.

Multiagent systems have been widely adopted in the development of complex systems. One of the most important reasons to use a multiagent systems paradigm is for handling the interaction of different entities or organizations with different (possibly conflicting) goals and proprietary information. A multiagent system is also appropriate whenever there is a need for representing individually each entity of the modeled domain, or if such entities have an intelligent behavior to be modeled.

Social or urban environments are dynamic and nonlinear and are made up of a great number of variables, characterizing a complex system. The use of multiagent systems to simulate social environments has become broadly used (Khuwaja, Desmarais, and Cheng 1996). Aggregating a geographical information system (GIS) to a multiagent system in the simulation of social or urban environments characterizes 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, such as geographic features, which must be exploited by intelligent tutorial systems in order to enrich learning.

This article describes the ExpertCop educational tutorial system, considering the primary characteristics we claim to be essential to the

general architecture of an educational geosimulation. ExpertCop aims to enable police officers to better allocate the preventive police force in urban areas. This software produces, based on a police resource allocation plan, simulations of how 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 use the system, making them understand the cause-and-effect relation of their decisions.

Geosimulation generates a great amount of data deriving from the interactions occurring 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—the pedagogical agent—as a data analysis supporting tool. 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 concepts learned. Moreover, it explores the reasoning process of the domain agents by providing explanations, which help the student to understand simulation events.

Urban Simulation and Intelligent Tutoring

Simulations based on multiagent systems are live simulations that differ from other types of computer simulations because simulated entities are individually modeled through the use of agents. According to Gilbert (Gilbert and Conte 1995), the multiagent approach (bottom-up) is appropriate for the study of social and urban systems. Social or urban environments are dynamic and nonlinear and are composed of a great number of variables. Multiagent systems are also appropriate when the environments are made up of a great number of entities whose individual behaviors are relevant in the general context of the simulation.

A particular kind of simulation, called *geosimulation*, addresses an urban phenomena simulation model with a multiagent 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. The geographic information system (GIS) is responsible for providing the “data ware” in geosimulations.

Simulation is widely used as an educational tool because the computerized simulation of

the activity studied allows the user to learn by doing (Piaget 1976) and to understand the cause-and-effect relationship of his or her actions. According to Kolb (1984), learning is favored when the learning process occurs within the following four successive steps:

Concrete Experience: Obtained through the activity itself or its simulation in a virtual environment.

Reflexive Observation: The experience is followed by the reflection phase. It is recreated internally in the user’s mind under different perspectives.

Abstract Conceptualization: In this stage, the experience is compared and its patterns, processes, and meanings are analyzed. Within this context, abstract concepts and new knowledge are created. The knowledge is generated in two moments of the cycle, in this step and in that of concrete experience. The knowledge generated in the concrete experience phase comes only from the simple observation of the external event, while the knowledge generated in the abstract conceptualization phase emerges as a consequence of an internal cognitive process of the student.

Active Experimentation: In this stage the student will conduct a new experiment with the newly acquired or modified concepts.

The simulation per se is not a sufficient tool for education. It lacks the conceptual ability on the part of the student to understand the simulation model. Therefore, some works (Taylor and Siemer 1996), (Angelides and Siemer, 1995) 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 of an ITS is the integration of artificial intelligence in computer learning systems. It aims at emulating the work of a human teacher who has knowledge of the content to be taught, as well as how and to whom it should be taught. To achieve this, we need to represent (1) the domain of study, (2) the pedagogical strategies, and (3) the student to whom the teaching is provided. A fourth component may also be considered (Kaplan and Rock 1995, Woolf and Hall 1995)—the interface with the user. The user interface determines how the interaction with the system is. Through the interaction of these components, the ITS adapts pedagogical strategies on a domain at the level of the student for his or her individual needs.

The ExpertCop System

Police resource allocation in urban areas to perform preventive policing is one of most impor-

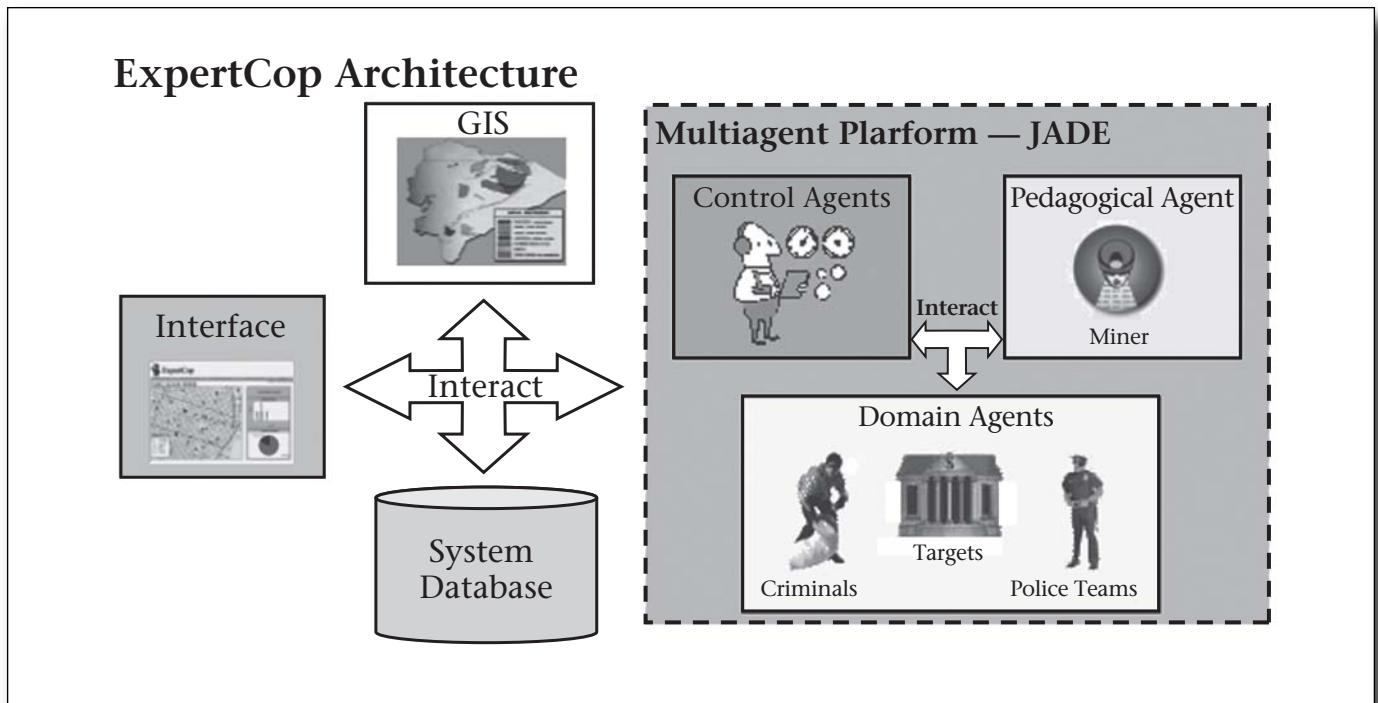


Figure 1. The ExpertCop System Architecture.

tant tactical management activities and is usually decentralized by subsectors in police precincts 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 crime is happening and the reasons associated to such crime, it is possible to make an 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 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 nontrivial task. In addition to that, experiments in this domain cannot be performed without high risks because they result in 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 simula-

tions 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 multiagent 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 generating, manipulating, and updating a map of the city to be studied in a small scale. The system database contains (1) the information about each student and about his or her simulations, (2) the configuration data, (3) the real data on crime and statistics on crime yielded for the department of state police, and (4) the domain ontology. The most important component is the multiagent systems platform, and it will be discussed in detail next.

The Multiagent Systems Platform

The structure, communication, administration, and distribution of the agents is provided by the Java Agent Development Framework—JADE.¹ The multiagent platform in ExpertCop is made up of three groups of agents: control agents, domain agents, and the pedagogical agent. The control agents are responsible for the control, communication, and flow in the system. The most important control agents are the GIS agent, which is responsible for answering requests from the graphical interface and the domain and control agents; the manager agents, which are responsible for the coordination and interaction with domain agents and control preprogrammed activities such as activation and deactivation; and the log agent, which is responsible for recording all interactions among system agents. Another important control agent is the pedagogical agent (PA). It is endowed with pedagogical strategies, and aims to help the user in understanding the simulation process and results. The PA will be discussed in detail in the pedagogical proposal section of this work.

The domain agents are the actors of the domain. They are notable points, police teams, and criminals.

Notable Points

Notable points are buildings relevant to the objective of our simulation, such as shopping centers, banks, parks, and drugstores. They are located on the simulation map and have the same characteristics as 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—which 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 AM to 4 PM. The team would work a first shift from 8 AM to 4 PM, and then rest for 16 hours, returning to work the following day at 8 AM. The patrol areas are composed of one or more con-

nected 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 8 x 16 should patrol an area (or areas) for repetitive periods of 8 hours every 24 hours. Suppose there is a police team called Beta who has two areas to patrol in its shift. The user or student should define the intervals of each area as follows.

Beta police team:

Work shift: 8 x 16; Work period: 8 AM to 4 PM.

Area of patrol 1(4hs): start 8 AM end 12 PM.

Area of patrol 2(4hs): start 12 PM end 4 PM.

The total work load is eight 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 by which 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 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 its objective point, the team places it at the end of the list and considers the new initial point of the list as its objective. Following this flow, the team moves along the points that make up the patrol area. This process of going to different patrol areas and different patrol points is repeated until the end of the team's work shift.

Criminals

The criminal manager creates each criminal agent in the simulation, with the mission of committing a specific crime. After selection of the area and simulation period by the student, the criminal manager loads, from the system database, 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

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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

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Figure 2. Example of Rules.

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

the events, it creates a criminal agent for each crime. 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 on crime from 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 with 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 burglaries, which are 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 with the type of 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 lower the risk is. We considered three categories for the evaluation of the criminal as to 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. These categories were defined by an experienced police officer based on the average person's visual range and the average length of a city block.

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 and directly influence the risk. The areas can be classified as poorly 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 that the crime will be committed. The classification as to the proximity of escape routes follows the same parameters as the distances of police teams. These areas may be close (0 to 200 meters), at average distance (200 to 500 meters), or far away (above 500 meters) from the place of the crime.

Benefit is defined starting at the type and amount of spoils that the target can offer. For example, a person is low while a 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, bold, and fearless) chosen randomly by the criminal manager and giving random airs to the criminal. A "bold" criminal evaluates risk with fewer criteria, giving more weight to the benefit. But an "apprehensive" criminal does the opposite, giving much more weight to the 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, which 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 a set of production rules for evaluating 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 whether or not to commit the crime. Figure 2 contains an example of rules. After deciding whether to commit a crime or not, the criminal sends a message to the GIS agent, which then marks the decision on the map displayed to the user (red if the crime is committed; green if it is not).

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 Establishment	High	Low	Low
Bank	Very High	X	x
Residence	Average	Low	Low

Table 1. Table of Risks per Type of Crime and Target.

The Pedagogical Proposal of the System

The pedagogical model of the system is based on the concept of the 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 or she initially interacts with the system allocating the police, which exposes his or 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 microlevel and at a macrolevel.

Microlevel Explanation

The microlevel explains the simulation events (crimes). ExpertCop 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 stored in the database. The student can obtain the information on the crime and the process that led the agent to commit it or not by just clicking the point that represents the crime on the map with the mouse. Each crime located

on the map is represented by a point in the color green (crime prevented) or red (crime occurring); these points function as hyperlinks to the explanation tree of the agent's decision-making process. When the student clicks a point, the pedagogical agent will present an explanation containing the crime data and a hyperlink to the explanation of the reasons this crime was committed or prevented. Follow-up questions can be done for the comprehension of the concepts of the domain. This type of explanation is obtained in ExpertCop because the agent's architecture has a cognitive module modeled explicitly in terms of ontologies, production rules, and problem-solving methods (see Furtado and Vasconcelos [2007] for details of this modeling). The tree of proofs is represented in node sets of the proof markup language (PML) (Pinheiro da Silva, McGuinness, and Fikes 2006) which is one of the components of the inference web infrastructure. Thus, proof fragments in PML can be shared with other applications, besides using the inference web infrastructure to abstract proofs into explanations and to present proofs and explanations to users.

Macrolevel 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 pedagogical 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

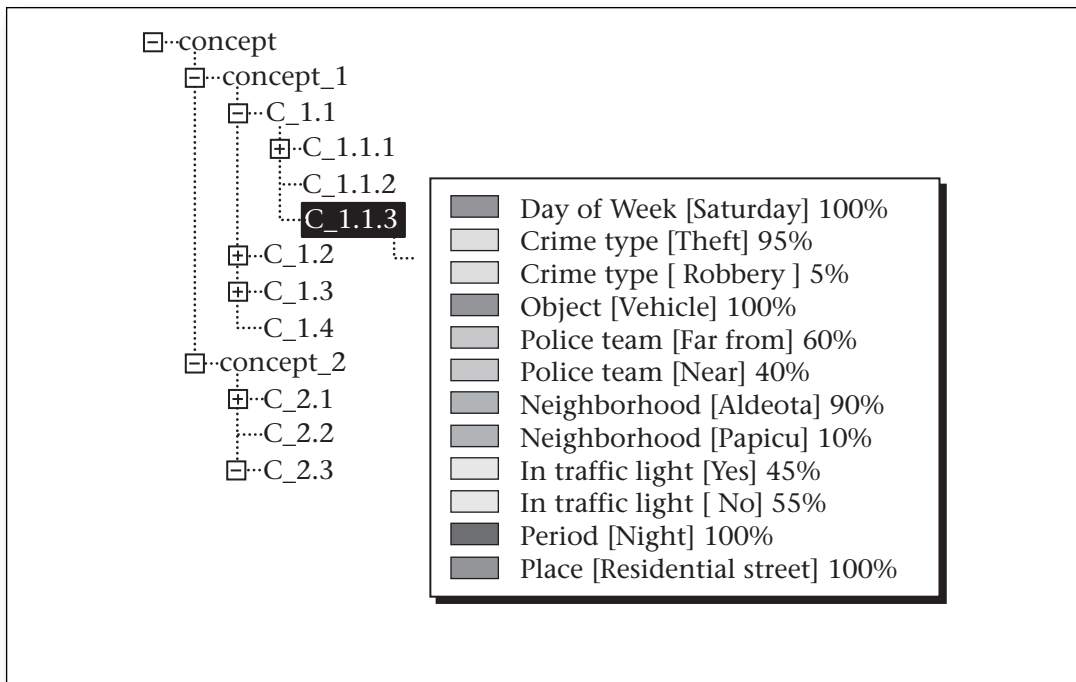


Figure 3. Example of ExpertCopy Concept Tree Formed by PA.

time, stretch]) and preprocesses it, adding geographic information such as escape routes; coordinates of notable places; distance between events, agents, and notable places; and social and economical data associated to geographic areas. After preprocessing, in the mining phase, the PA identifies patterns by means of the probabilistic concept formation algorithm COBWEB (Fisher 1987), which generates a hierarchy of probabilistic concepts. Probabilistic concepts have attributes and values with an associated conditional probability of an entity having an 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 or value conditional probabilities. That is to say, a conceptual description is made of attribute or values with high probability. Having the probabilistic concept formation hierarchy constructed, the agent identifies and filters the adequate concepts for being transformed into 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 (1) concept must cov-

er at least 10 percent of the total of examples—we assume that fewer than 10 percent of the examples would make the concept poorly representative; (2) an attribute value is exhibited in the question only when it is present in at least 70 percent of the total of the observations covered by an example; and (3) 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 the Cobweb result is the concept depicted in figure 3. That concept is displayed to the user or student as the following question: "Did you realize that crime: theft, victim: vehicle, day of the week: Saturday, period: night, place: residential street, neighborhood: Aldeota frequently occur together?" Having this kind of information, the user or student can reflect on changes in the allocation, aiming to avoid this situation.

System Function

Initially, the student must register with the system and configure the simulation parameters using a specific interface. After that, the stu-

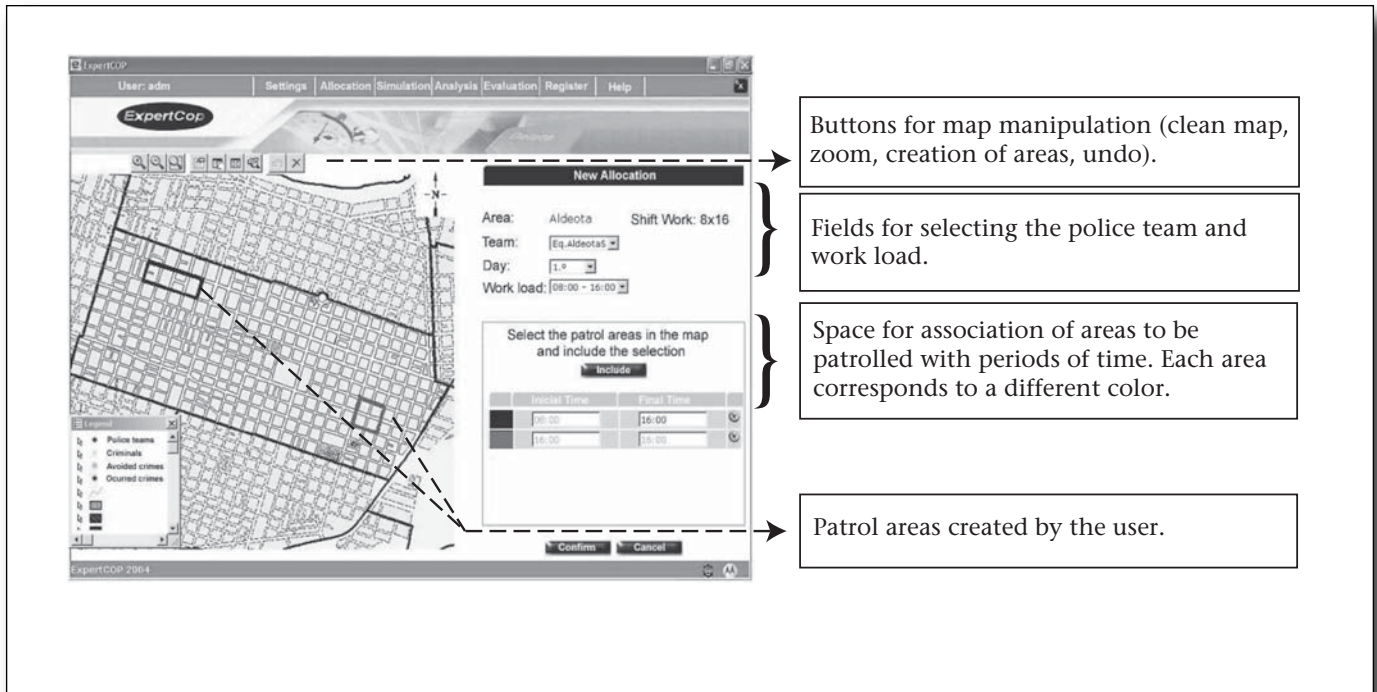


Figure 4. ExpertCop's Police Allocation Interface.

dent 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 his or her 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 or she defines the period of time that the police team will be in each patrol area. The sum of each period of time must be equal to the team's workload. Figure 4 shows the interface for the allocation process.

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 that prevents the highest number 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 5 shows the functionalities for visualization.

Besides the visualization functionalities, the student can access the explanation capabilities

(described previously). A microlevel explanation can be obtained by clicking any red or green points on the screen, which indicate crimes that occurred or that were prevented, respectively. The student can request a macrolevel explanation by pressing the hint button represented on the screen. A set of questions is shown to the student in order to make him or her reflect about possible patterns of crimes.

At each new allocation performed, the system will comparatively evaluate the simulated moments, showing the student whether or not the modification brought about a better effect upon the crime rate. PA also makes comparisons among results obtained in each simulation tour to evaluate the student's learning improvements. The student can also evaluate the results among a series of simulations on the evaluation screen. On this screen, the results of all simulations made by the student are shown in a bar graph.

Evaluation of the System

ExpertCop was used to support a course at the Brazilian Ministry of Justice and the National Secretariat of Public Safety—SENASP. The objective of this course was to emphasize the importance of information technologies in public safety. ExpertCop was intended to help police officers reflect on the forms of treatment and analysis of information and how this influ-

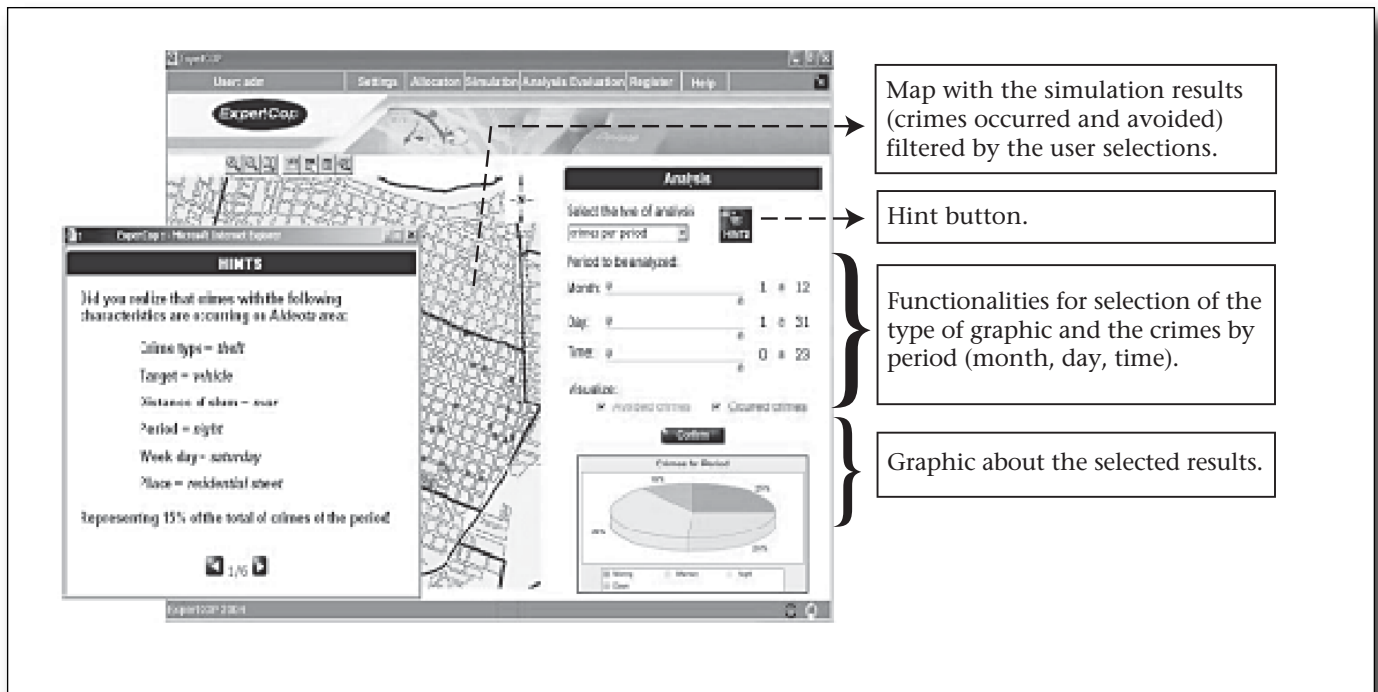


Figure 5. Visualization Functionalities.

ences the understanding of crime. The audience was made up of 30 professionals in the area of public safety: civil police officers, chiefs of police, and military police (which are the majority). These groups of professionals compose the target public towards which this tool is geared.

Methodology

ExpertCop's workflow tries to improve the learning process proposed by Kolb (1984) in the following four successive steps: (1) the process of simulation as a concrete experience; (2) reflection and observation of the results with the aid of the support tools offered by the system; (3) abstraction and conceptualization, supported by the hints offered by the pedagogical agent on the patterns revealed in the simulation; and (4) new experimentation with the concepts acquired in a new process of simulation. 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 allocating 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. After concluding this stage, the participants made use of the tool in an illustra-

tive simulation to familiarize themselves with the functionalities.

In the second stage, training was carried out by a set of at least three simulations in city areas. 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 so by observing the map of the crimes that occurred and those that were prevented. We requested that the participants not mention complex factors of political or socioeconomic order, such as unemployment or taxes, because we focused on geographical or visual factors that directly affect the crime rates. After collecting the participants' beliefs, we allowed them to use the pedagogical support of the system (clues, explanations, and evaluations). After the use of the pedagogical support tools, the collection of beliefs about the crimes was carried out again. In the subsequent simulation, we repeated the same area to serve as a comparison with the initial simulation already completed, and allowed students to make their allocations and use the pedagogical support of the tool according to their needs. Afterwards, we performed two other simulations with areas different than the first one. Using different areas for each simulation

allows us to evaluate whether the student was able to abstract the modified or acquired concepts by applying them in different contexts (characteristics), since the new concepts are applicable to all of the characteristics that the environment presents. During the simulations, the time needed to accomplish the allocation process in the training simulations was measured for a sample of the participants (two from each different group, civil police officers, chiefs of police, and military police).

We formulated the hypothesis that the system will make the students improve their understanding of the results (causes and effects), acquiring new beliefs or modifying old beliefs regarding crime and the allocation process. Based on the belief that the percentile of crimes prevented in relation to the total number of crimes attempted represents the participant's performance in a simulation, we formulated the second hypothesis: The acquisition of new concepts and beliefs will make the students improve their allocation and consequently obtain better results in the simulations.

Results and Discussion

From the analysis of the collected beliefs, we made a number of observations. First, 87 percent of the students changed or included new beliefs about motives and causes of crime. Second, in the evaluation, beliefs that were more specific and practical replaced those initially observed, which were more generic. Third, new beliefs about specific factors such as public illumination, patrol route distances, the existence of slums, and work shifts, were included by the students in the second collection. Fourth, 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. Fifth, a large number of beliefs were mentioned related to the importance of the analysis of the characteristics of the geographical area for good policing. Sixth, the military police 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.

According to the data, it is possible to conclude that our hypothesis is valid, confirming that the system offered subsidies so that the student modified his or her beliefs on the domain or acquired new beliefs.

Based on an analysis of the relation between the number of times the system's pedagogical support was accessed and the results of the simulation, it was possible to observe that students with a higher number of accesses obtained better results. We also observed that the average of the results of the simulations after the use of the pedagogical support (second and third simulations) was greater than the average of the results in the simulation before the use of the support offered by the system. In further experiments with a set of 90 students, we measured a statistically significant increase of 9.09 percent. A detailed description of these and other results can be seen in Furtado and Vasconcelos (2007).

We also observed that although the students demonstrate more ability in handling the tool as time goes by, they spend more time during the allocation process. We think that this indicates a more reflexive allocation process. Another observation is that an atmosphere of cooperation (or competition) was created among the students, and they often compared results and patrol routes seeking to identify similar strategies among themselves. Effectiveness of learning depends on the student profile. A novice in computer science tends to concentrate on the tool instead of on the allocation process. Experienced students in the allocation process improve their performance to a lesser degree. Based on the results, we may also conclude that the learning level is higher in participants with little or no experience in the domain or in the treatment of information. Also evaluating these results, we conclude that the pedagogical support offered by the system helps the participants 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 analyzing the data in the allocation process. The tool was revealed as easy to use and attractive to the students. They continue using the system even after the end of the course.

We observed as a negative fact that two students who obtained very low results were not motivated to follow the subsequent simulations. Another important aspect that merits discussion is how learning is influenced by the quality of the model. In our discussions with educators, we were advised to be careful that students do not come away thinking that everything they did in ExpertCop will be reproduced equally in their area of work. For this reason, we prefer not to present students with the areas where they actually work. The objective of the

tool is to make them reflect on causes and effects considering that the student is capable, through practical situations, of reflecting upon alternatives regarding allocation of police officers.

The matter of modeling the criminal also deserves mention. Cognitive modeling of the criminal is a difficult task, and it is practically impossible to acquire and represent all the nuances of its cognitive model. What is intended is to model the basic knowledge that is found in the literature as well as heuristics supplied by police officers. In this way, the explanation of why crimes are committed leads the student to know some of the factors that were considered during the elaboration of the crime. This knowledge is shown opportunistically within a precise context. If, for any reason (perhaps due to his or her field experience), the student is led to disagree with the performance rules of the criminal agent or to elaborate other characteristics that were not observed, ExpertCop has nonetheless fulfilled its role of making the student reflect upon these factors. Moreover, maintaining these rules that determine the cognitive model of the criminals, since they are explicit in an ontology, can be easily modified and adapted to different realities with no need to change the source code.

Related Work

Previous use of multiagent systems simulation in education (Khuwaja, Desmarais, and Cheng 1996; Querrec et al. 2004; Gibbons et al. 2001), ITS (Johnson, Rickel, and Lester 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 (2004), is a system based on the Mascaret model that uses multiagent systems to simulate realistic, collaborative, and adaptive environments for training simulation. Intelligent GIS, such as the system proposed by Djordjevic-Kajan et al. (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. The 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.

A number of intelligent tutoring systems have been designed, such as the one built by Wisher et al. (2001), which describes an intelligent tutoring for field artillery training, and the Sherlock system by Lesgold et al. (1992), which provides advice for impasses while using a simulated system. The architecture proposed by Atolagbe and Hlupic (1996) and Draman (1991) for educational simulation is similar to this work, although Atolagbe and Hlupic do not emphasize the power of simulation in GIS or the use of knowledge discovery and data mining (KDD) to improve student learning. Several works in games and entertainment (Galvão, Martins, and Gomes 2000; Leemkuil et al. 2003) use simulation with an educational purpose. 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 aspect is the process itself. Another differential is that few games are adapted to the student level. In order to diminish this, we have proposed putting ITS features in games as was described by Angelides and Siemer (1995).

Conclusion and Future Work

This article described the ExpertCop system, a pedagogical geosimulator of crime in urban areas. The ExpertCop architecture is based on the existence of multiagent systems 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 for relations in the facts generated in the simulation. ExpertCop is focused on police officers' education, related to resources allocation.

Initial training sessions with police

officers interacting with the system were performed aiming to evaluate learning by using this tool. As a complement to the use of the system, a course was held 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 an 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 the research on the ExpertCop system, enhancing its functionalities such as rendering it multiuser and making it available on the web. Other ongoing work aims at transforming it into a decision-making support tool. To accomplish this, we are adopting a different approach for the crime simulation model. The criminal model is based on self-organization systems inspired by biological systems. Self-organization refers to the phenomenon of a society of agents that demonstrate intelligent behavior (as a collective) out of simple rules at the individual level. We model the criminals as distributed entities by agents with the ability to demonstrate self-organization from their individual (local) activities as well as taking into consideration the influence of other criminals in the community in which they live (Furtado et al. 2006). We are also designing an evolutionary approach that integrates with the simulation tool and is devised to assist police officers in the design of effective police patrol routes. Our approach is inspired by the increasing trend of hybridizing multiagent systems with evolutionary algorithms. Our idea is to uncover strategies for police patrolling that cope with the dynamics of the crime represented by criminals that learn on the fly. To uncover good police patrol routes in this context, we are integrating into the simulation model a genetic algorithm. Preliminary experiences have shown that such an approach is very promising (Reis et al. 2006).

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Note

1. TILab S.p.A. Java Agent Development Framework. JADE. 2003. At sharon.cse.it/projects/jade.

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