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To cite this version:

Gildas Morvan, Daniel Jolly, Daniel Dupont, Philippe Kubiak. Modélisation de la température d'un corps par automates cellulaires. MOSIM 2008, Mar 2008, Paris, France. hal-00693701

HAL Id: hal-00693701

https://hal.science/hal-00693701v1

Submitted on 2 May 2012

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A DECISION SUPPORT SYSTEM FOR FORENSIC ENTOMOLOGY

Gildas Morvan[1], Daniel Jolly[1], Daniel Dupont[2], Philippe Kubiak[3]

[1]LGI2A EA 3926,
Université d'Artois, Faculté des Sciences Appliquées - Technoparc Futura - F-62400 Béthune, France
[2]ERASM-HEI,
13 rue de Toul F-59046 Lille Cedex, France
[3]LAGIS UMR CNRS 8146,
Ecole Centrale de Lille - Cité Scientifique - F-59651 Villeneuve d'Ascq, France

gildas.morvan@fsa.univ-artois.fr (Gildas Morvan)

Abstract

This paper presents a multiagent-based model of insect development on a dead body and a three layers Decision Support System architecture able to perform retrodictive (abductive) reasoning from multiagent-based models or more generally, complex systems models. This architecture is used in order to compute post-mortem intervals from entomological data sampled on cadavers. Knowing the exact time of a death is fundamental in criminal investigations. Thus, it is necessary for experts to guarantee the reliability of their results. We show that post-mortem interval estimated with traditional entomological methods can lead to important overestimations. Indeed, these methods do not take into account all the interdependent processes involved in the development of insects such as fly population dynamics in the ecosystem or the gregarious behavior of insect larvae that can lead to local temperature increases on the body. Forensic Entomology is widely used in several countries; it is then important to develop new methodologies and tools to improve the efficiency and reliability of entomological expertises. ForenSeek – the implementation of the model and Decision Support System architecture – aims to be a software program that can be used as a post-mortem interval estimation tool and as a virtual laboratory, to simulate colonization and development cases.

Keywords: forensic entomology, multiagent-based simulations, decision support systems, retrodictive reasonning.

Presenting Author's biography

Gildas Morvan. Ph.D. Student at LGI2A, Faculté des Sciences Appliquées, Université d'Artois. Graduate of IG2I, department of Ecole Centrale de Lille.

1 Introduction

Forensic entomology is widely used in criminal investigations to determine post-mortem intervals (PMI) and possibly information about the victim such as death location [1]. This is done studying entomofauna, *i.e.* insects, mainly maggots (flies larvae), found on the corpse. PMI is usually estimated by experts using analytic models of insect development. These models can be easily employed to perform retrodictive (abductive) reasoning but do not take into account the ecosystemic context. Thus, estimations performed using these methods are often overestimated and not as precise as they could be. This paper presents ForenSeek [2]: a multiagent-based model of insect development on a dead body and a Decision Support System (DSS) architecture able to perform PMI estimations using this model.

2 Introduction to Forensic Entomology

2.1 Overview of the corpse colonization process

A cadaver is an important source of nutriments for insects, especially for necrophagous Diptera species. A few hours after the death, the first Diptera females are attracted by the body and, under specific conditions lay eggs on it, mainly on natural orifices. Diptera insects have to achieve their development cycle to become adults. Once the eggs hatch, Diptera larvae colonize the body to feed.

Three larval stages named L1, L2 and L3 will succeed. Each one of them is defined by morphological characteristics and a specific behavior. When a larva ends its development cycle, it leaves the corpse to find a suitable place for pupariation, an inactive stage where the larva eventually turns into an adult fly (Fig. 1).

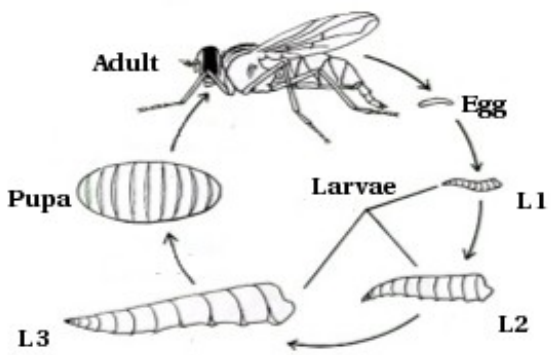

Fig. 1 Development cycle of Diptera species

Larvae unintentionally cooperate to speed up their development period, aggregating themselves. Indeed, each larva emits heat. This can cause an important and local increase of temperature. When temperature exceeds viable limits, the aggregate scatters.

Many species will succeed on the body. Each one of them is interested by a particular stage of decomposition. The first necrophagous species to colonize the cadaver are Diptera but in advanced stages it is common to find Coleoptera species.

As many living organisms, the development of Diptera is temperature-dependent. Thus, the development rate a of an individual is given as a function f of the temperature T varying in the time t, *i.e.*:

$$\frac{da}{dt} = f(T(t)) \tag{1}$$

Various development models have been developed, some assuming the increase of development is linear in the viable temperature interval, some are more complex. A review of development models can be found in [3]. We will not discuss the validity of those models in this paper.

2.2 Forensic expertises methodology

When a cadaver is discovered, investigators take samples of eggs, larvae or pupae from the body. Entomologists determine the species and accumulated rates of development (denoted Δa) of the oldest individuals. Then, for each one of them, the laying time τ_1 (considered to be close to the time of death) can be calculated from the following equation:

$$\Delta a = \int_{\tau_1}^{\tau_2} f(T(t))dt \tag{2}$$

where τ_2 represents the time of the cadaver discovery. Data from the nearest meteorological station are usually used in order to estimate the temperature $T(t)$.

Considering that the temperature at any point of the body is equal to the temperature recorded by the nearest meteorological station is not exact for three reasons. Firstly, ecosystem specificities can radically influence the temperature around the body as shown in [4]. Secondly, corpse thermal inertia is important, especially in the first hours after death [5]. Thirdly, the heat generated by larvae aggregates can raise the temperature locally up to 20 °C. This phenomenon and its consequences on PMI estimation have been discussed by many authors [1]. Thus in many cases, entomological expertises results are inaccurate and given with an important margin of error.

The model presented in the next part focuses on the second and third causes of inaccuracy: it describes the whole process of corpse decomposition, and insect colonization and development.

3 Model description

In order to understand the process of decomposition, we have to take all the interdependent processes involved into account; *i.e.* compute at any moment: the temperature felt by each larva on the corpse, the state of the body, the amount of Diptera females about to lay in the ecosystem attracted by the cadaver, the laying behavior of those Diptera females, the

development rate, the stage, the behavior, *etc.* of each maggot on the body.

A multiagent-based model describes each actor of a system as a computational agent, *i.e.* an autonomous and communicating computer system possibly situated in an environment. Thus, the model is composed of different types of agents and an environment representing the corpse. An agent encapsulates two kinds of models: those which define the evolution of its properties and those which define the modalities of its interactions with the environment and other agents. In this way, we can easily reuse models previously developed in independent contexts. Model's agent types and environment are described in this section.

3.1 Multiagent system environment

Agent environment represents the cadaver in 2 dimensions. It is divided into 2cm*2cm square cells. A set of variables V is attached to cells:

$$V=\{h, s, d_t, n, t\} \quad (3)$$

where h represents the hydrometry, d_t the density of tissue, s the value of a presence signal emitted by *Larva* agents, n the nutritional resources, and t the temperature of a given cell. h, d_t, n and t are called cell variables. Cell variables have their own behaviors: diffusion and evaporation coefficients are attached to them and model their intrinsic dynamics. The shape of the modeled body is roughly simplified. However, we respect strictly its proportions, the properties of each type of tissues. Simulations and field observations have shown that the shape of the body does not affect larvae development although body specificities such as wounds can affect colonization.

3.2 *Larva* agent

A *Larva* agent represents a Diptera larva. It implements development, mortality, feeding and behavior sub-models. Larva agents life cycle is composed of three steps: a growing step, when the agent updates its properties (development rate, stage, speed, length, *etc.*), a consuming step when the agent modifies its local environment (increasing the temperature, decreasing the nutritional resources, propagating a presence signal, *etc.*) and a moving step when the agent moves in the environment. The moving step is divided into s sub-steps (fundamental moves from a cell to a next one), where s represents the speed of the agent, depending on species and development rate. Fundamental moves are computed recursively and determine complex and realistic paths.

A fundamental move relies on a simple probabilistic algorithm: it uses environment properties to compute an utility measure of its neighboring cells and then a probability of moving there. Let N be the set of the agent's neighboring cells. The probability to go in a cell ce, denoted $P(ce)$, is computed from V and the *Larva* agents density, d_L, in ce. Thus, the set of choice criteria for a Larva agent to go in a given cell, denoted C, is:

$$C=\{h, s, d_t, n, t, d_L\} \quad (4)$$

For each criterion, it is possible to compute the corresponding utility measure from maggot physiological models. The utility of a criterion c measured in a cell ce is denoted $u(c(ce))$. To compute $P(ce)$, we postulate that choice criteria are independent. Thus for each neighboring cell, we compute the probability that the agent goes there according to all the choice criteria taken independently:

$$\forall ce \in N, \forall c \in C, p_c(ce)=\frac{u(c(ce))}{\sum_{\forall ce' \in N} u(c(ce'))} \quad (5)$$

$p_c(ce)$ is then the probability of the agent to go in the cell ce, according to the criterion c. Once $p_c(ce)$ is computed for each c in C and each ce in N, local probabilities have to be merged. $P(ce)$ represents the probability that the agent is attracted by all the choice criteria simultaneously:

$$\forall ce \in N, P(ce)=\frac{p_h(ce) \cap ... \cap p_{d_L}(ce)}{\sum_{\forall ce' \in N} p_h(ce') \cap ... \cap p_{d_L}(ce')} \quad (6)$$

The behavior of larvae and thus maggot groups simulated with this algorithm is realistic and the global behavior of the mass exhibits some emergent properties, such as thigmotactism (a tendency to follow the linear discontinuities of an environment). The key improvement of this model for PMI calculation, is the estimation of heat felt by larvae in complex maggot masses frequently observed on a body which enhances the estimation of larvae development [6].

3.3 *Layer* agent

A *Layer* agent implements Diptera population and laying sub-models. It creates and situates Larva agents in the environment. We use models developed by Goulson et al. [7] to predict populations of Diptera species in an ecosystem from weather variables such as hygrometry, pluviometry, or temperature. The general form of this model is given by the following equation:

$$\ln(P_{t+1})=a + b_0 \cdot \ln(P_t) + b_1 \cdot W_1 + b_2 \cdot W_2 \quad (7)$$

where P_t is the population at time t, P_{t+1}, the population at t+1, W_1 and W_2 are weather variable values, and a, b_0, b_1 and b_2 are free parameters.

It is obvious that geographical location, and in particular latitude, affects Diptera populations. For that reason, trapping experiments are in progress at Institut de Médecine Légale et Sociale de Lille (Forensic and Social Medicine Institute of Lille) to determine population models specific to North of France.

Population models tell us how many female flies *could possibly* lay on the corpse. It is also important to know how many flies *will effectively* lay on the

corpse and when. Bird & Allen [8] developed a generic laying model where the probability of a Diptera to be present in the environment is given as a function of the attractiveness of the cadaver and the nychtemeral (day-night) cycle. Each species has a different attractiveness model (each species is attracted by a specific stage of decomposition). Attractiveness, denoted *at*, is a function of time since death given by the following equation:

$$at(t)=e^{\frac{(t-s)^2}{2\cdot w}} \tag{8}$$

where t is the time since death, s the time when the corpse is the most attractive and w the laying window. t, s and w are expressed in hours. s and w are proper to each species.

The oviposition probability of a Diptera female, denoted $o(n, p)$, depends mainly on the nychtemeral cycle n and the flies activity peak, pa, which is the time of the day when flies are the most active. We use the generic definition of $o(n, p)$ given in [8]. The resulting laying probability $p(at(t),o(n, pa))$ is given by the following equation:

$$p(at(t),o(n,pa))=at(t)\cdot o(n,pa) \tag{9}$$

Each female lays 200 eggs on uncovered natural orifices, basically on the face and the anus, with an equivalent probability.
Many factors can affect Diptera colonization. As we stated earlier, body specificities can lead to unusual situations: in the case of wounds or amputations, the laying sites can be totally modified, in the case of special body treatment, such as partial or total cremation, insect succession is generally altered. Many of such factors such as transportation or burial could be cited. The fact is we only have a qualitative knowledge of the consequences of such specificities on Diptera laying behavior. For this reason, we only consider simple situations where the cadaver does not exhibit specificities. This is clearly a strong restriction. However, most cases are simple.

3.4 *Temperature* agent

A *Temperature* agent computes the temperature of the body using Henssge sub-model (know in medicolegal literature as Henssge equation [5]). It is a popular model of temperature cooling of a dead body based on Newton law of cooling. The temperature of the body is then a function of the ecosystem temperature.

The main problem with this approach is that we consider the body as a monolithic temperature unit. Based on [9,10], a thermal cellular automata model which predicts temperature at any point of the body according to conduction and convection laws has been developed. This model integrates the heat emitted by larvae as a fundamental parameter for temperature prediction.

3.5 Model execution

Simulating the decomposition process consists in defining an environment (a corpse or more generally a nutritive substrate) and launching a *Temperature* agent and *Layer* agents (one per species present in the ecosystem) according to the appropriate ecosystemic context (climatic data, body specificities, *etc.*). A scheduler controls the system execution.

4 DSS architecture

The PMI estimation tool can be divided in three functional layers: a *simulator* implementing the multiagent predictive model presented in the last part, an *hypothesis evaluator* and a *solution space explorer*. The purpose of this architecture is to use the predictive model to perform retrodictive (abductive) reasoning. Abductive reasoning, sometimes called inference to the best explanation, consists basically in discovering the most probable cause c of a fact f knowing the rule r which transform c into f. In our case, this definition has to be modified: inference to the best explanation is by definition a conjectural form of reasoning, however results of a criminal expert cannot be conjectural. Thus, we will try to identify *all the possible* causes $C = \{c_1, ..., c_n\}$ (each possible time of death) of a fact f (entomological data about a victim) knowing the rule r (the model of Diptera colonization and development presented in section 3) which *can* transform an element of C into f.

4.1 Hypothesis evaluator

This functional layer determines a "compatibility measure" between a set of expert observations and an hypothesis (in PMI estimation case, the time of death). Basically, it consists in transforming the observations into a set of *control rules*. These rules are implemented into agents called *Observers* which continuously monitor some simulation variables and, if a rule is violated, log the causes and, if necessary, order the simulation manager agent to restart the simulation. Running several simulations assures to explore "all the possible futures" (or at least a representative part of them) that the evaluated hypothesis implies. When a stop condition (*e.g.* a condition about the number of runs) is positively evaluated, a compatibility measure of the hypothesis, expressed as a possibility measure, is returned (Fig. 2).

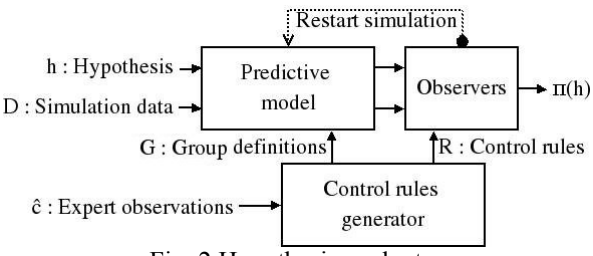

Fig. 2 Hypothesis evaluator

The multiagent nature of the model imposes to determine an efficient method to monitor simulations.

Multiagent monitoring is a difficult problem that has been essentially studied in the context of heterogeneous agents deployed in a real environment [11,12]. These approaches are based on message exchanges monitoring to determine agent plans or prevent overloads of system components. In a model like ours, composed of a large number of reactive agents, the problematics are quite different: for instance we cannot monitor message exchanges because the agents communicate through the environment using pheromone-like signals. Our approach is close to the *report based monitoring* method in which each agent reports its state to a supervisor. The major drawbacks of this method are bandwidth and CPU requirements needed when many agents must report their state (which is the case here) as shown in [11]. But, is it necessary for all the agents to report their state ? In other words, is the monitored information carried by all the agents or a subset of them ? these considerations bring us to the concept of *filtrated report based monitoring.*

We use the *group* concept to monitor simulations. In a multiagent system, a group is generally described as a collection of agents, sharing common characteristics, goals, *etc.* [13]. Our framework uses a very simple group definition: A group is defined as a set of constraints on agent properties. An agent is a member of a group *iff* it respects these constraints. A group represents the set of agents carrying the necessary information to compute the value of a monitored variable. Constraints are evaluated by the simulation agents themselves; thus, they "filter" the set of observed agents. Then an *Observer*, computes the value of a monitored variable and evaluates the corresponding control rule.

When initiating the PMI estimation process, a c*ontrol rules generator*, transforms expert observations into *group definitions*, which are implemented into the simulation agents, and *control rules*, which are implemented into *Observer* agents.

An expert observation is an information about the state of the entomofauna at the body discovery time. We implement four types of observations: species found on the body, for each species, the development rate of the oldest individual and its larval instar (stage of development), and finally the abundance of entomofauna. These data are traditionally used by forensic entomologists to determine a PMI. For each information, two kinds of control rules are generated: those which are evaluated during the simulation and those which are evaluated at the end. The first kind allows *Observers* to stop a simulation before its end by exploiting properties of monitored variables such as monotony. This can save CPU time and be useful to compute the next hypothesis to evaluate.

4.2 Solution space explorer

This layer uses the *hypothesis evaluator* to explore the solution (hypothesis) space. It is composed of two heuristics H_1 and H_2 and a memory that stores hypothesis evaluation results. H_1 implements the ADD (Accumulated Degree Day) method to determine the first hypothesis to be evaluated. Entomologists usually perform PMI estimations using this simple method which assumes a linear relation between temperature and development rate. It gives a first approximation of the time of death. Once the first hypothesis has been evaluated, H_2 computes the next hypothesis to be evaluated using, for the moment, a simple dichotomy method. It allows the solution space to be fairly explored.

5 Implementation and preliminary results

This system has been implemented as a MadKit plugin. MadKit is a multiagent platform based on a powerful organizational model called AGR (Agent, group, role) [13,14]. The entomological model has been developed using the TurtleKit API [15].

In this section preliminary results about interesting aspects of ForenSeek are presented.

5.1 Behavior of *Larva* Agents

We reproduced in this experiment the 2m*2m artificial environment of blood and agar-agar used in the laboratory to study larval behaviors. The temperature is constant at 20°C. We monitored the density of 1000 *Larva* agents in the environment over time, expressed in hours, during 100 hours (Fig. 3). The darker the image, the denser the maggot mass is. Once they hatched, *Larva* agents optimize their density by forming a large mass (t = 24).

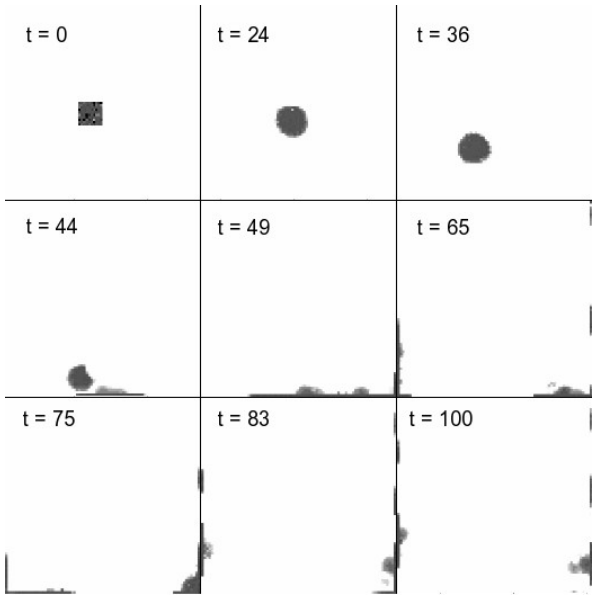

Fig. 3 Gregarious behavior of maggots

After a few hours (t = 44), the mass reaches an environment edge and then splits into several small groups (t = 65). The small groups keep hugging the walls until the end of the experiment (t = 100). This is an interesting illustration of thigmotactism, a behavior systematically observed in such experiments.

It would be difficult to present systematic results of the behavior of *Larva* agents, however we will see

how it affects PMI estimations. PMI computed with the ADD method and PMI computed using our model are compared in the next section.

5.2 Influence of temperature on PMI estimation

ForenSeek can be a good way to analyze practices in Forensic Entomology. In this section, we study the influence of the temperature felt by larvae on PMI estimation; we intend to show here that methodologies traditionally used in Forensic Entomology can lead to important PMI overestimations. This demonstration is based on a computer experiment where the simulated increase of temperature due to maggot mass is important. We monitored the temperature felt by six randomly chosen *Larva* agents of *Lucilia sericata* species (to simulate the sampling process of entomological expertise) over time. The ecosystem temperature is constant at 18°C. About 2000 eggs are laid soon after death on natural orifices (the cadaver is naked). Results show clearly a difference between the temperature felt by larvae and the ecosystem temperature as it has been reported in real cases (Fig. 4).

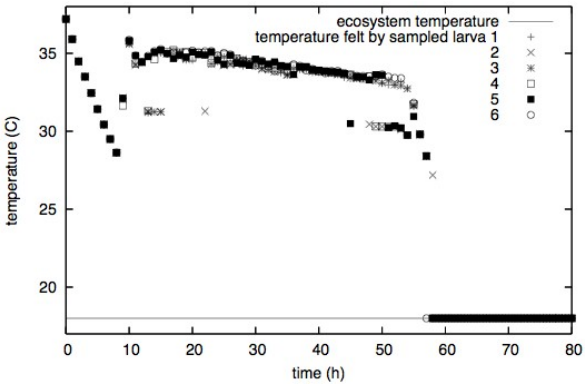

Fig. 4 Simulated increase of temperature

We can see that in their egg stage of development, the temperature felt by larvae follows the cooling of the body. A few hours after hatching, larvae warm the local temperature to their optimal temperature (about 35 °C). Temperature regulation is maintained until larvae gradually leave the body to end their development cycle.

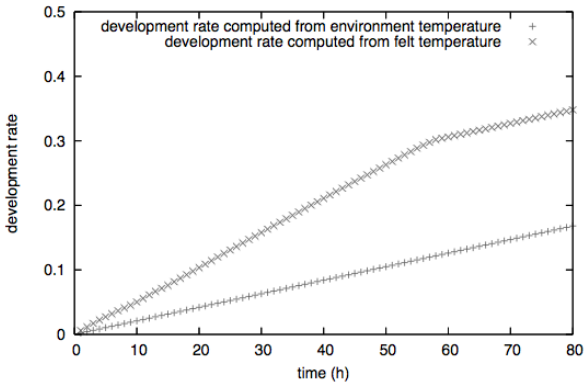

Fig. 5 Development rate evolution

The temperature felt by larvae during pupariation is of course the environmental temperature. From beginning to end, the difference between temperatures felt by larvae is negligible. Thus, next figures and observations will be arbitrarily based on the temperature felt by the first sampled larva. The Fig. 5 shows the impact on the development rate evolution, considering the temperature felt by larvae and considering the ecosystem temperature. Then, we can analyze the difference between a PMI estimation computed from data taken from [16] and using ADD method and the computation performed by the DSS (which is accurate in this simple case). We assumed

that there was no lack of precision during the development rate identification process. The result, presented in Fig. 6 shows (logically) that the longer the PMI, the more important the error with the ADD method is.

This result has to be seen as an extreme case. It shows that in particular cases (when Diptera colonization starts just after death and the increase of temperature due to maggot mass is important) PMI estimations performed with traditional methods are not accurate and lead to important errors.

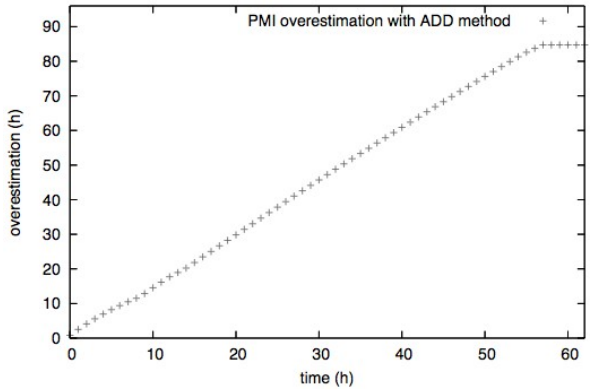

Fig. 6 Evolution of PMI overestimation

To confirm this result, more systematic studies should be done to compare PMI estimations manually performed by experts and by a DSS such as ForenSeek. On the other hand, it could be interesting to analyze the accuracy of temperature increase predictions computed by ForenSeek and "guessed" by experts.

6 Conclusion

This paper presents a multiagent DSS based on an original model of corpse decomposition by maggots. This model encapsulates various models developed in independent contexts (ethology, ecology, entomology, *etc.*). We showed that this software program allows forensic analysts and entomologists to determine more reliable PMI estimations in particular cases. Experiments are in progress to extend this to more general cases. Moreover ForenSeek can be used as a virtual laboratory to perform complex simulations.

7 Acknowledgments

This study is carried out as part of a collaboration between LGI2A (Université d'Artois, Faculté des Sciences Appliquées), Institut de Médecine Légale et Sociale de Lille (Université de Lille II), Faculté Libre des Sciences et Technologies de Lille, HEI, and LAGIS (Ecole Centrale de Lille). We would like to thank Damien Charabidze and Benoît Bourel of Institut de Médecine Légale et Sociale de Lille for their constant support on this project. We are grateful to Alexandre Veremme for his work on the thermal cellular automata.

This study is supported by French Ministry for Research and Norbert Ségard Foundation.

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