A HMM-Based Approach to Modeling Ant Behavior

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Abstract. Modeling societies of individuals is a challenging task increasingly attracting the interest of the machine learning community. Here we present an application of graphical model methods in order to model the behavior of an ant colony. Ants are tagged with RFID so that their paths through the environment can be constantly recorded. A Structured Hidden Markov Model has been used to build the model of single individual activities. Then, the global profile of the colony has been traced during the migration from one nest to another. The method provided significant information concerning the social dynamics of ant colonies.

1 Introduction

This paper addresses the problem of analyzing the behavior of an ant colony, in order to discover social rules and social roles, which are still not well identified and understood. In the specific case, an ant colony has been observed after creating an artificial climatic mutation, which caused the migration from one nest to another. Facing the emergency, the different elements of the colony change their current social activity, and assume specific roles in order to accomplish the migration in the new nest. Afterwards, they return to normal activities, not necessarily the same they were accomplishing before the emergency. Individual activities are tracked using a network of RFID detectors, which provides rough information about the position in the environment of every single ant. The fundamental issue investigated here is the construction of the model of the activities an individual can undertake, such as: nursing, transporting, foraging, and so on, according to the emerging needs of the colony. Starting from the activity models, global parameters characterizing the global colony behavior are inferred from the RFID logs.

The activity models are based on Structured Hidden Markov Models (S-HMM), a variant of classical HMM [1], well suited to combine a priori structural information from the domain experts with statistical information inferred from data. The paper describes both the methodological approach and the in field experimentation. Even if the work presented here is only a preliminary phase of a larger project, the obtained results already provided information considered interesting and novel from domain experts.
2 Experimental Setting

Among social animals, the *Formicidae* family certainly shows the greatest diversity of social structures and related behaviors. Its study is central in evolutionary biology: kin selection theory [2] states that worker sterility is transmitted to the next generation through fertile kin. This criterion is fulfilled in some *Ponerines* society with simple familial structure (one queen mated with one male). This familial structure is the basis of the apparent harmony and cohesion of a colony.

The dynamic of task allocation through worker ontogenesis has widely been described in anterior theoretical studies, but the difficulty in acquiring the data and the lack of automatic tools discouraged the collection of associated experimental data. Yet, it is essential to find the rules that govern ant individual behavior and its integration at the colony scale. Understanding this phenomenon necessitates to be able to integrate the two levels of analysis. Thus, the individual monitoring of ant foragers showed the elementary rules that each ant follows [3, 4]. The use of RFID technology may be very useful to obtain highly interesting results, such as a knowledge database about social agents and the analysis of its dynamic features. Indeed, the different nest chambers segment social life in relation with the presence of the queen and brood. We have shown that the simple spatial monitoring of ants in the different chambers allows to predict with 99% probability the social status of individual workers.

In this paper we aim at studying the dynamic of a nest change in an ant’s colony. The kinetics of departures from the original nest, passages through the foraging area (outside) and arrival sequences in the new protected nest will be studied. These movements necessitate a high coordination between workers, and it is likely that foragers initiate the exploration of the new nest. It is also likely that foragers will initiate recruitment to lead more static ants (nurses and inactive ants) toward the new nest. Which ants will transport the brood and more importantly which ants will take care of the queen movement toward the new nest is unknown. Similarly, we do not know whether the established division of labor in a stable situation will influence particular individuals to play a key role in the organization of colony movement. Ultimately, what we focus on here is the logistics of dynamic sequences of movements between the original and the new nest. It is particularly difficult to follow this phenomenon in real-time and only a RFID system will allow the acquisition of such data and the extraction of significant patterns from them.

However, RFID applied to ants poses some feasibility problems because weight limitations imply a good miniaturization of the tags and good performances of the readers. Yet Streit et al. [5] recently used RFID technology to study bee longevity and the respective length of foraging and nurse activities. For this study, we chose a big-sized tropical ant *Pachycondyla tarsata*, which establish subterranean nests distributed in several interconnected chambers distributed over 10m. Colonies of these species are typically composed of ten to a few thousand ants. RFID tag consists of a chip attached to an antenna weighting under 40 mg (i.e., 25% of an ant weight), glued on the animal thorax (Fig. 1).
Preliminary tests showed that the tags don’t disturb the ants behavior and the colony dynamic significantly.

2.1 Measurement Device

The movement between nests of a colony of 55 *Pachycondyla tarsata* workers was monitored in a RFID device (about 4 hours recording, i.e. 30 000 scans). Each worker had a tag attached to its thorax (Fig. 1).

![Ant with RFID tag](image)

*Fig. 1. Ant with RFID tag*

The experimental device for this experiment of three rooms each and a foraging area, linearly connected by six tunnels (Fig. 2). At the beginning of the experiment, the queen (not tagged) and its brood (eggs, larva and cocoon) are located in Room 3 of the first nest, the farthest from the foraging area. Each tunnel is equipped with two RFID readers (number 1 to 12 from Room 3 in Nest 2 to Room 3 in Nest 1) that detect the passage and the direction of tagged individuals between rooms. The position of an individual may be inferred unambiguously by the information provided by the six readers in the tunnels. The lack of detection implies that the individual is out of the tunnel and thus in one of the seven rooms. The exact location of a tag (i.e., of an individual) can be deduced from the travel direction. The information recorded by readers is handled by an RFID electronic device, and then sent to a computer that creates and store the data files.

At $time = 0$ we switch on a strong neon light (strongly repellent for ants) over the first nest and we open the entrance of the second nest, then we record the colony movement until the entire brood is moved into the second nest (~4 hours).

2.2 Data

The data files are in text format. They indicate, for each antenna scan (about three scans per second), the scan number, the date, time, and, for each individual (i.e., for each tag), which antenna is activated (Fig. 3). If, during a scan, none is detected, nothing appears in the data file.
If an ant moves from one room to another, it is detected successively by the two antennas in the tunnel that connect the rooms. This allows us to infer the exact position of each ant at any moment (it is considered that an ant has changed room when it is detected by the second antenna). A simple treatment on these files makes it possible to obtain spatial information for each individual.

3 Modeling Social Activities

The RFID apparatus only provides a partial observation of the individuals. No information is provided concerning what happens inside a room, but only the duration of the permanence of an ant inside it can be known. Moreover, sensors are not reliable. A missing detection rate ranging from 5 to 15 % has been observed.

The goal is to reconstruct the evolution of the activity of the single individuals in the context of the social environment, under the pressure of the simulated ecological mutation. More specifically, we want to discover which kinds of activities are undertaken during the migration phase, how many individuals are dedicated to each activity, and when an individual may change activity.

Achieving this goal requires to solve the following problems: (i) to reconstruct the most likely paths made by ants considering that many transits in the tunnels are unobserved due to missing detections; (ii) to characterize the different activity patterns emerging from the data; (iii) to infer the activity models; (iv) to segment and label the paths according to the activity, which most likely produced the observed action sequence.
Fig. 4. Snapshot of a room of the ant colony.

The major requirements a modeling tool must satisfy are the capacity of handling partially observable status, and modeling the duration of the permanence in the different areas of the environment. To this purpose, the graphical model approach [6] is the most promising one. In particular, two tools emerge as candidate for the specific task of segmenting and labeling sequences in presence of hidden states: HMM [1] and Conditional Random Fields [7]. Recent findings [6] are in favor of CRF, which in many cases outperformed HMM. Nevertheless, the requirement of modeling duration suggested to us to try first the HMM. In fact, well assessed methods for extending HMMs in order to cope with durations are available, while CRFs have been little investigated in this sense [8]. The adopted tool is then a HMM variant called S-HMM [9], which offers specific features for modeling permanence inside rooms.

S-HMM are block structured according to the paradigm used in Object Oriented Programming. A block consists of a set of states, only two of them (the initial state $I$ and the end state $E$) are allowed to be connected to other blocks. Blocks can be nested inside each other.

Two kinds of blocks are possible: basic blocks and composite blocks. The states of basic blocks produce observable emissions according to the classical HMM paradigm. The states of composite blocks correspond to basic or composite block defined at a lower abstraction level. When a transition into a state $q$ occurs in a composite block, a call is made to the lower level block associated to $q$ and the activity is suspended until the call returns.

All basic algorithms for computing probability distributions and estimating model parameters from sequences, such as forward-backward and Viterbi algo-
3.1 Modeling Duration

The problem of modeling durations in the HMM framework has been principally faced in Signal processing. Two approaches to the problem emerge from the literature. The first one produced an extend modeling tool called Hidden Semi-Markov Model (HSMM), which corresponds to HMM augmented with probability distributions over the state permanence [11–13]. The alternative approach is the so called Expanded HMM [14]. Every state, where it is required to model duration, is expanded into a network of states, properly interconnected. In this way, the duration of the permanence in the original state is modeled by a sequence of transitions through the new state network where the observation remains constant. The advantage of this method is that the Markovian nature of the HMM is preserved. Nevertheless, the complexity increases according to the number of new states generated by expansion.

In the framework of S-HMM, the approach of Expanded HMM is used and specific basic blocks are provided to model the probability distribution of the permanence inside a macro state. The specific HMM topology we adopted for the present application is reported in Figure 5 (c). Basically, this model exhibits an Erlang’s distribution (Figure 5 (d)), when the Forward-Backward algorithm is used to compute the probability distribution. Basically, an ant activity model assigns a probability distribution over the set of all possible paths an ant accomplishing a specific activity can go through the artificial environment. Let $s$ be a sequence of observations. Comparing the different probability assigned to $s$ by a set of different activity models, it is possible to infer the activity that most likely generated $s$.

3.2 Ant activity model architecture

The observation of a path is a sequence of pairs $\langle t_i, s_i \rangle$ collected from the RFID sensors, being $t_i$ the time of the detection in msecs, and $s_i$ the id of the sensor. In the S-HMM framework discrete time is assumed. Then, a transformation from the numeric representation from the sensors to a discrete (symbolic) representation has been defined, which preserves the accuracy implicit in the original coding. The symbolic sequences are encoded using an alphabet $A = \{A, B, C, D, E, F, G, H, J, K, L, .\}$, where letters from $A$ to $L$ correspond to the RFID detectors from 1 to 12, respectively, and “.” denotes a time interval, in which no observation from the sensorial apparatus is received. The transformation, from a numeric to a symbolic sequence is obtained by subdividing the time into discrete intervals of one second. A numerical sequence is scanned from the beginning to the end moving ahead of one interval at a time. If a signal from a detector is found, the corresponding symbol in the symbolic sequence is appended; otherwise a “.” is inserted. After the translation, the permanence in
a room, is be represented as a string of ’.’. Moreover, undetected transit in a
tunnel will be report as a ’.’, as well.

After experimenting with different model architectures, the one reported in
Figure 5 has been chosen. It is a two level S-HMM, where the upper level models
the long range path through the environment, while the lower level models the
observations detected by the RFID sensors, and the duration of the permanence
inside rooms and tunnels. States in the upper level defines a double chain sharing
the ends. The states denoted with single circles represent the permanence in a
tunnel, while the ones denoted with double circle represent the permanence
in the rooms of the nests or in the foraging area. States denoted with squares
represent sensors. Each state is associated to a block at lower level, which models
the probability distribution for the permanence in the associated location, or the
process of generating the observable emissions of the sensors. Referring to Figure
5(a), the upper chain models the action of going from the old nest to the new

Fig. 5. Structured HMM used for modeling ant behavior. (a) High level model; (b)
basic block encoding the sensor behavior; (c) basic block modeling the duration of
the permanence in a room; (d) shape of the probability distribution encoded by the
duration model.
nest, while the other models the action of going from the new nest to the old nest. Changes of directions cause switching from one chain to the other.

4 Learning from the activity traces

From the model architecture described in Figure 5, the activity models have been estimated in order to construct an activity tagger. This is program used to infer the most likely path of an ant, and to segment and label it according to the activity, which most likely generated the signals reported by the RFID detectors. From the labeled paths the global behavior of the colony along the migration phase has been reconstructed.

4.1 Activity Tagger Architecture

An activity tagger is a three-level S-HMM, obtained by layering a new block on top of the activity models. As show in Figure 6, this new layer defines a fully connected graph among the blocks modeling the different activities. Then, the activity tagger interprets ant traces as a sequence of segments each one corresponding to a different activity phase. By exploiting the S-HMM compositional properties the activity tagger can be refined by training single blocks independently as well as the entire structure using the classical Baum-Welch algorithm.

The standard method for interpreting a sequence using an HMM (S-HMM) makes use Viterbi algorithm [15, 1] in order to find the maximum likelihood path in the model state space, which corresponds to the observed events. In our case this method does not work because the HMM modeling the duration of the permanence in the rooms and in the tunnels, requires forward-backward algorithm.

Then we adopted an alternative method, also described in [1], which consists in finding, at each time $t$, the maximum likelihood state $q_t$ of the model, as
defined by the following equation:

\[ q_t = \arg \max_i (\alpha_t(i) \beta_t(i)) \quad 1 \leq i \leq N \quad (1) \]

In expression (1) \( \alpha_t(i) \) is the classical function that estimates the probability for model \( \lambda \) of being in state \( q_i \) after generating (in all possible ways) the sequence of observations from \( t_0 \) to time \( t \). Symmetrically, \( \beta_t(i) \) is the probability for \( \lambda \) of generating the remaining part of the sequence from \( t \) to \( T \) starting from status \( q_i \).

### 4.2 Learning Procedure

The complete learning procedure for learning the activity tagger integrates data-mining algorithms with the manual action of an expert of the domain. The domain expert is very good in detecting where the activity pattern changes, and in providing an episodic interpretation of fragments of the paths, but it is poorly performing in tasks requiring the systematic analysis on large amount of data. On the other hand, the learning algorithms is very good in discovering regularities and similarities among different episodes discovered by the expert. From this cooperation, the groups of characteristic activities are progressively individuated and modeled. The procedure consists of the following steps, which are repeated until the convergence to stable models is achieved:

1. Let \( L \) be the set of sequences to be labeled. Let, moreover \( L_i \) a subset of \( L \), used for iteration \( i \).

2. label sequences using the current tagger version;
3. refine the assigned labels with the help of an expert of the domain;
4. segment every sequence according to the assigned label;
5. cluster segments according to the assigned label;
6. from every cluster \( C_k \) estimate a model \( \lambda_k \);
7. construct a new tagger using the models learned in the previous step, and optionally train it using the Baum-Welch algorithm;
8. add new sequences extracted from \( L \) to \( L_i \) obtaining a new learning set \( L_{i+1} \).

Finally, after the procedure iteration stops, all sequences in \( L \) are labeled using the tagger constructed at the last step.

Notice that, the first time the procedure is executed, no tagger exists. In this case, the first step has been carried using an algorithm based on Kohonen maps [16, 17], which was able at providing a rough segmentation. Then the domain expert manually corrected the output of the program. As this task is time consuming, we started with a small learning set extracted from the a set \( L \) containing 57 sequences (one for each individual of the colony). The procedure has been iterated three times incrementing the learning set up to 40 sequences. Afterwards, all 57 sequences have been labeled using the final tagger. An example of labeled sequence is reported in Figure 7.
4.3 Tracing the colony profile

From the labeled sequences three groups of global parameters have been extracted tracing the profile of the ant colony during the migration phase:

1. The temporal evolution of the number $N_j$ of individuals present in every room $R_j$ of the old and of the new nest.
2. The temporal evolution of the number $n_{ij}$ of individuals involved in the activity characterized by model $\lambda_i$, in every room $R_j$.
3. The global number $N_i = \sum_{j=1}^{7} n_{ij}$ of the individual involved in each activity $\lambda_i$.

5 Extracted Knowledge Analysis

Nine groups of activities (A1, ... A9) emerged as easy to characterize by means of a S-HMM. A last group (A0) has been defined, which corresponds to activity segments where a clear pattern is not detectable.

The first information extracted from the sensor logs, using the activity tagger, is the path made by every ant during the migration phase. From it, the global parameters $N_j$ ($1 \leq j \leq 7$), reporting the temporal evolution of the number of individuals in the different rooms, have been computed. The results are described by the diagram of Figure 8. Three facts are emerging:

(i) Since the beginning a small number of ants is present also in rooms $R'_1$, $R'_2$ and $R'_3$ of the new nest. This means that the colony started to explore the new nest as soon as the door has been opened. Anyhow, this does not produce remarkably effects until the neon light begun to trouble the colony.

(ii) After the migration phase was concluded, no more ants where present in the internal rooms $R_2$ and $R_3$ of the old nest, but the presence of ants in room $R_1$ was remarkably higher than in the corresponding room $R'_1$ of the new nest before the migration. This can be explained considering the combined effect of the residual pheromone, which acts as an attractor for the ants in the old nest,
and the neon light, which acts as a repellent.

(iii) The final repartition of individuals on rooms $R'_2$ and $R'_1$ is quite different than the one in the corresponding rooms of the old nest before the migration phase. More specifically, the percentage of individuals in room $R'_2$ is much higher. The explanation is that ants were busy with cocoons located in room $R'_2$. The distribution shows tendency to returning to the normal values at the end of the period of observation. Figure 9 shows the evolution of parameters $N_i$ corre-

![Fig. 8. Distribution of the individuals on the different rooms of the environment during the migration phase.](image)

Fig. 8. Distribution of the individuals on the different rooms of the environment during the migration phase.

sponding to the number of individuals involved in activity $A_0, \ldots, A_9$. From the analysis of the distribution of the activities on the rooms $(n_{ij})$, it appears that $A_2$ and $A_9$ are just variants of a same type of activity. This is also confirmed by

![Fig. 9. Evolution of the number of individual involved in the different activities.](image)

Fig. 9. Evolution of the number of individual involved in the different activities.
the distance from the two models computed according to the similarity measure described in [1]. Moreover, $A_8$ exhibits the same pattern as $A_2$ and $A_9$, with the difference that it occurs in the rooms of the new nest while the others occur in the old nest. Also in this case the distance among the models supports this hypothesis. Finally, a regular pattern, where activities $(A_2|A_9), A_1, A_7,$ and $A_8$ regularly occur in sequence has been found in about the 60% of the individuals. This sequence find a plausible explanation. $A_2$ and $A_9$ correspond to a routine phase of exploration of the old nest, $A_1$ is a short phase where the new nest is actively explored, $A_7$ is the phase in which eggs, cocoons and food are moved in the new nest, and $A_8$ is the return to the normal activity of routinary exploration of the new nest.

6 Final Remarks

We have presented a novel application of graphical model methods to the interpretation of data collected from an ant colony. Very encouraging results have been obtained using S-HMM, a variant of HMM, well suited for modeling duration. On the basis of these finding a new research phase will start where the experiment will be repeated with a larger colony (120 individuals) in a more complex environment. Further experimentation with other kinds of graphical models, such as CRF will also be investigated. It is worth noting that the presented application is very innovative with respect to the current state of the art. In fact, even if several authors addressed the problem of modeling insect colonies, this has been made with different goals. In general the interest has been to study the emerging behavior of the colony, seen as a complex system, starting from a simple model of the individuals. In our case, we started from the opposite point of view proposing a method for observing and modeling the medium/long term behavior of real individuals, as it has been induced by the conditioning of the social environment, in an emergency condition. Finally, RFID methods for tracking the positions of people or animals begin to be quite a diffused practice, which is attracting the interest of data mining community. Nevertheless, no methods for constructing a complex model of the behavior of an individual traced by an RFID had been proposed until now.

References

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