Motion Recognition of Physical Agents Constrained to Two-Dimensions

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Abstract: We propose a method to recognize the behavior of a physical agent moving in two dimensions. The problem is to characterize the behavior of the agent purely by observing its physical motion relative to its environment. Data is taken by a vision based tracking system which returns a stream of time-stamped (x, y) positions. From this data features are extracted. These features help make up a set of observations about the physical agent in its environment. Based upon these observations we want to identify a model that characterizes the agents current behavior. The use of Hidden Markov Models to represent predefined behaviors allow us to capture the fact that true internal state of the agent is unobservable by us. We calculate *Pr(Model | Observations)* for each model and select the model with the highest probability at any given point in time. To test our research we are interested in characterizing the motion of insects on a two-dimensional surface. We have selected social insects as research subjects because they can be observed in a laboratory environment and they provide a rich source of data for testing our algorithms.

1 Introduction

1.1 Problem

For systems that use vision as a sensor it may be important that the system construct a model of the environment. To do this it must identify objects and entities in the field of view. If they see a physical agent moving around in a scene there is motivation to know what the agent is doing and what it may be thinking. Such problems are getting more attention in certain areas because of advances in vision systems. Our motivation stems from research in Multi-Agent Modeling. We are interested in building *Recognizers* that can take visual information as input and identify behaviors of physical agents moving in a two dimensional scene. The proposed research addresses the problems involved in how to characterize and measure features of the motion of a physical agent, relative to its environment, so that meaningful inferences can be made about the possible goals the physical agent is pursuing.

For this research we have an interest in biological colonies. Social insect colonies have become a source of inspiration in the area of Multi-Agent Modeling, and in other areas of computer science. We have brought a colony of Ants to germination in our lab, to be a source of data for multi-agent interaction, and have developed a unique vision system that is capable of tracking hundreds of ants at one time.

We want to analyze this data to automatically recognize what an individual ant is doing at any particular time. It is first necessary to examine each particular trail that an ant leaves as the tracking system monitors it. From such traces features must be extracted which are complete enough to allow for meaningful interpretations. Once we have a collection of features we can

summarize these as a set of observations. The second main part of the task is to select a model which best characterized the ants behavior, at any given time, based upon this sequence of observations. We intend to use Hidden Markov Models to encapsulate predefined behaviors that have been developed with insights from biologists, and develop an algorithm capable of mapping the observations of an ant to one of these HMMs. If we have several HMMs to choose from we will use a classifier to select the model that has the highest probability of explaining the data given a sequence of observations.

So far we have implemented some measures based on moving averages over the length of an ant trace and labeled its relative path motion as Left, Right, or Forward. There has been considerable accomplishment in developing infrastructure, and we currently have a robust tracking system capable of logging hours of data for one up to hundreds of ants at a time. We are continuing to extend our feature-detection algorithms in order to extend the types of behaviors we can recognize.

1.2 **Approach and Deliverables**

Our method has two phases. The first part of the task is to extract features from the time-stamped (x, y) positions of an ant as it moves about the environment. From these we generate a sequence of observations. Next, we want to predict which of our models best explains this sequence of observations. We can do classification of the input signal by calculating the probability of each model given the sequence of observations, and choose the model with the highest probability at a given time. The main scope of this project will then be to identify good features to be used for recognition and to test our model selection criterion. Recognition happens when a HMM has been selected as the best description of the possible goals in the observed state of the ant world. If successful we will

- Determine a useful set of features to describe the motion of an entity moving in two-dimensions.
- Generate a set of HMM's which may describe actual biological goals of individual ants and/or the colony.
- Test our Tracking Systems architecture and determine if this is a proper model to use for other sophisticated tracking systems.

Practical Impact

The proposed research will address problems at the center of Multi-Agent Modeling and will give biologists new tools for understanding social insects, and in particular Ants. We will:

- Develop new algorithms for Multi-Agent Modeling
- Provide biologists with new techniques for investigating the dynamics of Social Insects.

2 Prior Work

Multi-Agent Modeling is the process of building models of multiple interacting agents based on observations of these agents over time. Such models allow us to identify the state of agents and the organizations of which they are a part. There has been work done in adversarial domains such as robot soccer[19][14] where the need to infer the opposing teams current tactical intent[17] is useful in planning a correct response in the robot soccer game. In order to

gain our information we are observing the entities using a color camera. These entities can be robots, or insects, or people. There have been interesting advancements in the area of gesture recognition[11] and in characterizing human interactions as they meet or pass by one another in open areas such as parking lots using a parametric model. Although we are developing a complete Recognition System for multi-agent modeling we are focusing our attention on recognizing ants and their movements.

Ants perform a variety of tasks outside their nests[6]. The one that comes readily to mind is foraging. Ants leave their nest in search of food and once they have located a food item they maneuver their way back to their nest. Usually, at the same time, there are scouts outside the nest walking around to detect items of interest for the colony or fighting to defend it. Trying to determine the intentions of the ants are what some biologists are working on when they study social insects. Previous work done in the mid 1990s have the researches out walking around on the desert floor watching what ants do during their daily activities and logging them in a notebook. Other researchers [5] have used a video camera in a laboratory and filmed ants in their foraging arenas, and then later went back and point-by-point annotated the ant's movements so that mathematical calculations could be done. For instance, in a need to characterize the motion of patrolling ants, Adler & Gordon [6], came up with the notion of a 'trace index'. This is viewing an ant's trail as a sequence of points and determining the standard deviation of the turning angle between the points for a given time period. Doing this for a group of several ants the researches were able to determine that the members of a group of patrolling ants adjusted their individual motion do to the presence of other ants. We hope to utilize such methods and extend them by incorporating the location of environmental landmarks to create a rich feature set that explains the motion of such patrolling ants. After we have a set of observations the next step is to attempt to select which behavior we currently think the ant is performing.

To do our model selection we will follow the work of Han & Veloso[8] who designed an algorithm to automatically recognize the behavior of a soccer playing robot. Here a vision system is reported to watch a robot move up to a soccer ball and determine if the robot is trying to maneuver itself into a position to kick the ball down the field. The incoming 'stream of actions' is viewed as the input signal to the system. In this work, a Hidden Markov Model represents a behavior. If the robot moves in a pattern which is encoded into one of these HMM's, the system will output that the robot is currently 'moving behind the ball', or doing a behavior x. We are attempting to identify behaviors that are biologically inspired such as 'foraging' or 'alert.' Since we are using an automated vision system to track and log ant movements we will be able to do many more calculations with a greater accuracy over what has previously been the state of the art in biology.

3 Approach

So far we have designed enough infrastructures so that a color vision system can identify and track multiple ants marching over a one-meter square area. This data is logged to a file for later analysis. We are also able to receive a live feed of ant data over the Internet. As stated before, there are essentially two phases to this recognition process. First we have to manipulate the raw data to extract features from it so that we can pass a sequence of observations on to the classifier. The classification phase involves calculating the probability that a given model will have generated such a sequence of observations, and the model with the highest probability will be selected as corresponding closest to the ant's current behavior.

3.1 Vector Decomposition and Single Parameter Metrics

Our ant data is a series of time-stamped (x, y) coordinates. Each ant is given a unique ID number. Since the data are (x, y) coordinates on a plane we naturally choose a vector representation for each time step that the ant moves. This vector will point 'from' the previous time step, 'to' the current time step. It is possible to calculate the straight Euclidean distance between any two points, and since there is a time associated with each step the length of this constructed vector corresponds exactly to the velocity with which the animal moved during that increment. For a single ant moving across the surface of our lab space its motion is decomposed into a chain of tiny vectors each beginning at one point and terminating at the next point. Immediately, we see that for any two of these vectors there may be a small deviation in angle from one to another. We have conveniently captured the ants Turning Angle at each step as the ant turns to investigate another direction.

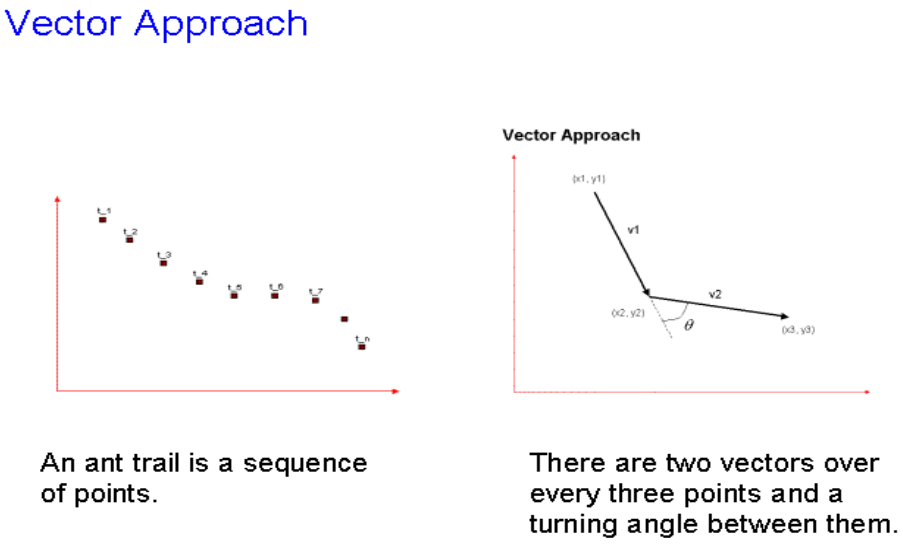


Figure 1

We can continue to decompose an ant's trace into a series of numbers, which correspond to the angle between two vectors along this path. The raw (x, y) data gives us two series of numbers (or signals) we can use: the Turning Angles, and the Velocity Vector between every to points. This is enough information to completely reconstruct the path that an ant followed.

The tracking system will also let us identify points in the environment that may correspond to items the ants may find interesting. These items may be food, such as sugar water, or the entrance to the nest. These (x, y) positions are considered to be fixed. As an ant patrols it environment another dynamic quantity of it motion we can identify is its current heading, or its egocentric orientation, with respect to the environment. It will then be possible to determine if the ant is heading toward a food source over some time period, or if it is moving toward the entrance to the nest. This will be done by directly comparing the (x, y) position of every identifiable item of interest out on the table with the animal's egocentric orientation.

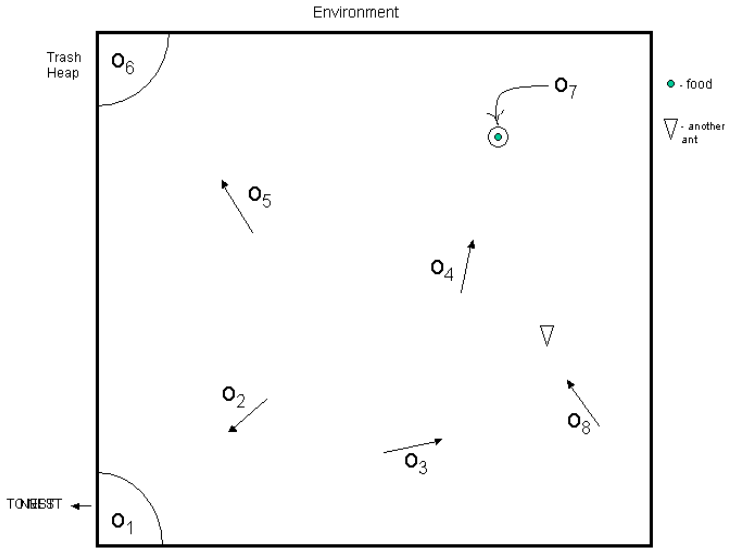


Figure 2

As the ant moves around its environment we can now make a series of observations about its current motion. It is this series of observations that will be given to the classifier for selecting a behavior. In figure 2, above, we see several types of observations:

O_1 – near the nest entrance
O_2 – heading towards the nest entrance
O_3 – wandering in the foraging area
O_4 – heading towards to food area
O_5 – heading towards the trash heap
O_7 – at the food
O_9 – heading towards another ant

3.2 Selecting a Behavior Model

As the animal moves about the observing arena it will be engaged in goal directed action. In order to carry out this action it must move around on its legs and interact with its world with its mandibles and antenna. So by watching what it is doing now, and in the past, we may be able to predict something about what it will do next. The sequence of observations made by watching the ant will be interpreted as the output of a Hidden Markov Model. We are developing a recognition system that will automatically select a Hidden Markov Model that has the highest probability of generating the observed sequence of observations. Each HMM will be labeled with the name of a behavior. Thus, selecting a HMM will correspond to picking a behavior that best describes the ant's plan by only observing its physical motion. We can calculate the probability that a particular model generated a sequence of observations by using the Forward Algorithm. If we have several models to choose from, we will calculate a probability for each model and then choose the model with highest probability.

Designing HMMs to describe ant biology

We may never know the true plans that are inside an ant's brain, but with the aid of biologist, who have thus far made extensive studies of ant behaviors, we can attempt to craft hidden state models which we think accurately correspond to an ants goal directed behavior.

Our work will closely follow the development of automatic robot behavior recognition developed by Han & Veloso. Their work represents an instance of the general plan recognition problem within uncertain and non-deterministic domains. Our ant observations will be viewed as an ant signal. This allows us to start at a high conceptual level of abstraction. There are many assumptions in our architectural approach and being that the internal state of an ant will never be available to us we believe that HMMs are suitable for this recognition process. The following paragraphs describing this work are drawn from [2].

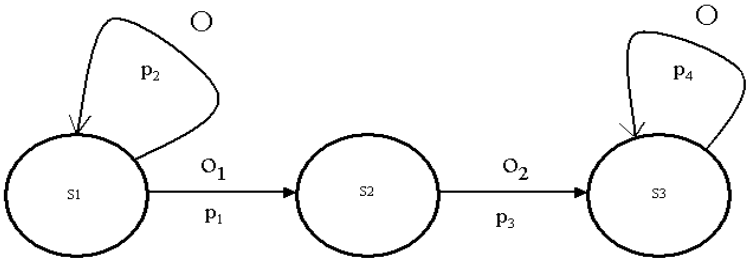
Most complex behaviors can be broken down into stages. The stages may not actually exist in the physical entities mental plan work, but it provides us with a level of abstraction to model potentially complex behaviors. Probabilistic transitions between any two states model the noise in the system and any discrepancies between the model and the actual behavior. It is possible to build on big HMM to represent all possible behaviors, but we are choosing to build one HMM for each behavior.

A Behavior HMM consists of four different types of states:

- Initial States – States identified with the beginning of a larger plan. As the insect moves it current trace may be recognized as the beginning state.
- Accept States – This states signifies the completion of a behavior. For the Recognizer, accept states serve as the marker for a successful detection.
- Intermediate States – A complex task may have any number of intermediate stages. These stages are captured in a Behavior HMM by the intermediate states. Normally, to reach an accept state from the initial states, one must transverse through intermediate states.
- Reject States – A reject state serves two different purposes. One, it labels states that the behavior should definitely not reach. Two, all other states not relevant to this behavior can be collapsed into one single reject state. Falling into these states during recognition means that the observed pattern does not follow the definition of this behavior as defined by the HMM.

For this work we will utilize two HMMs. The first will be for the foraging behavior. This action will be defined by an ant traveling to a food source and then returning to the nest immediately.

BHMM representing an ant moving from the nest entrance to a food source



Set of Observations:

$O = \{ o_1, o_2, o_3, o_4, o_5, o_6, o_7, o_8 \}$

p_i = probability of a state transition

Figure 3

Evaluation

We will evaluate our system by comparing the output of the Recognizer with that of a human expert. The human expert will sit and watch the ant at the same time as the system is collecting data, and later a comparison between what the system outputs and how the human labeled the ants behavior will be made. If the system can recognize a behavior at any point in time in which the human labeled it as happening we will conclude our system has merit.

4 Work Plan

Our work plan will be broken down into two stages. The first is to complete the coding of the system and verify it works with test data. The second is to run the system on real ant data and test the result. Finally, a paper must be written and turned in.

March 1: Finish design of, and implement HMMs
March 10: Have recognizer running in simulation
(this will test the HMM selection criterion)
March 30: Have system running with on real ant
data. (one ant, multiple ants)
April 2: Begin writing paper.

5 Summary

The main question addressed by this research is how can we model the behavior of a physical agent by observing its movement in two dimensions. We are designing algorithms that will map a sequence of observations about the agent's motion to a model that describes it current state of behavior.

When these agents are constrained to a plane it is natural to draw upon Cartesian based features to obtain features. Given a sequence of observations about a physical agent we will utilize the idea of Hidden Markov Models to represent global plans the agent may be engaged in. After gathering features we attempt to select the appropriate Behavior based HMM that corresponds to this activity by calculating the probability that a given model generated this sequence of states. This is the output of the Recognizer.

To test our research we are working with a social insect colony. This is a colony of ants that are able to move around on a one-meter square foraging area. We have a color vision camera mounted above the arena that is able to track and log the position of hundreds of ants at one time. Features are extracted from this data to generate a sequence of observations. As the system runs it will continually compare what it is observing with the probability that a particular behavior model may have generated that sequence of observations. The model with the highest probability is returned as being the most likely candidate behavior. If we are successful we will contribute new recognition algorithms for Multi-Agent modeling, and provide biologists with new experimental tools to aid in their research.

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