Motion Recognition of Physical Agents Constrained to Two-Dimensions

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Abstract: We propose a method to recognize the two dimensional motion of a physical agent. The problem is to characterize the behavior of the agent purely by observing its physical motion relative to its environment. Observations are a series of coordinate positions over a known time interval. We propose to calculate a number of one-dimensional Cartesian features from these observations and then interpret them to build a model of the observed activity.

When encountering entities in the real world it is good to know what their intentions and possible goals may be so that you can plan effectively. In certain circumstances it may not be possible to communicate with these external entities, either because we are unable to or because we are not allowed to, so the only information we have is the observed actions along with domain knowledge. This is true for computer vision systems and robust algorithms to automatically recognize and label the activity of agents in a scene are being developed.

To test our research we are interested in characterizing the motion of insects on a two-dimensional surface as a first step. 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. Ants are allowed to forage on a one-meter square surface while being observed by a color camera and their (x, y) coordinates are logged and time stamped. Given a series of observations parameters such as velocity, turning angle, and relative heading in the environment can be calculated. We can then characterize what the ant is doing at any particular point or over a specific time period in the environment. For example, we can know what direction the physical agent currently moving; i.e. it is moving left or right, it is moving in straight path from point A to point D. After characterizations of movement are generated they will be grouped and labeled to form features and statistical analysis will be performed on them.

So far we have implemented some measures based on elementary statistical calculations. We do a moving average over the length of an ant trace and label its relative path motion as Left, Right, or Forward. There has been considerable accomplishment in developing the 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. If we are successful in developing further recognition and feature-detection algorithms, in order to extend the types of behaviors we can recognize, we will continue to be at the forefront of Automated Tracking research.

1 Introduction

1.1 Problem

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 in two dimensions, so that meaningful information can be obtained about the possible goals the physical agent is pursuing.

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 rich data for multi-agent interaction and combined this with a unique vision system we developed which is capable of tracking hundreds of ants at one time. This data is collected into large log files which can be poured over in an attempt to automatically recognize what the colony was doing at any particular time. However, it is first necessary to examine each particular trail that the ants leave as the tracking system monitors them. It will be necessary to construct statistics that are robust enough to allow for meaningful interpretations. Such metrics will be used to characterize the state of motion of an ant. By also taking into account environmental landmarks relative motion to and from/around objects can be measured and relative movement to other ants may be correlated. Next, we want to be able to determine which *mode* an individual ant, or possible the whole colony, may be in. We intend to use Hidden Markov Models to encapsulate predefined behaviors that have been collected from biologists, and develop an algorithm capable of mapping the low level 'trace' features of ants to one of the HMMs. Thus, we will have the means to select a possible model that may represent the current goal of an ant or the colony.

1.2 Approach and Deliverables

The approach is to construct a number of Newtonian type characterizations of an ant trace. The ant data is stored as time-stamped (x, y) positions in a flat file along with a few other string-fields to allow for domain specific labels. These one-dimensional parametric characterizations will be formed into features that can be used in further statistical processing. The main scope of this project will be to identify good features to be used for recognition and to test the model selection criterion. Recognition happens when a previously hand-crafted 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 a physical agent moving in two-dimensions.
- Generate a set of HMMs which may describe the 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.

1.3 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 the agents and the organizations of which they are a part. There has been work done in adversarial domains such as robot soccer[1][7] where the need to infer the opposing teams current tactical intent[11] 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 has been interesting advancements in the area of gesture recognition[16] and in characterizing human interactions as they meet or pass by one another in open areas such as a parking lots using a parametric model. Although we are developing a complete Recognition System for multi-agent modeling work we are focusing our attention to working with recognizing ants and their movements.

Ants perform a variety of tasks outside their nests[4]. 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 [3] 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 1992, came up with the notion of a 'trace index'. Which is viewing an ant 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 did adjust their individual motion because of 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 to explain the motion of such patrolling ants. After we have statistics over a set of features 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 [2] 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 whether it is trying to maneuver itself into a position to kick the ball down the field. The incoming ‘stream of actions’ is viewed as a time varying signal. Such signals are the bread and butter of signal analysis work, like radar tracking, and there are many rich mathematical theories to explain them. In this work, a basic behavior is represented as a Hidden Markov Model. If the robot moves in a pattern which is encoded into one of these HMMs, the system will output that the robot is currently ‘moving behind the ball’, or doing a behavior such as ‘blocking robot’ or ‘going to defend.’

We attempt to identify behaviors that are biologically inspired such as ‘foraging’ or ‘intruder alert.’ There has also been some work done in the area of behavior classification [7][11] where simple sufficient statistical methods are used to classify an entity’s current action into one of several hand designed behavior models. One of our aims will be to formalize and extend these statistical procedures. We are also planning to extend other previously done work on ant trace recognition[4]. 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 infrastructure to allow a color vision system to identify and track multiple ants marching over a one-meter square area. This data is logged to a file for later analysis, or a live feed of ant data can be received over the Internet.

3.1 Vectors and Single Parameter Metrics

Our ant data is a series of time-stamped (x, y) coordinates. Each ant is given a unique ID number and it is possible to read one particular ant’s data upto the full number of ants being tracked. 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 the next. We have conveniently captured the ants Turning Angle at each step as the ant turns to investigate other directions as it moves along. Thus, we can immediately continue to decompose an ants trace into a series of numbers which correspond to the angle between two vectors along this path. The raw 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 a sugar water, or the entrance to the nest. These items will also be given a unique identification number and have the salient feature that they do not necessarily move about the table. Their (x, y) position can then be considered to be fixed.   As an ant patrols it environment another dynamic quantity of it motion that can be identify is its current heading, or its egocentric orientation with respect to the environment. It will 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 for example. This will be done by directly comparing the (x, y) position of every identifiable item of interest out on the table with the animals egocentric orientation. Thus, for certain lengths of time it will be possible to calculate exactly what the ant is heading towards. There is an immediate inference that can be made from these comparisons. If an ant is moving, and if its egocentric orientation is pointed at some item, e.g. a food source, then we know that given time this ant has moved closer to the item. This is a simple example of a possible Spacial-Environmental inference that can be made, but more of these may be necessary for accurate model selection to be done later on.

3.2 Statistical Considerations

Once we have the series of Turn Angles and velocities we want to be able to characterize the type of motion that has occurred along an ant's trace. This is necessary when we are looking at ant behavior that corresponds to its alert state, for example. We know that this state is characterized by many quick turns (i.e. wiggles) and a considerable increase in the velocity of the animal during this period of movement. A necessary first step is to identify where the ant is turning left or right as it moves along. Given a sequence of Turning Angles we can use many naïve statistical techniques to quantify this data into a new form. At the moment we take a moving average of Turn Angles over a period of time we called the Trace Window. Currently, we use a time period of about two seconds. We can then define that a positive average over this time is a left turn, and similarly a negative average will be a right turn. It should be noted that there are some assumption built into this statistic about what we call the proper motion of an ant. We assume that ant does not suddenly stop and do a complete 180 degree turn in the middle of its trail. We assume a proper ant would first begin turning in some direction with turn angles not more than 90 degrees, and that if it continues on like this for a few more time steps it will complete a 180 degree turn this way.   We also arbitrarily define what Turn Angle is normal forward movement for an ant. If the average turn angle over the time period of the Trace Window is not more than ten degrees, then we consider the ant to have moved straight ahead. Over longer time periods a gentle turn of even five degrees will produce a considerable deviation off a straight line course, but if we use the knowledge that our laboratory environment is only one meter wide and for long movement at these small angles the ant will appear to have gone almost in a straight line.

Along with these statistics we have to be concerned with noise in our data. It is possible for our tracking system to loose track of an ant as it moves and to later rediscover it as another ant. So we have the problem of broken ant traces. At the moment we have held our work down to only one ant trace, but methods to deal with type of noise will have to be discovered during the course of this work. Also, it is necessary to 'tune' some of the parameters in the moving average of Turn Angles so that we capture the characteristics of the ants motion at the proper resolution. Since, this is research in progress, there are still unanswered questions about how best to extract feature from a moving ant trace, and these will have to be dealt with in time.

3.3 Designing HMMs to describe ant biology

We are developing a recognition system that will automatically select a Hidden Markov Model that best describes the overall ‘plan of activity’ that an ant is doing by only observing its physical motion. 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 where it will move next. We may never know the true plans that are churning inside the ant’s brain, but with the help of biologists, who have thus far made extensive studies of ant behaviors, we can attempt to craft hidden state models which we think accurately correspond to the ants current 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 architecual 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 are going to build two HMMs. The first will be a foraging behavior. This action will be defined by an ant traveling to a food source and then returning to the nest immediately. The other one will be an alert state. This is defined by a sudden increase in velocity over the length of a Trace Window corresponding with a sharp increase in value of the animals trace index over the same region.

3.3 Mapping observed motion onto an HMM

To have a complete system we must be able take our observed two dimensional ant motion and a select the HMM that we think best describes what the animals goals may be. We will continually monitor the ant's trace, and compare this signature to the defined state transitions in a Behavior HMM. Once, the animal enters the Initial State of a BHMM the system will continue to monitor the animal's trace to determine if it should transition to an Intermediate State or if it should move to a Reject State. The later case would indicate the Recognizer does not know what the ant is currently up to.

A pseudo algorithm for recognition and selection of a BHMM is as follows:

1. Instantiate a Recognizer
    a. Load a copy of all BHMMs
    b. Begin analysis of incoming trace data. Time stamped (x, y) coordinates.
2. Forever until done
    a. For each active BHMM
        - compare current trace data to State Transition definitions.
        - if definition satisfied, make the Transition.
    b. Out put current state of Recognition
    c. Gather next data set as defined by the Trace Window Size

This is a high level view of the proposed activity of the entire system and an excellent area to advance the state of the art in recognition technologies.

4 Work Plan

Our work plan will be broken down into two stages. The first is to get the complete system working in a simulated environment. This environment will contain only one agent. After we have demonstrated the ability to select BHMMs by observing our simulated agent we will be to use real ant data collected from our tracking system.

Progress will be check against the following dates:

- March 1 – Be able to create Cartesian features by analysis of (x, y) data. Have the hand crafted HMMs implemented
- April 1 – Have the simulated recognition system completed.
- May 1 – Have the recognition system looking at real ant data.

5 Summary

Multi-Agent modeling is the process of building models of multiple interacting agents based on observations made of these agents over time. When these agents are constrained to a plane it is natural to draw upon Cartesian based features to do the recognition with. Having captured statistics about the motion of an agent we want to select a model that describes the current over-all behavior of the agent. We will utilize the idea of Hidden Markov Models to represent possible global plans that agents may be engaged in. After gathering statistics over the observed features we attempt to select the appropriate Behavior based HMM that corresponds to this activity. 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 positions of hundreds of ants at one time. Features are extracted from these observations and Time Series Analysis methods are used to do the statistics. As the system runs it will continually compare what it is observing with possible state transitions in hand-made HMMs. These HMMs have been designed with aid of biologists and we are attempting to possibly capture the real intentions of the animals.

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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