Generating Trajectories from Inferred Intentional Behavior States

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Abstract

Humans have the demonstrated ability to infer a wide variety of narratives and intentions to relatively arbitrary sets of dynamics movements. An arbitrary shape moving in relationship another arbitrary shape is more than just moving—it is chasing, or evading, or performing a myriad of other intentional actions. A great deal of work has been done to simulate this behavior of inferring intention from movement in machines. Given current models for describing multi-agent, two dimensional movements in a social context, I developed a model that takes an existing intentional detection framework, and utilizes the intentional information it finds to generate new movements based on an original set of trajectories. A version of the intentional recognition model developed by Christopher Crick was implemented and modified to provide dynamics and social information that is relevant to generating agent trajectories. Working from a set of pairwise states that describe an agent's dynamic behavior in relation to the other agents on the field, the system is able to derive a set of goals for the agent based on their inferred intention, modify those goals to reflect qualitative features of the agent's internal state, and use them to generate a new trajectory for the agent that reflects both the set of qualitative features contained within the agent itself, and also the current intentional state of the agent that the system recognizes.

Introduction

A large body of work exists pointing towards humans' ability to attribute a rich set of descriptions and narrations to a relatively simple set of dynamics movements. Heider and Simmel first showed that humans were capable of attributing intentions even to the movements of geometric shapes moving within an arbitrary environment.[5] Cohen, has further demonstrated that this ability exists in young children, and that their attributions are not only rich and varied, but also highly consistent and descriptive of the motion that they are seeing.[2][6] A number of artificial learning systems have been devised that are able to simulate this particular human behavior—take non-contextual, purely dynamic data, and infer intention and motivation from it. Given the existence of models that are able to derive intention from trajectory information, this project is an attempt use one such model to develop a system that is able to do the opposite: take one such model that creates a set of intentional information between multiple agents moving within a two dimensional field, and generate a set of trajectories that retains that intentional information. The design implementation of such a system demonstrates that while dynamics based intentional information can be used to describe motion to a satisfactory degree, there is also a great deal of information about the behavior of the agents that is lost. In developing a model that can work backwards, the holes, particularly in respect to the qualitative features associated with an agent's movement, can be filled and a richer means of expressing movement can be developed.

The Model

Intentional State Recognition

Before anything can be done to generate a set of motions, we need to know exactly what it is we are generating! The system used to read scenes and perform intent recognition of what is going on on those scenes is based on the model developed by Christopher Crick for inferring intentional states for agents playing a series of playground games. The system originally utilized real time movement data gathered from the Cricket sonar sensor system installed in the Yale Social Robotics Lab.[4] For our purposes, the system was modified to work with prior logs of the recorded sensor data. Given a set of two dimensional coordinates for a set of four agents, the system first calculates a set of pairwise social coefficients.
corresponding to the degree to which a particular agent is attracted to or repulsed by another agent. This task is done on the assumption that each agent's velocity is determined by the combination of social influences that is exerted by its peers. The influence that is exerted on some agent i's velocity by all other agents on the field is defined as:

\[ V_{xi} = \frac{C_{i\alpha}(X_{\alpha} - X_i) + C_{i\beta}(X_{\beta} - X_i) + \ldots}{D_{ig} D_{ij} \ldots D_{ik}} \]

Where \( C_i \) is the influence that agent j has on agent i's velocity, D is the distance between i and j, and so on for every other agent. The best fit for \( C_i \), the combined influences on the agent within a brief time interval, is found by finding the least squares solution to the system.[3]

Given the set of immediate pairwise values, the system must then combine these values to make inferences about an agent's overall behavior toward its peers over a period of time. The key to performing this task lies in the calculation of a value associated with the system's belief in each of the possible states that the overall movement can be in. It is at this point that the current model diverges from the original intentional recognition system. The original system defined a particular intentional state in a global context—one particular state consists of every agent's behavior toward every other agent within the time interval that the state is taking place. Beliefs, then, are calculated across combinations of all agent behaviors.[4] In order to use the resultant belief values to generate trajectories, however, the basic intentional state and belief were modified in this model to described:

\[ B_n(S) = B_{n-1}(S) + \frac{1 + \lambda \sum_{s(C_i)}(s(C_i))}{Z} \]

Where the belief value for one of all possible states an agent can possess, S, is calculated by amending the previously calculated belief in S with the summation of \( s(C_n) \), a function that returns +1 for each pairwise relationship coefficient the agent possesses that is consistent with S, and -1 for each coefficient that is inconsistent. Z is the sum of all belief values for the agent, and serves to normalize the new belief value. Lambda is a coefficient used to calibrate the rate at which new information can impact a current belief.[4] I found that a value of 0.04 yielded the best results for the agent-level definition of an intentional state. Compared to using a global state that encompasses all agent relationships, localizing the intentional state to reflect the behavior of single agents decreases the size of the state space that must be taken into account for belief calculations. In the most common case of 4 agents and 3 possible relationships between agents—attraction, repulsion, and apathy—there exist 27 possible states a single agent can be represented by at a given time. By taking this belief value over multiple time intervals, the state that emerges as dominant with the highest belief value is determined to be the agent's intentional state.

While this belief calculation is useful in determining the intents that will be modeled upon when generating trajectories, the combining of all of an agent's attitudes toward other agents into a single state with a single belief value results in a loss of information that is important in movement generation, specifically any indications of the magnitude of an agent's attitude toward another agent. It is certainly possible to proceed without knowing whether A's velocity seems to be determined more by its attraction to B than its repulsion to C, this information, as will be seen later, will prove useful in manipulating the way in which an agent's trajectory can be generated. Thus, the same belief formula used above is used to derive a second set of belief values that correspond to the belief in an agent's specific attitude toward another agent, k:

\[ B_n(S) = B_{n-1}(S) + (1 + \mu C_{nk} M_{nk} + \lambda C_{nk}) / Z \]

The state space for S in this set of calculations was 3, reflecting the 3 possible relationships between any two agents. The new term, \( \mu C_{nk} M_{nk} \), is the magnitude of the pairwise social constant between the agent and k, multiplied by the consistency sign operator and a coefficient that, like lambda, calibrates the strength of the term in impacting the overall belief. For this belief function, I utilized a value of 0.04 for lambda, and 0.1 for \( \mu \). Here, if the magnitude of the current social coefficient is high, but the attitude itself contradicts the current state, then the magnitude will have a negative impact on the belief in this particular attitude, as it should. Note that because this belief calculation deals only with one specific attitude toward one specific agent, there can be only one measure of consistency—whether or not the agent's behavior towards j conforms to the behavior described by the attitude. This calculation serves to provide the system with information not just regarding the intentional state of an agent over a specified period of time, but also the relative strengths of each of the component attitudes that are contained within that intentional state. While it is possible to simply use the magnitude of the pairwise intentional coefficients derived from the least squares solution to an agent's velocity, those coefficients were calculated to represent instantaneous or near-instantaneous measures of attraction and repulsion, and are subject to more noise than the measure of intentional magnitude calculated by aggregating evidence for or against a particular intent over time. With this system in place, we are able to derive the set of intentional state intervals and state changes that the system will use to generate the new movement.
Generating New Movement

In generating intentional movements based on a template motion, we are essentially moving backwards from the narrative labels assigned to the action taking place, going from high level descriptors to basic dynamic information and ultimately, raw positional data. The basic unit of the intentional state is the pairwise relationship between one agent and another associated with a particular time interval. The statement “A is chasing B from time X to Y” yields a great deal of information as it is, enough to create a basic sketch of what is happening at that time interval. We can determine the trajectory of agent A by drawing a straight line from A’s position to B’s position. The basic goal positions associated with the other two possible relationships are similarly derived. For each of the three possible relationships with a particular agent A toward some other agent B over a certain time interval, there is a corresponding goal position:

Seeking – The agent's objective is B's position at that time.

Evading – The agent's objective is to move as far away from B as possible. This can be simply expressed as the opposite of the normalized distance vector from agent A to agent B.

Ignoring – The agent has no particular attitude toward B, and as such, no objective goal position is calculated in the case of apathy from one agent to another.

Translating agent attitudes into tangible goals to pursue is the first step in the generation model, but the objective positions themselves do not provide enough information to proceed just yet. Consider a game of tag that is being played between four different agents, with agent A being “it.” This new social environment is perfectly consistent with the pairwise statement above. However, there much more information that must now be integrated, namely that agent A, and indeed every other agent, now have multiple motivations, all of which have their own associated goal positions. Given that for each intentional state, an agent must negotiate between multiple and sometimes incompatible motivations, I found that the method for translating multiple intentions into a single normative goal position and one that is flexible enough to allow for modifications to how an agent prioritizes its different goals, and combine them into the normative goal state through a weighted average. The following average calculates the x component for the goal position:

\[ P_x = \frac{\sum (C_i X_i) + \sum (C_j X_j)}{\sum (C_{tot})} \]

Where \( X_i \) is the x coordinate for each agent i for which the agent is attracted to, \( X_j \) is the x component of the unit vector that maximizes the distance between the agent and each agent that it is repulsed by, and C is the weighting for each objective and also represents the relative strength of system's belief in the agent's attitude toward either j or i. Note that here, the second belief calculation performed in the analysis of the original movement becomes useful, providing a measure of the strength of the pairwise social components for agent attraction and repulsion. The same calculation is used to derive the y component of the normative goal position.

This method of combining multiple perceived intentions is relatively simple and, by itself, will not necessarily provide results that accurately reflect the agent's intents. An agent caught between multiple peers with which it is judged to be chasing, for example, would end up simply waffling between its disparate objectives. In addition, information regarding how the agent is pursuing its goals, whether it tends toward avoidant behavior or behaves more aggressively, for example, may be present within the social contexts of the movement, but is lost when that movement is distilled into an intentional state. I explored several qualitative features that would potentially make the generated movement more descriptive and flexible in its ability to characterize different behaviors while retaining their intentional character. Initially, a set of six features were considered.

The first, and simplest feature, was that of intensity, the magnitude of the agent's “effort” to close with its goal position. The feature proved to be trivial, in all its forms a function on an agent's velocity or acceleration, and also provided very little descriptive information to the generated movement that could be measured. Since the model tracks the changes in intentional states based on their direct mapping to when such changes are perceived to occur within the original movement, and the trajectories generated by intentional states themselves are unaffected by the qualities of the other agents (though the intentional states themselves may be derived from agent interactions),

An agent (blue) with vectors pointing toward each of its objectives, and the corresponding intentional belief for that objective. Unmodified weighting would result in little to no movement toward any of the intended goals. Setting a high fixation, however, would result in greater priority toward red, while a low negative aggression coefficient would bias blue toward fleeing from black.
arbitrarily modifying agent intensity outside of the context of the original movement served little purpose. Thus, the current model maps an agent's speed to the magnitude of the its corresponding velocity in the template movement.

Another feature that was considered but shelved was the concept of foresight, or the degree to which an agent “looks ahead” or lags behind their target. An agent that intercepts or leads another agent can be said to have a high level of foresight. This feature was implemented as a modification on each objective position in an agent's goal set to reflect the positions of attractive agents at time intervals in the future, calculated by looking at the target agent's current velocity. Unfortunately, the addition of foresight did not produce noticeably different results in the generation process due to noise within the data that led to highly chaotic velocity calculations over greater intervals.

The two features that, after the period of design and implementation of the system, that survived the cut, both act upon the relative weights of each of the objective states that make up an agent's final goal position. They address precisely the problem that emerged when attempting to recreate trajectory data from a set of intentional states, namely how an agent should negotiate several different objectives. The features, called “fixation” and “aggression,” represent methods by which objectives that meet certain criteria may be compared and ranked with others:

**Fixation**—Given the existence of multiple goals, an agent can proceed in one of two ways. First, it can move in a manner that maximizes its progress toward all of its objectives equally. Second, it can act more myopically and move toward a smaller set of goals. In exploring ways to implement the behavior of focus on a single or few targets versus relative indecision to all of them, several approaches were considered. First, applying a sharpening function to the entire set of weights in order to bias the agent toward objectives with higher belief magnitudes only served to produce more noise within the weights, as the belief magnitudes do not correspond to agent location, a smaller set of objectives with higher weights is just was likely to be in an indecision inducing spatial configuration as if they were not modified. Thus, fixation was instead defined to be the tendency to gravitate toward a single objective. This tendency to fixate or waffle between multiple goals is expressed as a coefficient that is increases the weight of the objective with the highest belief magnitude, reflecting a focus on the goal that the system perceives the agent “wants the most.”

**Aggression**—This feature expresses an agent's bias toward either attractive or repulsive objectives. Like fixation, this feature may serve as a “tie-breaker” to prioritize certain classifications of objectives over others. This feature was theorized to be useful in describing and generating situations in the social situation favor aggressive or conservative behavior. In a game of tag, for example, the presence of an evasive intention is indicative (though not necessarily conclusive) toward an agent not being it, and thus behavior that places more weight on evasive behavior would likely reflect the agent's intentional state more accurately. The measure of aggression is a coefficient that, if negative is multiplied to the set of evasive objectives in an agent and then negated so that the , and if positive, is instead applied to the attractive objectives.

Fixation and aggression represent a range of descriptive factors that are not expressed in the basic intentional states of each agent. While they may also be used to represent certain internal states associate with individual agents (such as actual aggression, for example), establishing metrics. For the purpose of developing this model, they are interpreted as being the purely arbitrary variables that can be used to adjust generated trajectories of each agent to conform more closely to the intentional states given by the template motion.

**Evaluation**

The system in its entirety was implemented in a single command line executable written in C. The system reads a single file containing formatted cricket data along with pertinent information regarding agent designations. The program served as the chief test platform for the model.

The basis for evaluating the model in its ability to express and retain intentional information is the similarity of the generated movement to the original, in terms of the intentions of the agents. Because the model is two-fold, with the ability infer intention from raw data as well as generate data from sets of intentions, any output produced by the system can just as easily be read back into the program to have its intentional states examined.

I sought to find out just how effective the two constructs of fixation and aggression were in allowing the model to mimic the intentional states of a template movement. Thus, my testing procedure was designed to attempt to maximize the similarity measure of intentional states between an original and generated state, and also to determine what values for fixation and aggression could be used, if any, to achieve those higher values.

Since the goal of the model is to utilize intentional labels to generate new movements that preserve the behavior associated with those states, evaluation of the model's effectiveness was very self contained. The data sets used to test the system consisted of a set of experimental Cricket data taken from prior work done by Christopher Crick on intentional state recognition, which consisted of three instances four different playground games—tag, reverse tag or “smear” (everyone chases the person who it “it’”), hot potato or catch (agents throwing a
ball toward one another, which is another agent), and keep away. Each of these motions represent a varying set of intentional states and intentional state changes that can be used to examine the system's ability to generate motion from a wide range of movement and intentional state sets. The proven intuitive measure of similarity that I elected to use to evaluate the model was to treat each agent's unique intentional state as a linguistic construct, and calculate Dice's coefficient by treating the detected state transitions in the original and generated movements as bigrams associated with the two strings that are the total set of intentional states in each movement.[4] The coefficient is given by:

$$s = \frac{2n_8}{n_x + n_y}$$

Where the numerator is twice the number of overlapping state changes in both movements, and the denominator is the total number of state changes observed across both movements. For each of the nine different experimental data sets, I generated movements for the combination of each value of fixation from 0 to 40, and each value of aggression from -10 to 10, for a total of 800 movements generated per data set. I then calculated the dice coefficients for the movements, and recorded the largest coefficient and its corresponding aggression and fixation values. Note that the bounds of 40 and -10 to 10 for the two variables were arrived at by initially taking higher bounds, and observing that none of the “winning” values for either variable (those that yielded that largest dice coefficients) were larger or smaller than those values.

The results of the test were mixed, at least with the current configuration of the model. Using the results from Crick's similarity metrics comparison of playground games as a baseline, the generation system seems to have the most success with generating games of keep away, had trouble with hot potato and performed with mix results on smear and tag. With the exception of one instance of smear and one instance of tag, the system was able to generate over half of the total state changes that also occurred in the original motion. While imperfect, the results here are encouraging.

Also, no discernible pattern of optimal settings of fixation or aggression were found. This is not surprising, because the two variables may be impacted by the internal states of agents and other factors associated with specific instances of motion. Regardless, the results indicate that the system can certainly be refined further.

### Discussion and Future Work

While the concept of deriving goal states from intentional beliefs and modifying them to generate new agent trajectories did not perform perfectly, the fact that they were able to generate significant portions of common intentional state shifts with the parent motion indicate that the overall approach is sound, and improvements can be made. There is a great deal of further work that can be done to improve the effectiveness of the system and the extent to which it is capable of creating more rich and varied movements.

The first and most salient improvement is the introduction of a system for detecting force relationships that correspond to intentional state changes. The model currently maps the state changes directly from the time that they occur in the template motion, which means that while the subsequently generated motion is able to mimic the original insofar as it generates trajectories from the same intentions occurring at the same time, but beyond the intentions themselves, the system has no sense of causation or association between agent interactions and state changes. This results in a relatively confusing picture when a generated motion is viewed through an animator. While the intentional shifts occur as predicted, they do not take place in any context other than timing. The ability to detect the rules behind state changes within the system and implement those rules would effectively decouple the generated motion from its template, making for truly independent and rule-based creation of agent trajectories.

A second major improvement to the system would consist of a wider variety of qualitative features that can give the system more expressive power. Features such as foresight, given a means to cope with noisy positional data, can potentially be very useful for generating trajectories. All in all, the development of a system that is able to work backwards, taking the limited amount of information represented by a dynamics driven intentional state and deriving a convincing and consistent set of agent motions from it, would not only provide insight into what it takes to generate movement, but also allow for motions themselves to be described more fully.

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References


