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Data-driven modeling of locomotor behaviors in game-based chase and escape interactions

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Abstract

Chase and escape behaviors are fundamental for the survival of many animals in the wild. Previous studies have provided mathematical models based on simple rules for understanding these behaviors, but these models cannot predict the various behavioral patterns of agents due to those simplicities. Here, we showed that our data-driven model based on LSTM can predict various movement trajectories of agents, and this result suggests that there are some predictable dynamics in chase and escape interactions even though such interactions appear to be complex. Our approach contributes to an understanding of the principles in chase and escape interactions.
Keywords: Chase and escape, One-on-one, Predator and prey, Sports

1. Introduction

Previous studies have provided many mathematical models based on simple rules for explaining chase and escape behaviors. These models predict agent's movement direction based on kinematic variables such as position, velocity, and inter-agent distance (Ghose et al., 2006; Howland, 1974; Kane et al., 2015). However, pursuers or evaders following these models always move a direction in a similar situation. In other words, these models cannot predict various movement patterns. Recently, it has been reported that, using large amounts of data, many machine learning models show generalization performances more than rules-based models. Especially for time-series data, a model called Long Short-Term Memory (LSTM), which incorporates long-term information into a recurrent neural network, shows better results than conventional models in predictions on a text sequence (Graves, 2013) and on a trajectory sequence in crowds (Alahi et al., 2016). In this study, we predict pursuers' and evaders' various trajectories using a data-driven model based on LSTM.

2. Methods

A virtual chase-and-escape task was performed using joysticks on a monitor, and 600 trials of position coordinates were obtained (N = 12). From these trials, 480 trials were used to train an LSTM model that uses series of position coordinates as input and outputs position coordinates at the next time step. The remaining 120 trials were used for verification, in which position coordinates were sequentially predicted until the next 500 ms, and we evaluated the model using the error from the actual observation. In addition, to compare the performance with that of the previous study (Ghose et al., 2006; Kane et al., 2015), we computed the movement direction at the next time step.

3. Results and Discussion

Our model accurately predicts the trajectories of pursuer and evader. There were high correlations between the predicted and the observed movement direction in the pursuer and evader (ρ = 0.95, 0.97) compared with the previous pursuer model (ρ = 0.80). In general, evaders' behavior patterns have more variations than pursuers, and it is considered that the variations increase unpredictability for pursuers. They are useful for preventing pursuers from learning the escapers' behavior patterns (Domenici et al., 2011). However, our LSTM model can predict the future trajectory accurately. This result suggests that there were some rules that appear to be complex. In addition, our model was superior to the time-optimal pursuit model in previous studies, suggesting that memory and forget, which are not in the input of conventional models, are important to accurately describe chase and escape behaviors.

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