A Clustering Based Approach for Realistic and Efficient Data-Driven Crowd Simulation

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Abstract—In this paper, we present a data-driven approach to generate realistic steering behaviors for virtual crowds in crowd simulation. We take advantage of both rule-based models and data-driven models by applying the interaction patterns discovered from crowd videos. Unlike existing example-based models in which current states are matched to states extracting from crowd videos directly, our approach adopts a hierarchical mechanism to generate the steering behaviors of agents. First, each agent is classified into one of the interaction patterns that are automatically discovered from crowd video before simulation. Then the most matched action is selected from the associated interaction pattern to generate the steering behaviors of the agent. By doing so, agents can avoid performing a simple state matching as in the traditional example-based approaches, and can perform a wider variety of steering behaviors as well as mimic the cognitive process of pedestrians. Simulation results on scenarios with different crowd densities and main motion directions demonstrate that our approach performs better than two state-of-the-art simulation models, in terms of prediction accuracy. Besides, our approach is efficient enough to run at interactive rates in real time simulation.

I. INTRODUCTION

Crowd simulation has become an active research field that has increasing applications in many areas such as virtual environment [1], [2], object tracking [3]–[5] and abnormal detection [6]. A fundamental issue in crowd simulation is to simulate the movements of individuals (agents) in virtual worlds in a human-like manner so that the simulation looks realistic. Although various models to simulate realistic crowd motions have been proposed over the last few years, most of them are based on simplifying assumptions (e.g., least biomechanical energy spent [7], collision-free velocities closest to the preferred velocities [8] and so on) and a set of rules that employed by all agents in crowd [9]. These models produce similar steering behaviors for all agents and thus fails to reproduce the complexity and variety of steering behaviors in the real pedestrians. Many researchers attempt to replicate complex crowd behaviors by introducing personal attributes such as personality, emotion, group interactions and cultural difference [10]–[13], or by defining more finely tuned situation-specific rules and strategies [1]. [13]–[16]. However, identifying the correct rules that influence pedestrian’s motions requires a great amount of manual work and can be non-trivial. What is more, the wide variety of steering behaviors are difficult to generate by considering limited number of factors.

Recently, some data-driven modeling techniques have been proposed to solve the above problems [17]–[19]. The key idea is to represent the implicit rules in crowd videos by using state-action samples extracted from videos. Here, state refers to the information agents observed and action is the future velocities. Compared to those pre-defined rules, state-action samples implicitly contains a large number of different situations and reactions learned from the source crowd videos. Besides, they are more adaptable to different scenarios. Velocities are predicted basically by selecting the nearest sample in the original crowd videos. Therefore the definition of a distance measure (or a matching function) is crucial to the simulation results. The matching function should capture the subtle details of agents’ states that trigger various actions and at the same time should be calculated efficiently in simulation to meet the real-time constraint. However, there are trade-offs between quality and efficiency. To fully model the states of agents, more features are required but more features lead to larger computation time. Furthermore, rules implicitly defined by state-action samples are lack of strategic meanings and these example-based models work like copy-paste systems without the ability of thinking and reasoning like human cognitive process. Crowds generated by these example-based models often perform random-like behaviors.

Our approach is also data-driven. However, we first discover interaction patterns from crowd videos, so that in simulation, agents can first select an interaction pattern and then select an action among the pattern. The benefit of doing this is twofold. First, these interaction patterns can be viewed as strategies or rules learned from crowd videos rather than predefined, which are more realistic and flexible. We apply video-learned rules to control the behavior of agents instead of simply matching to one of the samples. Second, by selecting an interaction pattern, the searching space of agents to search for an action is reduced and searching actions in the same interaction pattern requires less features. Therefore, the calculation time can be reduced compared to other data-driven models.

The contribution of the paper are as follows.

• A data-driven crowd modeling approach is proposed to generate realistic steering behaviors of pedestrians. Rather than specifying behavior rules manually, our approach can generate a wide variety of steering behaviors based on pedestrian behaviors from crowd videos.
• An unsupervised method is proposed to automatically
identify the new interaction patterns to capture the features of steering behaviors of pedestrians.

- A hierarchical matching mechanism is proposed to reduce the search space when agents selecting action to extend their movements. This mechanism can improve the simulation efficiency to meet the real-time response.

We compare our algorithm with state-of-the-art models both qualitatively and quantitatively in two real world scenarios with various crowd densities and main motion directions. The experimental results demonstrate that the proposed approach gives more accurate predictions of agents' steering behaviors. Furthermore, the proposed approach is efficient enough to satisfy real-time response.

The paper is organized as follows: We first report related work in Section 2 together with an overview of the proposed approach in Section 3. Section 4 describes our method to automatically discover interaction patterns, followed by pattern learning and action selection in Section 5. Section 6 describes the velocity prediction procedure for agents in simulation. Section 7 presents the experimental results and Section 8 concludes the paper.

II. RELATED WORK

Numerous crowd simulation models have been proposed over the years. One of the early works, rule-based models proposed by Reynolds [9], [20], define a set of steering rules that agents will follow based on their local view of their state. Many works followed thereafter focus on introducing more rules in the aspect of group interaction [10], higher level navigational behaviors [1] and real-time simulation in complex and structured environment [21]. The Cellular Automation (CA) based models discretize space into squares, triangular, hexagonal and so on. The values of all cells depend on the values of their neighboring cells and are updated synchronously at each time step [22]–[25]. In the social force models [26]–[29], agents and obstacles impose forces to others and are influenced by the forces of others at the same time. The motion of agents is then derived according to Newton’s Law of Motion. In recent works, Van den Berg et al. [8], [30]–[35] proposed models which can calculate the velocities that guarantee collision-free motion in next \( \tau \) time while closest to the preferred velocities in an efficient and robust way to handle dense scenarios with tens or hundreds or thousands of agents.

Most recently, real-world videos are applied to estimate the parameters of pedestrian models to improve the accuracy of motion prediction [2], [4], [36]–[41]. However, a hand-specified model is still needed before the calibration process. Other data-driven approaches [17]–[19], [42] directly extract state-action samples from crowd videos to form a sample database. In simulation, agents match their current states to the nearest ones in the database to decide future positions. In order to improve the matching efficiency, a graph-based data structure is formed before simulation in which similar states are interconnected with actions to avoid continuous database searches [19].

III. OVERVIEW

Similar to other data-driven models, we focus on simulating low level pedestrians motion, where a pedestrian’s velocity is mainly affected by other pedestrians and obstacles, and the preferred velocities of agents (direction and speed) are obtained from higher level path planning models. In this paper, the preferred velocities are estimated from input data as accurate as possible.

The proposed model needs to be trained from input data before simulation. At pre-processing stage, interaction patterns are discovered in an unsupervised way from input data and learned by a neural network classifier, which is used to assign interaction patterns for agents in simulations. Actions of different interaction patterns are stored in \( k \)-d trees using a vector consisting of 4 features, in order to achieve efficient action selection in run-time simulations.

A. Pre-processing

Based on the trajectories annotated from crowd videos, interactions between two pedestrians are extracted (we call this the pairwise interactions), which are essential to understand steering behaviors and is described in Section IV-A. We then employ an unsupervised learning approach to discover patterns in the pairwise interactions which can be used as rules to control agents in simulations (Section IV-C). These interaction patterns are learned by training a neural network classifier and one \( k \)-d tree is built for each pattern to store feature vectors of actions as index. Actions, each consisting of two sequences of velocities of two interacting pedestrians are represented in their own local coordinate system (Section V).

B. Simulation

In simulation, pedestrians are represented as circular agents. The start positions, goal positions and preferred speed of agents are pre-defined together with the time step of entering the scenario. At every time step, agents observe the scenario (i.e., other pedestrians and obstacles) to generate pairwise interactions similarly to the pre-processing stage. These pairwise interactions are classified to one pattern using the neural network classifier trained in the pre-processing stage. And one action is selected by searching the \( k \)-d tree of that pattern. An action includes future velocities for both interacting agents. If no interaction is detected, agents simply move towards their goals with its preferred speed.

IV. PAIRWISE INTERACTION PATTERN DISCOVERY

We first describe how to identify pairwise interactions from crowd trajectories. Pairwise interactions contain information about two pedestrians interact with each other. It starts with determining one nearby pedestrian who has profound influence. Then a clustering method is proposed to discover underlying patterns among them.

A. Pairwise Interaction Identification

The trajectory of a person in a scenario is described as a sequence of observations \((s, t)\), where \(s\) is the position vector of a person at time \(t\). A pedestrian \(i\) can sense other pedestrians in his sensing range. Among these nearby pedestrians, one pedestrian who has the key influence on \(i\)‘s future motion behaviors is called the core neighbor \((CN_i)\) of pedestrian \(i\).
In order to quantify the influence of nearby pedestrians, we define a variable $Inf_i(j, t)$ to denote the influencing factor of pedestrian $j$ on pedestrian $i$ at time $t$, which is inverse proportional to the smallest distance between $i$ and $j$ throughout the entire future temporal overlap $\Gamma$ of $i$ and $j$.

$$Inf_i(j, t) = \frac{1}{\min_{t'} \left\| s_i^{t'} - s_j^{t'} \right\|} \quad t' \in \Gamma$$

(1)

where $s_i^{t'}$ and $s_j^{t'}$ are the positions of $i$ and $j$ at time $t'$ respectively.

The intuition behind this distance-based influencing factor is that if two pedestrians will be very close to each other in some future time, it is highly possible that they have interactions, e.g., collision avoidance.

If more than $thr_{group}$ percent of the steps in $\Gamma$, the distance between pedestrians $i$ and $j$ are smaller than $thr_{dist}$, which indicates $i$ and $j$ walk as a group, the influence factor of $j$ is set to positive infinite, $Inf_i(j, t) = +\infty$. Pedestrians from a group tend to keep similar velocities in order to walk together towards their goal, while collision avoidance behaviors between pedestrians are much more complicated and therefore worth more attention. By doing this group identification, pedestrians in the same group would be exclude from core neighbor consideration to give other nearby pedestrians more chances.

The influencing factors of all the other pedestrians in the sensing range of pedestrian $i$ are calculated and among them, all agents where $Inf_i(j, t) > thr_{inf}$ are selected as the candidate set $CN_i(t)$.

$$CN_i(t) = \{ j | Inf_i(j, t) > thr_{inf} \}$$

(2)

If there are more than one agent in the candidate set $CN_i(t)$, we select the one with the smallest distance to interaction $TTI_i(j, t)$ with $i$ as the core neighbor of $i$ at time $t$.

$$CN_i(t) = \arg \min_j TTI_i(j, t) \quad j \in CN_i(t)$$

(3)

where $TTI_i(j, t)$ is defined as the number of time step from current time $t$ until $i$ and $j$ has the smallest distance.

$$TTI_i(j, t) = \arg \min_{t'} \left\| s_i^{t'} - s_j^{t'} \right\| - t \quad t' \in \Gamma$$

(4)

Let’s take pedestrians interactions in Figure 1 as an example, which illustrates one case in crowd videos. Pedestrian $i$ has sensing radius $r$ and $270^\circ$ field of view. Figure 2 draws the distance between $i$ and his nearby pedestrians as a function of time and Figure 3 illustrates the influencing factors of pedestrian $i$’s nearby pedestrians as a function of time. At $t_1$, there are 7 pedestrians in the sensing range of $i$ (see Figure 1a). The future trajectories of all pedestrians are shown in Figure 1b and the calculated influencing factors of nearby pedestrians are shown with various colors in Figure 1c. The pedestrians with higher influencing factors are shown with darker colors. Among them, pedestrian $a$ is the only one with influencing factor larger than $thr_{inf}$ at $t_1$ (Figure 3) and therefore is the core neighbor of $i$ at $t_1$. At $t_2$, pedestrian $b$ enters the sensing range (Figure 1d) and also has an influencing factor larger than $thr_{inf}$. However, pedestrian $a$ has a smaller time to interaction $TTI_i(a, t_2) = t_3 - t_2$ than pedestrian $b$, $TTI_i(b, t_2) = t_4 - t_2$. Thus pedestrian $a$ is still identified as the core neighbor of agent $i$ at $t_2$.

For pedestrian $i$, his core neighbor $CN_i$ at every time step $t$ ($CN_i(t)$) is a time series of most influencing nearby pedestrians. The consecutive time steps at which $i$ has the same core neighbor are combined as interaction period. During one of these time periods, pedestrian $i$ interacts with the same core neighbor $CN_i$ and thus is called as a pairwise interaction. Pairwise interactions extracting from crowd videos describe the knowledge of how human solve interactions fluidly and naturally. By learning and reproducing them, naturally motions can be generated in simulation.

The pairwise interactions between $i$ and $CN_i$ are recorded
by the relative positions of $CN_i$ in a coordinate system centered on $i$ and oriented along $i$’s current facing direction. A pedestrian’s facing direction is quantized according to the number of main motion directions of the scenario. For example, in a corridor scenario, pedestrians walk bi-directionally. So the facing directions are quantized into 2 sets.

B. Pairwise Interaction Similarity

A pairwise interaction between pedestrian $i$ and $j$ is a temporal sequence of observations $PI_{ij} = \{rel_{ij}, t\}$, where the observations $rel_{ij}$ at time step $t$ is the relative position of the core neighbor $j$ in a coordinate system centered on $i$. One simple way to calculate the distance between two $PI$s is to add up all the spatial distances between observations at the same time step. However, considering the small annotation time interval of crowd videos and the tracking noise, comparing the observations at the same time step is a strict constraint. Therefore, we adopt the dynamic time warping method (DTW) with a window size $w$ to allow an observation to find its closest match within certain time window. Let $\Gamma$ be the longer temporal duration of two pairwise interactions $a$ and $b$. The distance between these two interactions $d(a,b)$ is calculated as follows:

$$d(a,b) = DTW(a,b), \quad (5)$$

$$\delta_l(a,b) = \begin{cases} 1 & \text{if } \tilde{d}_l(a,b) \leq \text{thr}_{\text{dist}} \\ 0 & \text{otherwise}, \end{cases} \quad (6)$$

$$\rho(a,b) = \sum_{l \in \Gamma} \delta_l(a,b), \quad (7)$$

$$d(a,b) = \frac{\tilde{d}(a,b)}{\rho(a,b) |\Gamma|} \quad (8)$$

The distance is scaled by the number of times that the spatial difference between two observations is smaller than the threshold $\text{thr}_{\text{dist}}$, similar to [43]. By doing this, two pairwise interactions that have similar observations over a long period of time would have a smaller distance. This helps to get better and meaningful clustering result against tracking noise by imposing aggregated measurement over time.

C. Pairwise Interaction Clustering

Before clustering, we first delete the outlier pairwise interactions, which are usually caused by tracking noise or personal abnormal behaviors. For example, a pedestrian suddenly decides to turn back and walks in the opposite direction during the interaction. These anomalous behaviors may be of interest in video surveillance area. But they are not the typical behaviors of pedestrians and the patterns discovered by the clustering algorithm will be more accurate if those outliers are removed. We delete those pairwise interactions whose $a$) average distance to its N nearest neighbors is large; b) length is smaller than $\text{thr}_{\text{len}}$.

We apply a bottom-up hierarchical clustering algorithm [44] which starts with treating each pairwise interactions as separate clusters and gradually merge pairwise interactions with smallest distances to build larger clusters.

In order to measure distance between groups of pairwise interactions, we extend the distance metric described in section [V-B] by using the modified Hausdorff distance similar to [45]. For two groups $M$ and $N$, the directed distance from $M$ to $N$ is

$$h(M,N) = \frac{1}{|M| \times |\Psi_i|} \sum_{i \in M} \sum_{j \in \Psi_i} d(i,\Psi_i(j)) \quad (9)$$

where $\Psi_i$ is a set consisting of $PI$s in group $N$ whose distances to $i$ are in the larger half among all the distances $d(i,l)$, $l \in N$. Hence $|\Psi_i| = \lceil |N|/2 \rceil$.

Then the symmetric distance between $M$ and $N$ is

$$H(M,N) = \frac{1}{2} (h(M,N) + h(N,M)) \quad (10)$$

We use the average value of the directed distances between two groups instead of the maximum value used in the original Hausdorff distance in order to average out noise.

One of the advantages to use the bottom-up hierarchical clustering is that the number of clusters is not required before clustering. To automatically discover the number of clusters, we define a stopping threshold to stop merging clusters if the symmetric distance between two clusters defined in equation [10] is larger than the threshold.

Fig. 1. Influencing factor calculation and core neighbor identification.
V. LEARNING PAIRWISE INTERACTION PATTERN USING CLASSIFICATION

After clustering, patterns of pairwise interactions are detected according to the relative positions of two pedestrians involved. Each pattern can be viewed as one rule describing how two people react with the presence of the other. In order to classify each agent into one interaction pattern to obtain a rule, a feed-forward neural network classifier is trained using any thriden consecutive observations in pairwise interaction sequences. The output of the classifier is the pattern membership of the input observations. The neural network has two layers. The first layer uses the tan-sigmoid transfer function and the second layer uses the linear transfer function. Among all the sample data, 85 percent are used to train the neural network and the remaining 15 percent are used for validation to prevent overfitting. The network is trained using Levenberg-Marquardt optimization [46].

The pairwise interactions are reformatted from relative positions to the velocity sequences of two pedestrians action = (vi(t), vj(t)). The velocities are transformed to their own local coordinate system oriented along their current motion directions respectively. In order to select the optimal action from all actions in the same pattern, actions are associated with an additional vector containing four features:

- Self speed: The average speed of a pedestrian in the past thriden time steps.
- Intended walking direction: The angle of a vector pointing from a pedestrian’s current position to the goal position.
- Relative position: The current relative position of a pedestrian’s core neighbor in the coordinate system centered on the pedestrian and oriented along the pedestrian’s current walking direction.

To improve efficiency, we store actions in the same interaction pattern into a k-d tree using feature vectors described above. Therefore, after pre-processing, a neural network classifier and various k-d trees (the same number as the number of patterns) are generated for utilization in simulation.

VI. SIMULATION

In simulation, for each agent at every time step, the core neighbor is first identified using the method described in section V-A where the influencing factor of each nearby pedestrian is calculated by comparing spatial distances throughout the entire future temporal overlap. In simulation, future positions of an agent is estimated using the linear extrapolation of its current velocity and the number of future time steps used in the influencing factor calculation is estimated by the average travel time of all agents using their preferred velocities. If no core neighbor is found, the agent is considered interaction-free and the preferred velocity is selected. Otherwise, interaction is detected. If the agent has previously selected velocities to execute and the core neighbor remains the same, no classification is required and velocity is obtained by executing the current action. Otherwise, new action is selected in two phases. First, the relative positions between the agent and its core neighbor in past thriden time steps are classified into one pairwise interaction pattern using the neural network trained in Section V. And then one action with the nearest feature vector is selected using the k-d tree of that pattern. Two velocities sequences in the action are assigned to both the agent and its core neighbor for execution. The stored velocities in the action are transformed from its own local coordinate system to the global coordinate system when execution.

Algorithm 1 Velocity Prediction

\[
CN \leftarrow \text{find\_core\_neighbor}(\cdot) \\
\text{if } CN = \emptyset \text{ then} \\
\quad \text{velocity} \leftarrow \text{preferred\_velocity} \\
\text{else} \\
\quad \text{if } me,\text{saved\_action} \neq \emptyset \text{ and } CN = me,\text{saved\_CN} \text{ then} \\
\quad\quad \text{velocity} \leftarrow \text{execute}(me,\text{saved\_action}) \\
\quad\quad \text{else} \\
\quad\quad \quad me,\text{saved\_CN} \leftarrow CN \\
\quad\quad \quad me,\text{saved\_action} \leftarrow classify(me, CN) \\
\quad\quad \quad \text{velocity} \leftarrow \text{execute}(me,\text{saved\_action}) \\
\text{end if} \\
\text{end if} \\
\return \text{velocity}
\]

VII. RESULT

We implement our method in Java using MASON multi-agent simulation library [47]. We also implement other two state-of-the-art models, RVO2 model [8] and social force model [27] on the same Java framework.

A. Datasets

We collect two unique datasets consisting of two public scenarios to validate our proposed method. The detailed information are shown in Table I together with the values of parameters used in the experiment. Crowd density is calculated as the average number of neighboring pedestrians who lie in the circle of 1 m radius around a pedestrian. In corridor dataset, pedestrians are walking through a store street, recorded in a shopping center (Figure 5). There are two main walking directions in this scenario. In crossing dataset (Figure 6), pedestrians are crossing Oxford Circus in central London from four directions at the same time, collected from Internet. All videos are annotated at the rate of 10 frames per second manually to eliminate tracking errors. After mapping the trajectories from image coordinate to real coordinate, each dataset is split into two part according to annotation time. First half of the trajectories in each dataset are used to train the model separately and the rest trajectories are used as the ground truth to test the proposed model’s performance. The proposed model is evaluated on the same scenario that trains it.

B. Pairwise Interaction Pattern Discovery

The discovered pairwise interaction patterns of two datasets are shown in Figure 3. The pairwise interactions in corridor scenario are clustered into four different patterns. Because pedestrians walk in two opposite directions, they avoid opposing pedestrians either from left-hand side or right hand side, which are represented by two clusters in green and magenta. The remaining two clusters shown in yellow and cyan demonstrate group walking behavior in corridor dataset. The pairwise interactions in crossing scenario are clustered
into 14 patterns because of more moving directions and higher crowd density. Among them, four major patterns (which have larger number of instances) are avoiding opposite walking pedestrians from two sides and interactions with pedestrians from the perpendicular directions. Group walking behaviors are also discovered.

C. Quality Comparisons

We compare the proposed model with two state-of-the-art models, social force model [27] and RVO2 model [8] in simulating crowd motion in corridor and crossing scenarios. Our proposed data-driven model is trained using motion data from the same scenario, while social force model and RVO2 model do not need training. We compare the simulated trajectories of three models with the ground truth trajectories using three error metrics introduced in [48].

- Average position error (m): the average spatial distances between the simulated positions and the ground truth positions.
- Average area error (m²): the area between the simulated path and the ground truth path after the simulation has completed, averaged across all simulated agents.
- Average speed error (m/s): the average difference in speed at every time step between the simulated agent and the ground truth agent.

The average position error quantifies the position prediction accuracy at every time step. The average area error measures the difference in shape between two trajectories, indicating the accuracy of predicting angular velocity, while the average speed error quantifies the accuracy of predicting how fast agents move.

The experimental result of corridor scenario is shown in Table I. The proposed model performs better than other state-of-art models in average position error and average area error, while the average speed error is slightly worse than RVO2 model. Therefore, the proposed model can predict where a pedestrian will walk more accurately than RVO2 model and social force model. However, it does not improve the prediction accuracy of how fast a pedestrian will walk. Besides, RVO2 model outperforms the social force model in all three error metrics.

Figure 5 shows the trajectories simulated by three models and the ground truth. A pedestrian is walking towards the right side of the scenario and another pedestrian is moving in the opposite direction. The social force model (SF) starts to avoid collision too late and has a sudden position change because of the repulsive force. The RVO2 model predicts a straight line indicating no velocity modification is needed because RVO2 model seeks the collision-free velocities that closest to the preferred velocities. Only our proposed model follows the trajectory from the ground truth.

The error metrics of simulating crossing scenario is shown in Table III. Compared to the corridor scenario, all models have larger errors because of a more complicated scenario and a higher crowd density that increase the difficulty of motion prediction. And the performance gap between models are also reduced. The proposed model still performs better than social force model and RVO2 model in position error and area error but worse than RVO2 model in speed error, similar to those in corridor scenario. RVO2 model still performs better than social force model but the difference is small.

Figure 6 compares the simulated trajectories of all models with the ground truth in the crossing scenario. Our model successfully detects the collision and produces a trajectory similar to the ground truth, while RVO2 model predict a path with smaller deviation and social force model has a sudden fluctuation and also steers in the wrong direction (Figure 6a). Sometimes however suggests meaningful, our proposed model estimates in the wrong direction (Figure 6b), increasing the prediction errors.

D. Timing Comparisons

We report the simulation frame rates (frm/sec) of three models on two scenarios in Table IV. The average number of

| Dataset | corridor | crossing |
|---------|----------|----------|
| # of frames | 1738 | 621 |
| # of trajectories | 332 | 93 |
| annotation rate (frm/s) | 10 | 10 |
| crowd density (ppl) | 0.346 | 1.849 |
| # of main flow direction | 2 | 4 |
| sensing radius (m) | 10 | 10 |
| field of view (°) | 270 | 270 |
| $t_{thrA}$ (m/s) | 1 | 1 |
| $t_{thrT}$ (percent) | 85 | 75 |
| $t_{thrS}$ (m/s) | 1 | 1 |
| DTW window size | 4 | 4 |
| $t_{thrE}$ | 5 | 3 |

**TABLE I. THE INFORMATION OF DATASETS AND THE VALUES OF PARAMETERS USED IN THE EXPERIMENT.**

| Model | Position Error | Area Error | Speed Error |
|-------|----------------|------------|-------------|
| Social Force | 0.4779 | 2.3821 | 0.1986 |
| RVO2 | 0.3557 | 1.5311 | 0.1287 |
| Proposed | 0.3355 | 1.5044 | 0.1295 |

**TABLE II. ERRORS IN MOTION PREDICTION OF CORRIDOR SCENARIO**

**TABLE III. ERRORS IN MOTION PREDICTION IN THE CROSS SCENARIO.**

*The original video is accelerated. The average speed of pedestrians is 7.2851 m/s.
In this paper, we propose a data-driven model to predict velocities by learning interaction patterns from crowd videos. We propose a clustering approach to automatically discover interaction patterns from pedestrian’s trajectories and apply them as interaction rules in the real-time simulation. We test our approach with two state-of-the-art simulation models on different types of scenarios. The simulation results demonstrate that our approach achieves better performance.

## VIII. Conclusion

In this paper, we propose a data-driven model to predict velocities by learning interaction patterns from crowd videos. We propose a clustering approach to automatically discover interaction patterns from pedestrian’s trajectories and apply them as interaction rules in the real-time simulation. We test our approach with two state-of-the-art simulation models on different types of scenarios. The simulation results demonstrate that our approach achieves better performance.

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