A Framework for Video-Driven Crowd Synthesis
(Supplementary material available at https://faisalqureshi.github.io/research-projects/crowds/crowds.html)

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Abstract—We present a framework for video-driven crowd synthesis. Motion vectors extracted from input crowd video are processed to compute global motion paths. These paths encode the dominant motions observed in the input video. These paths are then fed into a behavior-based crowd simulation framework, which is responsible for synthesizing crowd animations that respect the motion patterns observed in the video. Our system synthesizes 3D virtual crowds by animating virtual humans along the trajectories returned by the crowd simulation framework. We also propose a new metric for comparing the “visual similarity” between the synthesized crowd and exemplar crowd. We demonstrate the proposed approach on crowd videos collected under different settings.

Keywords—crowd analysis; crowd synthesis; motion analysis

I. INTRODUCTION

Raynold’s seminal 1987 paper on boids showcased that group behaviors emerge due to the interaction of relatively simple, spatially local rules [1]. Since then there has been much work on crowd synthesis. The focus has been on methods for generating crowds exhibiting highly realistic and believable motions. Crowd synthesis, to a large extent, remains the purview of computer animators, who painstakingly fiddle with numerous parameters in order to achieve believable crowd motions. Many animation tools exist for generating high-quality crowds for computer entertainment industries. MASSIVE [2], Golaem Crowd [3], Miarmy [4], and Maya [5], for example, are popular crowd animation tools. All of these tools have steep learning curves and these require a lot of manual tweaking to animate crowds having the desired motion/appearance characteristics. Exemplar-based crowd synthesis appears a promising direction of future research [6]. Here, crowd synthesis parameters are learned by observing “real” crowds. These parameters can subsequently be used to synthesize crowds in previously unseen settings, i.e., different viewpoints, new environmental settings, etc.

Within this context, this paper develops a framework for crowd synthesis via analysis (Figure 1). Videos exhibiting crowds are analyzed to extract high-level motion patterns. These motion patterns are then combined with (spatially) local behavior rules, such as collision avoidance, path following, velocity matching, etc., to synthesize crowds. Specifically, we use Reciprocal Collision Avoidance for Real-Time Multi-Agent Simulation (RVO2) to synthesize crowd animations given the constraints extracted from exemplar videos [7]. RVO2 provides us with trajectories for individual agents and we use motion graphs to animate 3D virtual humans moving along these trajectories [8]. Figure 2 shows frames from videos of real and synthesized crowds and the motion information extracted from these videos to compare the crowds seen in these videos.

Crowd analysis is an active field of research within the computer vision community. Many species, including humans, exhibit coordinated group behavior: schools of fish, flocks of birds, herds and packs of animals, and human crowds [9]. Some argue that such group behaviors are important for survival [10]. Humans also have a great facility for perceiving group behavior [11]. There is mounting evidence from the psychology literature that humans are able to perceive group behavior without decoding the individual motions. This work explicitly assumes that individual motions (i.e., trajectories of individuals seen in the exemplar videos)
are not available.

We also introduce a new metric for comparing the original crowd with a synthesized crowd. In order to compare the synthesized crowd with the original crowd, we render the synthesized crowd from a viewpoint similar to the one used to record the video of the real crowd. Motion parameters are extracted from the rendered footage and compared with those extracted from the real footage. Preliminary results seem to suggest that this metric is able to rank crowd pairs according to their motion similarities. More work is needed to further study this aspect of this work. The ability to compute the similarity between two crowds is needed when setting up a feedback loop that iteratively refines the synthesized crowds to better match real crowds.

II. RELATED WORK

Crowd analysis generally falls into one of three categories: density estimation, pedestrian tracking, and behavior detection & recognition. Crowd density, although a useful metric for determining how occupied an area is, is not used in this system presently. Pedestrian tracking [12] is useful for observing the movement of individual members in a crowd. Behavioral understanding, such as crowd event detection, can be used to assist with surveillance systems by alerting of suspicious or dangerous events.

Many approaches to pedestrian tracking suffer from issues related to occlusions. Eshel et al. [12] propose a method of minimizing these problems through multiple overhead cameras. Head tracking is performed across multiple videos to produce the pedestrian tracks through the scene. Although the results are promising, this limits the crowd analysis to crowds that have been observed by these multi-camera setups. This paper strives to work with single videos of crowds that are as unconstrained as possible. For the purposes of this work, we refer the kind reader to [13], [14] that discuss estimation global motion fields from crowd videos.

Motion tile/patch based crowd synthesis approaches [15]–[18] have received popularity in recent years for their scalability. These approaches to crowd synthesis are great for large-scale dynamic crowds however they are not ideal for synthetic crowd reproduction. Although these crowds are interesting to the viewer, they are not well suited for reproducing a crowd that their focus is simply optimizing the actions that are occurring for and among agents. Velocity fields [19]–[21] offer quality agent navigation results with the benefit of offering navigation from any position in the environment. The work of Patil et al. [19] offers a solution to directing crowd simulations using velocity fields. Similarly, Wang et al. [20] perform direct crowd simulation with velocity fields generated from videos.

Flagg et al. [22] propose a video-based crowd synthesis technique utilizing crowd analysis for the purpose of generating crowd videos with realistic behavior and appearance. Their approach generates pedestrian sprites by segmenting pedestrians from input video and crowd tubes are used to avoid collisions and ensure accurate agent navigation. Their approach produces promising results but it is constrained to the field of view of the original video. Butenuth et al. [23] also produce a simulation restricted to 2D, with discs representing agents. Their approach focuses on more dense crowds.

3D approaches [6], [24]–[26] to synthesis via analysis offer flexibility in that they can be heavily manipulated and customized by the end-user. However, previous approaches rely on very constrained input video. The work of Lee et al. [24] relies on a top-down facing camera to observe the crowd and extract trajectories. Lerner et al. [25] make use of this technique but also rely on user input to annotate extracted trajectories for the purpose of agent behavior detection and recognition. Similarly having a reliance on motion capture [6], [26] data to feed a simulation can be restrictive as input. Ideally a system would be capable of accepting an unconstrained video of a crowd and being able to reproduce it, which is the focus of this paper.

Methods for crowd entropy, a measure of a crowd’s disorder, can be useful as a metric for observing and identifying crowd activities. Various methods for calculating crowd entropy have been proposed and used for different purposes. Guy et al. [27] propose a method for computing an entropy score for a given crowd navigating through a scene. Their method is used to evaluate steering methods and requires real-world data to compare the motions of an individual agent. The proposed system is more interested in comparing the output video of the pipeline versus the input crowd video. Ihaddadene et al. [28] perform real-time crowd motion analysis in which they maintain an entropy value to watch for specific variations. Their method is not used for the evaluation of crowds but by observing the entropy they can estimate sudden changes and abnormalities in the crowd’s motion.

It is not uncommon for crowd simulations to be evaluated with a visual comparison performed by study groups [29], [30]. Performing study group visual comparisons is lengthy and does not leave automation as a possibility, which is a goal for this system.
III. CROWD ANALYSIS

We have experimented with three schemes for extracting motion information from crowd videos: a) dense optical flow estimation technique proposed by Farneback [31], b) sparse optical flow estimation [14], and c) SIFT based tracking. We found that the sparse optical flow estimation technique serves our purpose well. It is also the most efficient of the three. This method is also suitable for dense crowds, since it doesn’t assume that individual members are tracked.

Given a sequence of (key)frames $I_1, I_2, I_3, \ldots, I_n$, inter-frame motion extraction returns a set of motion vectors $(x, y, u, v, t)$, where $t$ refers to the frame id and $t \in [1, n-1]$. Motion vectors are stored as $(x, y, \theta, l, t)$, where $\theta = \arctan \left( \frac{y}{x} \right)$ and $l = \sqrt{x^2 + y^2}$. This representation facilitates orientation-based grouping of motion vectors.

The goal is to combine these motion vectors to construct dominant paths. This is accomplished, following the work of Ozturk et al. [14], through binning, pruning and clustering steps. The image space is first divided into cells (Figure 3)—cell extents are defined in pixel locations. Motion vectors belonging to the same cell are aggregated into 8-bin orientation histograms $H^{(i,j)}_\theta$, $(i, j)$ here refer to the location of the spatial bin—in the example shown in Figure 3, $i \in [1, 40]$ and $j \in [1, 40]$—and $H^{(i,j)}_\theta(k)$ refers to the $k$th bin of this histogram, where $k \in [1, 8]$. After this step each cell is represented by an 8-bin orientation histogram. Vectors belonging to diagonally opposite bins in the orientation wheel are shown in the same color. Following the work of Ozturk et al. [14], 8-bin orientation histograms yield acceptable results. However, it is straightforward to change the number of bins. Aggregating nearby motion vectors into orientation histograms has a desirable side-effect. It allows us to discard motion vectors that fall in orientation bins with little support, i.e., if the number of motion vectors in a particular orientation bin is less than a threshold, it can safely be ignored for that direction (for that spatial location) in subsequent processing.

1) Spectral Clustering: Motion vectors within orientation histogram bins that survive pruning are then clustered to compute spatially local dominant directions (See Figure 3). The Self-Tuning Spectral Clustering scheme proposed by Zelnik et al. [32] is used for this. The affinity matrix is computed as follows:

$$A(m, n) = \exp \left(-\frac{|p_m - p_n|^2}{\sigma_m \sigma_n} \right),$$

where $p_m$ and $p_n$ represent spatial locations $(x, y)$ of the $m$th and $n$th motion vectors in bin $H^{(i,j)}_\theta(k)$, $\sigma_m$ and $\sigma_n$ represent scale values. Specifically, $\sigma_m$ is the Euclidean distance between $p_m$ vector and its $k$th-nearest neighbor (in the same orientation histogram bin), and $\sigma_n$ is the Euclidean distance between $p_n$ vector and its $k$th-nearest neighbor. Specifically we use the $7$th-nearest neighbor is used when computing these values. The details of this algorithm are found in Zelnik et al. [32]. Clustering yields spatially local dominant directions $(x, y, \theta, w)$, where $(x, y)$ represent the position, $\theta$ denotes the orientation, and $w \in [0, 1]$ indicates the weight (or support) for that direction (Figure 4(a)).

A. Path Generation

The final step is to combine these locally dominant vectors into global paths using the approach described in Ozturk et al. [14]. Given a (dominant) direction vector, search in its neighboring cells to find vectors having similar orientations and group the two vectors to grow the path. If the neighboring cells do not contain a vector with similar orientation, then consider vectors in other orientations. In practice the cells are swept from left-to-right and from top-to-bottom to
grow dominant direction vectors into global paths. Different sweeping methods can be used (such as opposite directions) and smaller temporal chunks can be processed and combined if more paths are desired. Figure 4(b) illustrates global paths generated from locally dominant directions returned by the spectral clustering procedure.

IV. CROWD SYNTHESIS

For crowd synthesis, RVO2 is used to provide a behavior-based agent simulation system to simulate the movement of agents on a 2D plane. 3D virtual humans are animated along the trajectories returned by the RVO2 simulator. RVO2 implements a behavior-based multi-agent simulation framework. Every agent is treated as an autonomous entity, complete with perception, decision-making, and action routines. Perception routines enable an agent to “observe” its environment, identify other agents, obstacles, and other items of interest. Decision-making takes into account the current state of the agent, its surroundings, and its goals. It then updates the current position and velocity of the agent. RVO2 implements start-of-the-art collision avoidance and goal arrival behaviors.

Each simulated agent has a unique goal stack which contains the information needed to navigate the scene successfully. Goal stacks currently contain nodes representing locations along the path that an agent must take. The stack updates as each goal is met. An empty goal stack suggests that the agent has reached the end of its path. At this point the agent can be safely removed from the simulation. Although the goal stack is used in this system purely for navigation, it can also be used to support layered behavior. Similarly subgoals can be pushed onto the stack to ensure they are completed first. Subgoals are currently used in the system to achieve smoother agent trajectories. Curve interpolation is used as a path smoothing method for agent navigation by providing interpolated subgoals. By navigating the subgoals, the agent is able to advance toward their goals with a more natural approach.

Crowd analysis returns dominant paths. If RVO2 is instructed to simulate agents that move along these paths only, the crowd simulation will exhibit an ant-like behavior: agents moving along invisible lines in the scene. This is undesirable. This issue is resolved through path diversification (Figure 5), which is the process that generates multiple, slightly different versions of a given path. Given a single path through the scene, path diversification allows us to assign a unique path to each agent. Experiments have been conducted with three methods for generating variations from a given path; square, triangle, and circle.

The square method defines a square region around each node and randomly selects a point from the area as the next node (Figure 5(a)). This occurs for each node until a diversified path is generated. The size of each square needs to selected carefully to avoid overlap between squares at two adjacent nodes, which may result in an awkward looking path for each agent.

In triangle method (Figure 5 (b)) the user defines the size of the base of a triangle drawn at the next node from the current node. The base is drawn as the average of perpendicular vectors of the current and next path segments. This method is less likely to suffer from overlap; however, overlap can still occur in some scenarios.

In circle method (Figure 5 (c)) the user defines a maximum circle size and the algorithm randomly generates circles of max size or less along the path to the goal. Sequential circles have related radii so the resulting paths do not have huge variations. This method has no overlap. It should be noted that the resultant path is randomly placed on one side of the crude path only. This logic was added to prevent the generated path from crossing the crude path and then crossing back. Criss-crossing can result in a jittery motion path, which is undesirable. Radii of adjacent circles are tied to each other to avoid having the situation where a circle with a very small radius is sitting next to one with a large radius. This prevents overlap and paths that seem to backtrack and loop over themselves. The circle method was found to work best and was used as the method of diversification in this system.

Motion vectors extracted from the exemplar video live in the image space. Similarly global paths also live in the 2D image space. RVO2 agents also live in the 2D space. This framework aims to synthesize 3D crowds. This is achieved by making a ground plane assumption; virtual humans only walk on a (2D) ground plane. This can be easily accompanied by back-projecting the global paths (and their variations generated through path diversification) onto the ground plane. Back-projection is easy if the location
and orientation of the camera is known with respect to the ground. This information is sometimes available for an exemplar video. In case this information is not available, the most likely location and orientation of the camera is selected by observing the exemplar video. This ground plane assumption has an obvious limitation. The framework currently only handles crowds that move in a single plane.

The simulation is rendered into a video that has the same framerate and resolution as the exemplar video. Furthermore, for similarity computations the location and orientation of the camera used to record synthetic video should be as close to that of the camera used to record the exemplar video. We do not assume calibrated cameras; however, if camera calibration information is available, it can be used during similarity computations.

V. EVALUATION AND RESULTS

A. Evaluation

To ensure that the synthesized crowd (output) is similar to the input crowd, a comparison is performed. One straightforward scheme to compare the synthesized crowd with the crowd viewed in the exemplar video is to employ user studies. That, however, defeats the purpose of this work—automated methods for synthesizing crowds from exemplar videos. Ideally this system will be able to replace user studies with a scoring system that can leverage image and video analysis for crowd comparison. This will allow for iterative, self-tuning methods for crowd synthesis in the future.

The scoring system is formed using histograms of motion. Histograms of motion show the distribution of motion directions for a given region in the image (Figure 6). In this system, the histograms of motion show the distribution of motion flow vectors using eight orientations. Recall that the first stage of the framework is to extract motion vectors. These collections of motion flow vectors are what are being compared using the histograms of motions.

The proposed method subdivides the image into rectangular regions and generates a series of histograms of motion directions. This is similar to how local bins are used to cluster flow vectors based on orientation and spatial location in the dominant path generation process. However, to remove discrete barriers between one histogram and the next, a sliding window is used to generate the series of histograms of motion. These histograms are normalized. For the remainder of this section, assume that the sliding window operation creates \( m \) histograms (i.e., unique sub-windows) for each video.

The system outputs a visualization of the histograms of motion (Figure 7). This visualization makes it easy to spot differences between scenes and how agents move through them. This visualization is good for us, but generating a relative score would prove even more useful for comparing histograms. The histograms between real video data and the synthesized crowd video data are compared using the Bhattacharyya distance. The Bhattacharyya distance measures the dissimilarity between two distributions (histograms), outputting a value between 0.0 and 1.0 with 0.0 meaning the histograms are a perfect match and 1.0 meaning the histograms are opposite. The Bhattacharyya distance is defined as:

\[
d(H_1, H_2) = \sqrt{\sum_{i=1}^{n} H_1(i) \times H_2(i)},
\]

where \( n \) is the number of bins and \( H_1(i) \) and \( H_2(i) \) are bin counts for \( i \)th bins of histograms \( H_1 \) and \( H_2 \). The final similarity score between the two videos is:

\[
s(v_1, v_2) = \frac{\sum_{i=1}^{m} d(H_1^i, H_2^i)}{m},
\]

where \( m \) is the number of histograms extracted for each video (through sliding window procedure), \( H_1^i \) and \( H_2^i \) are the \( i \)th histogram for videos \( v_1 \) and \( v_2 \), respectively.

B. Results

The proposed framework is tested on 3 crowd videos, each with its own challenges and intricacies. One video comes from the BIWI Walking Pedestrian Dataset, the second is the Grand Central Station Dataset, while the final is from the UCF Crowd Dataset. All three videos are recorded from an overhead camera.

Each video is tested in twelve scenarios to see how the proposed metric performs. The crowds are tested with three different densities which are scene specific. Furthermore the crowds are tested with tight or loose goals. This is pertaining to how easily a goal is achieved. In the case of tight goals, an agent must be very close to the goal before they can advance, whereas loose goals are a bit more forgiving. This
was included as it generally causes problems with the natural flow of the crowd if goals are too tight. Agents tend to circle a goal (i.e., location) or twitch if they are close to a goal and many agents are near. This scenario would easily be picked up by a human observer and labelled as unnatural. Lastly, the crowds are tested with and without path diversification. This test is performed because a human observer would be able to see agents forming single file lines. Tests to see if the metric likes diversified paths or not.

Figure 8. Campus video histograms. (Left) Histograms of Motion from the real video. (Middle) Histograms of motion from the best (15 agents, loose goals, no diversification) synthetic crowd. (Right) Histograms of motion from the worst (05 agents, random paths) synthetic crowd.

![Image](image_url)

| Synthetic Crowd Characteristics | Score |
|--------------------------------|-------|
| 05 agents, random paths        | 0.5506|
| 10 agents, random paths        | 0.5080|
| 15 agents, random paths        | 0.5033|
| 05 agents, tight goals, no diversification | 0.5462|
| 10 agents, tight goals, no diversification | 0.4970|
| 15 agents, tight goals, no diversification | 0.5001|
| 05 agents, loose goals, no diversification | 0.5487|
| 10 agents, loose goals, no diversification | 0.5120|
| 15 agents, loose goals, diversification | 0.5372|
| 05 agents, loose goals, diversification | 0.5210|
| 15 agents, loose goals, diversification | 0.4901|

Table I

| Synthetic Crowd Characteristics | Score |
|--------------------------------|-------|
| 10 agents, random paths        | 0.2573|
| 20 agents, random paths        | 0.2428|
| 30 agents, random paths        | 0.2423|
| 10 agents, tight goals, no diversification | 0.3774|
| 20 agents, tight goals, no diversification | 0.2858|
| 30 agents, tight goals, no diversification | 0.4390|
| 10 agents, loose goals, no diversification | 0.3508|
| 20 agents, loose goals, no diversification | 0.3328|
| 30 agents, loose goals, no diversification | 0.2436|
| 10 agents, loose goals, diversification | 0.3254|
| 20 agents, loose goals, diversification | 0.2949|
| 30 agents, loose goals, diversification | 0.3026|

Table II

Figure 9. Grand central video histograms. (Left) Histograms of Motion from the real video. (Middle) Histograms of motion from the best (15 agents, loose goals, no diversification) synthetic crowd. (Right) Histograms of motion from the worst (05 agents, random paths) synthetic crowd.

1) Campus Video: A population size of 10 agents was arbitrarily chosen as a starting point from the observed Campus video, 05 and 15 are values selected relative to this. The results are shown in Table I. The only characteristic that can be seen to consistently beat the random case on this dataset is when using 15 pedestrians. The 15 pedestrian scenarios seem to produce the best scores, and best score overall, 0.4619, was accomplished with 15 agents operating with loose goals and no path diversification. The worst score was found to be 05 agents operating on random paths, the score being 0.5506.

2) Grand Central Video: The crowd population sizes (50,75,100) in these tests are much larger than the other two data sets. The results can be seen in Table II. This dataset has mixed results. The worst performing scenario being 50 agents operating with tight goals and no diversification. The best performing scenario being 100 agents operating with loose goals and diversification. The worst and best scores being 0.6091 and 0.4082 respectively. The best score obtained with this dataset is what should be expected from human

3) UCF Crowd Video: Results (Table III) are mixed, and the metric generally favours random motions. The metric performs poorly on this dataset. However, the original video has very unpredictable motions for pedestrians. The best performing synthetic scenario is 30 agents operating on random paths, resulting in a score of 0.2423. The worst performing scenario was 30 agents operating with tight goals and no path diversification. The difference between the best
and worst score makes sense as the input video has a very random naturally occurring crowd while the tight goals and no diversification simulation is very restricted. However, in this scenario random paths performed the best. It should be noted that the difference in score between the best random scenario and the best processed scenario is only 0.0013.

C. Interacting with Synthesized Crowds

A strength of this framework is the ease at which the environment can be manipulated. Items (obstacles) can be moved, added, or removed, and the synthesized crowd responds appropriately. Similarly camera angles can be changed to alter how a crowd is observed. These manipulations can be used to test changes in simulated scenarios. For example, testing evacuation scenarios with different obstacles involved. We leave this for aspect of our work for another time. Figure 7 shows how crowd responds to changes in its environment.

VI. Conclusions and Future Work

This paper presents a vision-based crowd synthesis framework. Motion extracted from crowd videos is used to control a set of 3D virtual pedestrians. Each virtual pedestrian is a self-animating autonomous agent. Motion histograms extracted from input crowd video is compared with those extracted from synthesized crowd video to compute a similarity score, which captures how faithfully synthesized crowd exhibits the motion characteristics of the crowd seen in the input video. In the future we plan to use this similarity score to auto-tune crowd synthesis, i.e., tweaking behavior parameters to improve the fidelity of the synthesized crowds with respect to one or more input videos. In order to achieve this end, we will need mechanisms for automatic camera pose and ground plane detection.

Using the histogram of motion has mixed results as a metric for determining which crowd is the best synthesized version of a real crowd. From preliminary results presented here, it seems that the metric provides a mechanism to rank videos according to their similarity to the exemplar videos. There are some limitations to the metric. Firstly, temporal information is disregarded in the global motion vector collection process which is used for comparison between scenes. This could present a problem in time sensitive scenarios such as a cross walk at a red light. We plan to address this limitation in the future.

The current set of animations is very basic. Agents are able to transition between walk and run states, with turns either left or right. They are also able to perform an idle animation whereby they shift their weight and perform subtle motions while remaining in a single position. Having a more intricate set of animations is desirable for this system. Incorporating some form of interaction between agents (talk gestures, shake hands, etc.) would help the simulation feel more realistic. Similarly having agents interact with the environment (sit on bench, stop and look at something in the scene, react to emergency) would contribute to the feeling of a reality and further improve the fidelity of the animations.

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Figure 11. Synthesized crowd responds to changes in its environment. (Left to right) original setting, the central obstacle has been moved to a new location, and two new obstacles added to the scene. (right most) crowd seen from a different viewpoint.

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