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Supplementary Material
MPACT: Mesoscopic Profiling and Abstraction of Crowd Trajectories

Marilena Lemonari[1,2], Andreas Panayiotou[1,2], Theodoros Kyriakou[1,2], Nuria Pelechano[3], Yiorgos Chrysanthou[1,2], Andreas Aristidou[1,2], and Panayiotis Charalambous[2]

[1]University of Cyprus, Cyprus
[2]CYENS Centre of Excellence, Cyprus
[3]Universitat Politècnica de Catalunya, Spain

Description: This supplementary material provides supporting information and additional experiments, complementary to the methodology and evaluation.

We first provide explanatory descriptions regarding the randomness of the input data (images) as a complementary part of the *pipeline* (Section A). Next, we experiment with MPACT predictions over a sifting window, as part of the *model utilisation* (Section B). Then, we provide a sanity check on the model's predictive power over clearly-defined behaviours, as a *preliminary result* (Section C). We include an example of a *smooth traverse* though the MPACT latent space (Section D). Also, we show an extra part of the *user study* (Section E) and also perform an analysis on the focus of the *expert study* participants during the experiment, which provides an interesting insight (Section F). Lastly, we include additional implementation details for the modCCP simulator (Section G).

A. Diversity in Synthetic Input Data

Figure 1 shows three example trajectory images generated by a goal-dominant behaviour profile, different due to initial randomisation. We randomise the initial agents' positions, scene objects, number of total agents, and number of agents in a specific cluster. Thus, we show that different simulation instances, using the same profile parameters, yield similar dynamics in the image encodings.

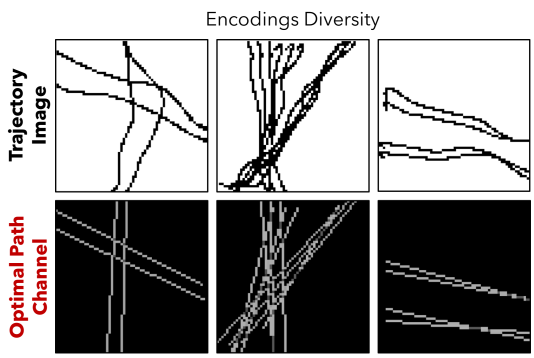

Figure 1: Tracked trajectories and their encoded Optimal Path Channels for a goal-dominant behaviour. We show same profiles can produce various trajectories and corresponding image channels, thus the input data is diverse.

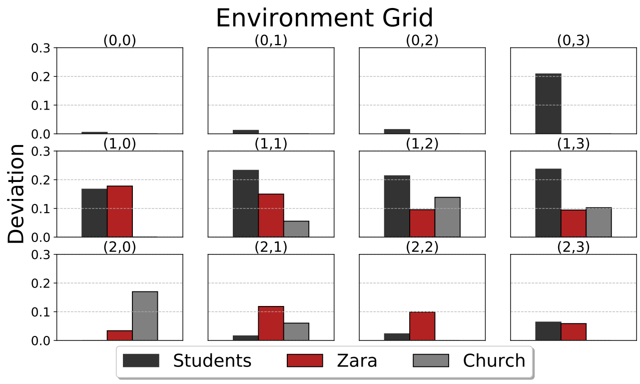

Figure 2: Average deviations in prediction values from the main cell weights when the prediction window is randomly shifted near each main cell 100 times.

B. Shifting Window Prediction Study

As part of further exploring our model's capabilities, we conduct an additional experiment. In detail, we split the trajectories of the three datasets (Students, Zara, and Church) into a 3x4 grid and get the predictions of our model for each cell (behaviour area); we use the predictions as centroid behaviour values for each cell. Then, we shift the prediction window randomly, both in direction and range ([0,32] pixels), and document the new prediction for this different area, which has a major overlap with the original behaviour area. We perform this procedure 100 iterations and calculate the mean deviation from the centroid behaviour value for each cell. We present our findings for each cell and each dataset in Figure 2. In scenarios where the deviation equals 0, it indicates that the current area is either obstructed by obstacles or points of interest (POIs), or there is minimal activity from agents.

The grid of Figure 2 reveals that, in all three datasets, the deviation is higher in areas where the agent density is higher. This is logical as in these areas, agents exhibits diverse behaviours and small shifts lead to slightly different behaviour predictions. This is neither right nor wrong since defining smaller (and hence more) behaviour areas of course leads to profile weights that fit the agents' behaviour in these areas better. However, very small areas may lead to insufficient trajectory data for the generation of image channels, thus a balancing between precision and information is required. Still, we can see that some areas could be merged into larger ones, while others can be split even further. This motivates a future study on how to discretise the behaviour grid according to the environment and the observed trajectories.

C. Sanity Check Experiment

Prior to assessing MPACT against other frameworks and real-world data, we conduct a sanity check to confirm that MPACT can recognise the dominants behaviours. More specifically, we define five behaviour profiles corresponding to the distinct behaviours: goal-only, group-only, interaction-only and goal-seeking with maximum and minimum connectivity i.e., weights of $\{1,0,0,0.3\}$, $\{0,1,0,0.3\}$, $\{0,0,1,0.3\}$, $\{1,0,0,1\}$, $\{1,0,0,0\}$, respectively. Then, we generate 100 simulations for each of the five sets of weights, and run the MPACT model on the constructed image encodings to obtain the predicted profiles. For each set type, we average the profile predictions over the 100 samples and display the results in the form of colour-coded heatmaps in Figure 3; we expect that the predicted profiles will roughly match the ground truths. For the first three behaviour types we keep the connectivity constant, whereas for the last two we fix $\{w_g, w_{gr}, w_i\}$.

The generated heatmaps reveal that in all five scenarios, MPACT clearly predicts the dominant behaviours and produces crowd profiles close to the expected numbers. The observation that no value reaches 1 or 0 can be attributed to the fact that agents exhibits diverse behaviours, and environmental influences like obstacle reforms and high-densities can affect the ability of agents to execute the "ideal" behaviour; these situations indirectly affect the prediction capabilities of our model. Still, the sanity check results reveal promising predictions for real trajectories.

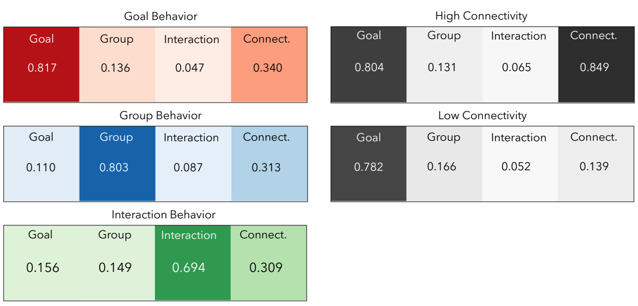

Figure 3: Sanity Check for Dominant Behaviours: Heatmaps of MPACT predictions for exclusively goal-seeking **(red)**, grouping **(blue)**, interaction **(green)**, maximum and minimum (**grey-top** and **grey-bottom**) connectivity, averaged over 100 samples.

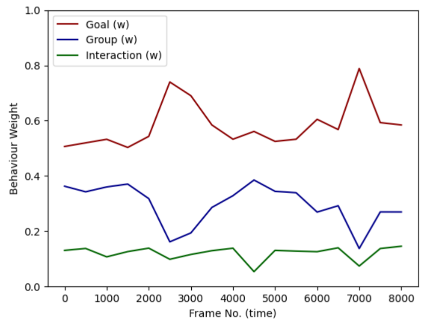

Figure 4: [A10] Latent Space Timewise Traverse. We show the over time, behaviour shift of a single grid cell selected from the Zara dataset.

D. Traversing the MPACT Latent Space

Another way to investigate the MPACT space structure is to explore the smoothness of the traversed path that corresponds to timewise-consecutive profile predictions. For the example in Figure 4, that represents a specific cell from the Zara dataset,we split the 6mins data into chucks of non-overlapping 20secs. We see that the points smoothly progress from a more goal-driven to a grouping-and-goal mixture, and back.

E. User Study: Additional Experiments

During our user study, we additionally show users four scenario-specific videos from the three datasets (Church, Zara, and Students). For each, we first present the real video, highlighting observed behaviours, followed by simulated videos (real, MPACT, and RVO-generated trajectories) in random order. We ask participants to rank behaviour similarity with the real video in a 7-point Like-rt scale.

Showing all three analogous videos, i.e., MPACT, RVO, and Real, we collect similarity scores are present them in Figure 5. We present two findings. First, when participants saw the source video, they successfully identified the real one, when without it, they failed to do so. Perhaps, by directly comparing individuals from the source video to each simulated path, users could identify the real path through one-to-one correlations. However, as our goal is capturing overall behaviours rather than replicating specific paths, this result does not necessarily imply that the simulated behaviours fail to reflect the essence of the observed crowd. Environmental context is an important factor in user perception, which we choose not to include, forcing users to purely focus on agent movements. Secondly, MPACT generally showed higher similarity than RVO, except in the Zara scenario. This exception likely arises because Zara emphasizes direct, goal-oriented navigation, a scenario for which RVO is optimized. Eventually, simulator preference depends heavily on the specific behaviours we aim to capture.

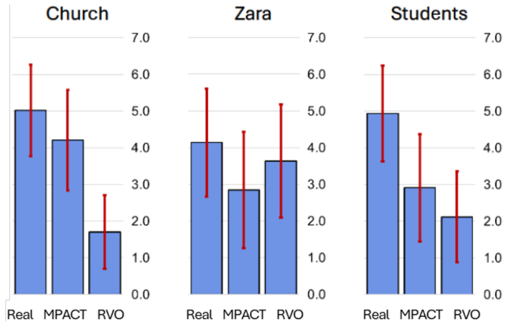

Figure 5: User Study Additional Results.

F. Participants Focus Analysis

After revealing the variety of profiles chosen by the study participants, we naturally wonder where the users focus when deciding the behaviour weights. Therefore, we find the behaviours that each participant gave more weight to, compared to their MPACT counterparts. We demonstrate the results in Figure 6 that shows the MPACT predicted profiles (far-left column) along with the "focused" behaviour weights. These weights are calculated by subtracting the MPACT weights from every participant's selected weights, and filtering to display only the positive values. Essentially this represents the behaviours that participants gave more importance to than necessary i.e., an indication of where they focused on; the illustrated results are an average over all behaviour areas and time windows. We note that, for this specific experiment, we ignore the connectivity weight (w_c) in visualisation, to give more importance to the distinct behaviours.

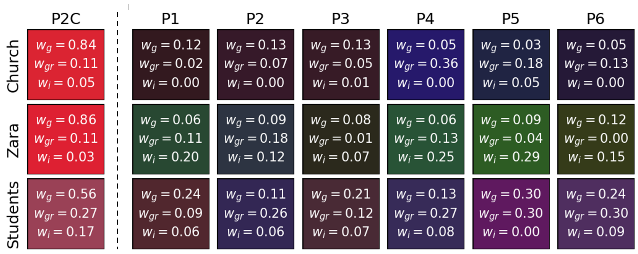

Figure 6: Average overall MPACT predicted baseline profile (left). Per-behaviour weight increase over MPACT baseline (right). Colours indicate weight combinations: w_g - red, w_{gr} - blue, w_i - green.

Overall, we can see that not all participants focus on the same things. However, closer inspection of the Church dataset reveals that P1-P3 and P4-P6 share a pattern, with the former overly focusing on goal-seeking and the latter on grouping. On one hand, in such scenario with a goal-seeking dominant behaviour, as a user, it is convenient to simply disregard more subtle behaviours and be content with maximising goal-seeking, especially considering the time and effort needed to achieve these subtle effects. On the other hand, the amount of focus on grouping differs in P4, P5, and P6 hinting at their attempts to produce the desired resulting by balancing group/goal weights which is not trivial. Moving to the Zara dataset, the observed focus on interaction is perhaps an influence of the store window - marked as POI in the UI - that may have subconsciously led users to opt for higher interaction, even though the actual people in the provided video rarely paid attention to the store. Finally, we see no trend for the Students scenario, once more suggesting that the more dense and complex a crowd is, the more confused a person is when it comes to breaking down individual behaviours. Finally, this user study highlights the practical challenges of system configuration, showing that users focus on different parameters, leading to bias. Users also struggle to convey their observations accurately, either due to difficulty in perception or in expressing their findings.

G. modCCP: Parameter Details

In this section we define further training parameter details for the modCCP crowd simulator. The total reward R^t, for each given timestep t is calculated as: $R^t = w_g R_g + w_{gr} R_{gr} + w_i R_i + w_c R_c + R_s + R_l$. The reward function consists of 5 individual reward terms.

Goal seeking (R_g). This reward term guides the agent toward its goal position. We decompose R_g into three components: $R_{ga} = 0.01$, $R_{gd} = 0.0025$, and $R_{g\theta} = 0.0025$. The term R_{ga} is a sparse reward granted when the agent reaches its goal (i.e., when the goal distance is less than $2m$). In contrast, R_{gd} and $R_{g\theta}$ are dense rewards provided at each simulation step. The agent receives R_{gd} if its current goal distance is smaller than in the previous step. Additionally, if the goal angle is less than $30°$, it also receives $R_{g\theta}$.

Grouping ($R_g r = .005$). This dense reward enables static grouping between agents. First, if the agent stays close to its nearest group member ($distance < 3m$), has fewer than 6 neighbors within a $3m$ radius, and the dot product between its forward vector and the group's center of mass is less than .3, the agent receives half of this reward. Additionally, if the agent maintains a movement speed below $.1m/s$, the remaining portion of the reward is granted.

Interaction with POIs ($R_i = 0.015$). This dense reward encourages an agent to stay near and interact with a POI. If the agent remains close to the POI and looks toward its center ($distance < 4m$, dot product $< .5$), it receives half of the reward. The remaining portion is granted if the agent maintains a low speed (below $.1m/s$).

Connectivity (R_c). This dense reward term regulates the cohesion of agents within a group by maintaining a desired interconnection distance; the parameter w_c defines this target distance. Specifically, the agent receives a positive reward of .02 if it stays near the desired distance, between its current position and its group's center of mass, and synchronizes its speed with other agents (group speed variance less than .05). Otherwise, the agent is penalized with a negative reward of $-.01$.

Smooth navigation ($R_s = -.015$). This dense reward encourages smooth and natural movement by penalizing deviations from the preferred velocity. The penalty is computed as $R_s \times \frac{|\Delta v|}{2.25m/s}$, where Δv is the difference between the agent's actual velocity and its preferred velocity; this reward is applied at each simulation step.

Living penalty ($R_l = -.005$). Finally, a living penalty is applied to the agent at every step to encourage it to perform the intended behaviors.