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Using Synthetic Crowds to Inform Building Pillar Placements

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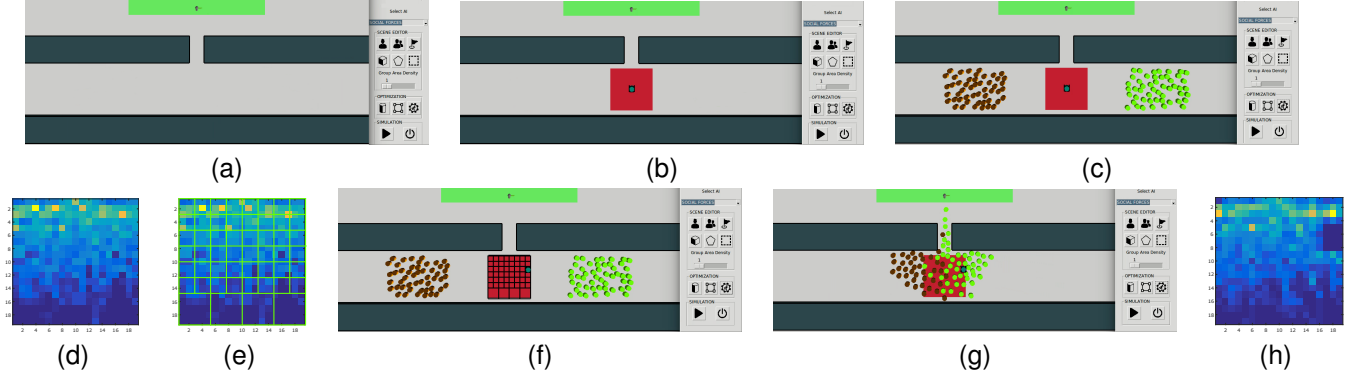


Figure 1: (a) The initial scenario with walls and target area. (b) Addition of the optimization region and initial best guess for the pillar location. (c) Addition of crowds to the scenario. (d) Flow heatmap for the scenario in (c). (e) The computed mesh sampling space. (f) The sampling mesh visualized in the scenario. (g) The visualized crowd simulation and resulting heatmap in (h).

ABSTRACT

We present a preliminary exploration of synthetic crowds towards computational tools for informing the design of environments (e.g., building floor plans). Feedback and automatic design processes are developed from exploring crowd behaviours and metrics derived from simulations of environments in density stressed scenarios, such as evacuations.

Computational approaches for crowd analysis and environment design benefit from measures characterizing the relationships between environments and crowd flow behaviours. We investigate the optimization of environment elements to maximize crowd flow, under a range of **LoS** conditions, a standard indicator for characterizing the service afforded by environments to crowds of specific densities widely used in crowd management and urban design. The steering algorithm, the number of optimized environment elements, the scenario configuration and the **LoS** conditions affect the optimal configuration of environment elements.

From the insights gained exploring optimizations under **LoS** conditions, we take steps towards user-in-the-loop optimization and design of an environment by applying an adaptive refinement approach to reduce the search space of the optimization. We derive the fitness of architectural layouts from background simulations. We perform a ground truth study to gauge the performance and quality of our method.

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Index Terms: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation; I.3.4 [Computer Graphics]: Graphics Utilities—Application packages; J.5 [Computer Applications]: Arts and Humanities—Architecture;

1 INTRODUCTION

Environments designed for pedestrian traffic require a complicated balance of subjective and objective design processes towards a final layout. Features of an environment may facilitate or adversely affect the flow of crowds, which is critical during certain scenarios such as heavy use or evacuations. Exhaustively searching this environment configuration space while considering the subtle and aggregate effects on crowd behaviour can be impractical and expensive in terms of computation and human labour.

Traffic and pedestrian dynamics communities often use a standard qualitative classification, Level of Service (**LoS**), to describe the crowd flow and density relationships in an environment. This classification system allows complex flow density contexts to be described in a communicable manner by assigning intuitive letter classifications to crowd densities. **LoS** condition labels span A-F, where A is low density good flow behaviours and F is high density bad flow behaviours [10]. For example, a stairwell or pathway may accommodate **LoS C** capacity conditions on average. This **LoS** classification system is based mainly on observations of typical crowd contexts and provides standards for design.

In this work we present the aggregate findings of an empirical analysis of **LoS** for synthetic crowds. Using established crowd simulation techniques, we quantify the relation between crowd density and synthetic crowd flow for evacuation scenarios across different simulators to discover whether they conform to qualitative **LoS** classifications. Furthermore, we study the effects of **LoS** conditions on architectural pillar layout optimizations and their resulting crowd flow. Building on the findings from this study, we propose a prototype computational tool for crowd aware design of environments. To the best of our knowledge, this is the first computa-

tional environment design tool that integrates the dynamic crowd flow simulation, analysis, and automatic optimization of the environment, as part of the design process. To facilitate the user-in-the-loop authoring method and provide fast results in the design feedback loop, we propose an adaptive mesh refinement (AMR) approach to guide the automatic exploration of optimal placements of environment elements. This method affords trading off the granularity of the search space and computation time by discretizing a typically continuous and non-convex problem. We present a comparative study of our AMR based approach to provide insight into the performance of the method.

2 RELATED WORK

Crowd dynamics and traffic flow has a long and rich history in the design and evaluation of environments. In particular, pedestrian traffic flow exhibits unique dynamics at different densities which must be planned for, originally discussed in [10]. [27] reviews the complexity and difficulty involved in the simulation of crowds in these critical situations. Current systems [25, 9] use simulations to provide visual feedback either in terms of trajectories, or other high-level features (flow), but require human experts to manually interpret these measures and integrate them into the design process.

Crowd Simulation, Analysis, and Optimization. The maturity of research in simulating crowd dynamics [21, 28] has resulted in a wide variety of approaches including social forces [15] and predictive models [30, 26]. There has been a growing recent trend to use statistical analysis in the evaluation and analysis of dense crowd simulations. The work in [11, 22] measures the ability of a steering algorithm to emulate the behaviour of a real crowd dataset by measuring its divergence from ground truth.

One approach to crowd optimization is to fit the parameters of the synthetic crowd model to meet different behavioural criteria [5] or to match real crowds [32]. Another approach is to modify higher level processes such as guidance or way-finding to optimize movement when path decisions are critical, such as in evacuations [18, 31].

Architectural Optimization. There is an established and growing interest in the use of architectural optimization to explore design spaces and provide optimal solutions with respect to problem criteria [7, 23].

Architectural optimization solutions generate new layouts or topologies for structures with respect to objective and/or subjective criteria. Data driven approaches learn layout configurations from a database of prior architecture design constrained to a particular design space (e.g., residential homes) [19]. Another approach is to model objectives as relationships between features. Design objectives can be modelled as forces applied to a physical features to generate layout designs automatically [1]. Hierarchical and spatial relationships of furniture objects can be modelled to produce realistic human designer-like configurations with respect to their computed visibility and accessibility [34].

The modelling of physical phenomenon is most related to our approach to environment fitness. These methods may incorporate simulation of sunlight [33], materials, subsequent energy savings [8], or even acoustics [2]. The most closely related to our work is the optimization of egress environments using crowds [17, 16]. This work does not incorporate the user-in-the-loop processes and is presented as analyses of the affects of egress obstacles and shapes on crowd evacuation.

Since subjective criteria are difficult to quantify, many tools select an optimization scheme to meet objective criteria then take a human-in-the-loop interactive approach to the subjective. The tools combine the aforementioned derivations for fitness with user guided optimization processes [24, 29, 20].

Our Work. We extend the analysis of pedestrian dynamics classifications to high density synthetic crowds. We leverage this wealth of synthetic crowd research and pedestrian dynamics to produce a computational design tool using background simulations to inform architectural optimization.

3 EVALUATION OF CROWD DENSITY OPTIMIZATIONS

Scenarios, such as evacuations, benefit from higher flow but suffer from the potentially dangerous behaviours found with increased density. The trade-off of flow and density occurs at a critical density, a point after which increasing density reduces flow. In the design of pedestrian environments, it is preferable to avoid bottleneck areas such as egress points where crowd density may rapidly increase in critical situations. However, previous research has shown that the placements of flow-affecting environment elements, such as pillars may facilitate flow [14].

3.1 Methodology

We make use of common, yet critical, portions of building geometry to explore the optimization of pillar placements with respect to synthetic crowd flow in evacuation scenarios. These benchmark environments are the uni-directional egress and bi-directional crowd flow hallways. The environments are populated with crowds at varying densities representing multiple LoS. All pillar placements are constrained to optimization regions. The design and layout of these environment can be seen in Figures 3 & 4. We formulate an optimization for pillar placements using an objective that maximizes flow rate and penalizes pillar overlap. We make use of an evolutionary approach, CMA-ES [12], to find an optimal pillar placement in a non-convex and continuous search space.

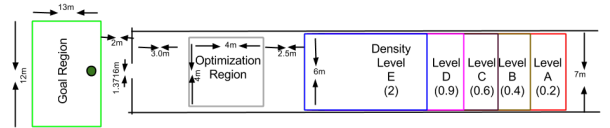


Figure 3: Uni-directional hallway scenario.

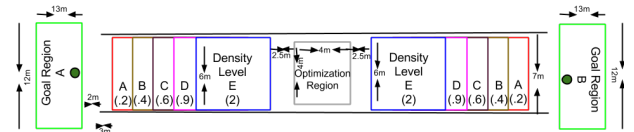


Figure 4: Bi-directional hallway scenario.

3.2 Synthetic Crowds and Density

Levels of Service (LoS), as defined in [10], provides a classification of the objective LoS for pedestrians environments by assigning labels to crowd densities. These LoS classifications are provided for various types of pedestrian environments such as walkways, queueing, and stairs. We study the flow-density relationships for three different synthetic crowd simulators: **ORCA** (reciprocal velocity obstacles) [30]; **SF** (social forces) [15]; and **PPR** (multi-phase rule based) [26]; by sampling the initial densities of crowds across LoS A – E, for both the uni-directional and bi-directional hallway benchmark, and computing the crowd flow for each of the three steering algorithms.

Synthetic crowd simulators are used to derive features of aggregate crowd behaviour. In particular, metrics such as flow and density are derived from large numbers of simulations. We sample the crowd density between LoS levels A (0.2 agents/m^2) and E (2 agents/m^2) in the uni-directional and bi-directional hallway

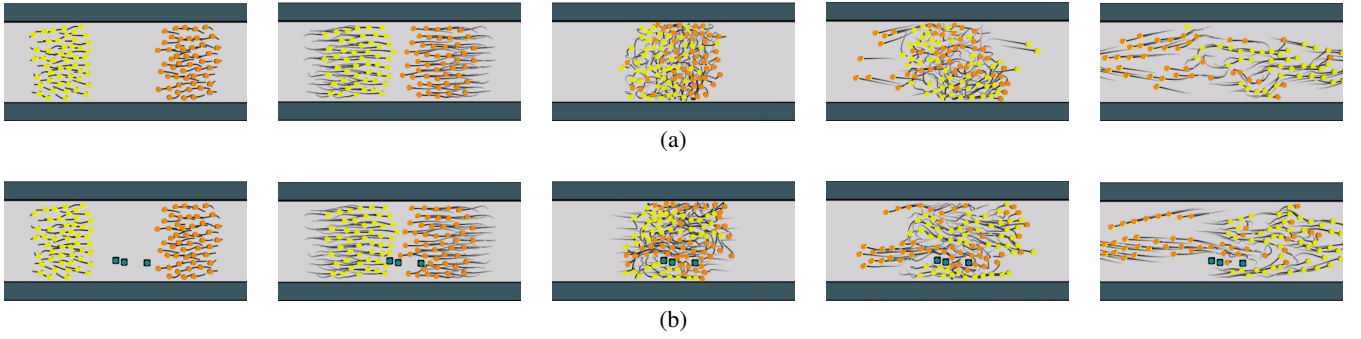


Figure 2: Simulation of **SF** steering algorithm in a bi-directional hallway for **LoS E**. Optimal pillar placements produce emergent lanes and increase the effective critical density.

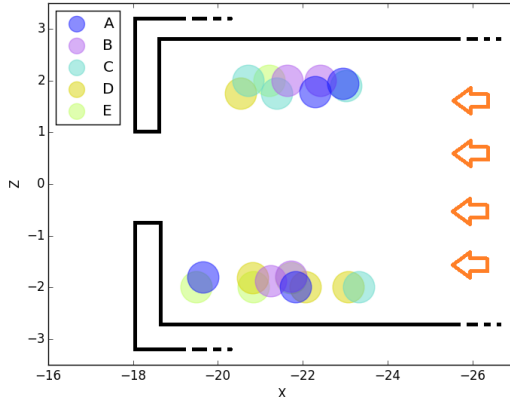


Figure 5: Optimal placement of 4 pillars across **LoS** conditions, A-E, using **ORCA** in the uni-directional hallway scenario. Each pillar is a circle coloured by the **LoS** condition it was optimized under, and the crowd flow is from right to left. **ORCA** results in out of the way wall-like placements. These formations caused crowd squeezing and lanes in low and high density conditions respectively.

benchmarks. We simulate a crowd using **ORCA**, **SF**, and **PPR**, and compute the corresponding crowd flow. In order to determine the sensitivity of our results to variations in the starting configuration of the crowd, each experiment is repeated 200 times with a different randomly chosen starting configuration of the crowd.

3.2.1 Optimization and Density

Optimizing Pillar Placements. Patterns in optimal pillar placement results across steering simulators for different **LoS** conditions. With **ORCA** flow is maximized by placing the pillars along the boundaries of the optimization region, forming wall-like structures for both the uni-directional and bi-directional hallways, as illustrated in Figure 5. **PPR** placements produce, lane-forming structures such as blocks or funnels, which become less regular at higher density conditions. The **SF** pillar placements show a tendency towards both wall-like and lane forming structures.

Level of Service Analysis for Optimized Environments. We observe that optimizing for an environment under particular **LoS** conditions may produce interesting results under other **LoS** conditions. For example, optimizing **ORCA** for a single pillar under **LoS E** conditions produced a higher flow rate across **LoS** conditions. Similarly, for **SF** across all number of pillars, optimizing under higher density **LoS** conditions led to higher flow rates across **LoS** condi-

tions, see Figure 2. The same may be true for **PPR** though flow rates were not significantly increased.

4 DENSITY GUIDED OPTIMIZATION

Optimizing environment elements can take several minutes on standard desktop machines, dependant on problem space and computing power. Motivated by results from Section 3 we synthesize focused sampling techniques to reduce the computation time while producing approximate near-optimal results.

4.1 Adaptive Mesh Refinement

Adaptive Mesh Refinement (AMR) is employed to reduce the search space of the crowd aware layout optimization. AMR is a technique applied in simulations of turbulent hydrodynamics [3], which we consider analogous to dense crowd simulations in arbitrary environments. The process discretizes the sampling space at finer granularity in areas of interest as defined by some heuristic. A mesh is adapted at each iteration to include, or enhance, information captured by the underlying data. Based on results from Section 3, our granularity heuristic is crowd density which focuses subdivision on areas of heavy crowd flow.

We apply the AMR technique to crowd aware building layout optimization, assuming the isomorphic analogy to hydrodynamics. This optimization is a non-convex and typically continuous problem. AMR affords tunable optimization results for crowd aware design of environments through subdivision depth and heuristic threshold. In our algorithm, each environment element is optimized individually given an initial best guess for all elements. After each element is placed, the crowd flow data is updated and the mesh is refined. We refer to this algorithm as Iterative Selection AMR with Backtracking (ISAB), which is illustrated in Figure 6.

ISAB iterates through all parametrized environmental elements, placing one on each iteration. At each iteration the environment is simulated and a density histogram is produced. A default flow value is computed by executing a simulation without the current pillar element. This histogram is then used to adapt a space-partitioning structure, or mesh. The nodes of this mesh are used as sample points at which to reinsert and place the current element. The resulting scenario is then simulated, and the flow value at the current node is stored. The index with the maximum value is then the optimal selection on this iteration. A back-tracking fail-safe ensures completeness in that we avoid being stuck in a local minima after an initial bad selection. This algorithm, in the context of CODE can be seen in Figure 1.

4.2 Evaluation Methodology

We evaluate the density guided approach, ISAB, through a ground-truth comparison with CMA-ES. With each method a number of environment elements are placed, ranging from 1 and 2 pillars, in

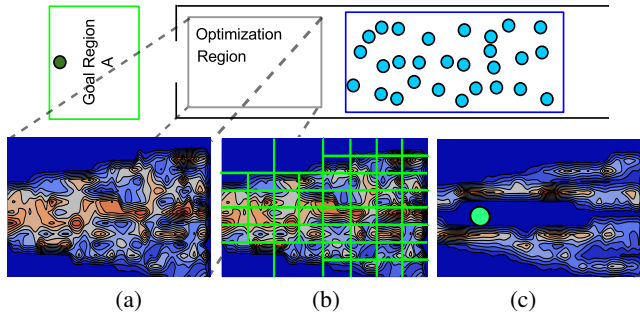


Figure 6: (a) The crowd flow density in the optimization region. (b) The AMR for (a). (c) The best pillar position according to the AMR sampling, and new crowd flow density.

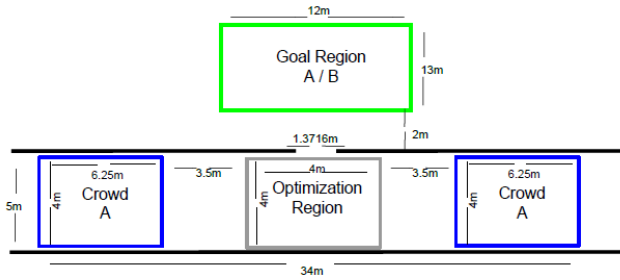


Figure 7: Bi-directional midpoint egress traffic in a hallway.

a set of scenarios. These include the similar scenarios from Section 3, Figures 3 & 4. We also investigate a bi-directional crowd flow hallway with a midpoint egress, as in Figure 7, and a four-way crowd flow hallway, as seen in Figures 8. These scenarios are simulated 100 times with randomly chosen uniformly distributed crowd agents of radius 0.2286m. We derive crowd flow performance from these simulations.

4.2.1 Ground-truth CMA-ES Experiment

To explore the performance of our ISAB method we compare it to the performance of CMA-ES results. CMA-ES has been used previously in this domain as an offline method for optimizing architectural elements [13, 6, 4], and it serves as a useful ground truth for this analysis.

Results. Figure 9 shows the average results and confidence intervals of CMA-ES and ISAB, based on a T-test. It is evident that the expected flows are relatively close to each other, and this closeness is not accidental since the 95% confidence intervals are very tight. We can conclude that the results generated by ISAB are mostly similar to CMA-ES results. The point of this argument is to show that ISAB results are valid and justified. Moreover, Figure 9c shows that in terms of number of simulations, ISAB greatly outpaces CMA-ES by performing considerably less evaluations to achieve approximately optimal results. ISAB is at least an order of magnitude, and up to two orders of magnitude, faster at 16 evaluations in comparison to CMA-ES at 100-1200 evaluations - a difference of seconds in comparison to up to several minutes respectively. Therefore, ISAB may be useful for user-in-the-loop designer applications, providing results on par with CMA-ES in considerably less time.

5 CONCLUSION

Synthetic crowds have been successfully used to predictively inform pillar layout optimizations to the benefit of the designer. The

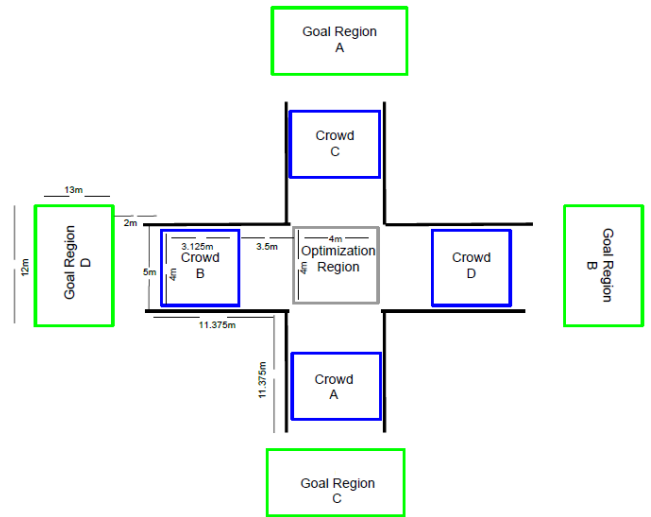


Figure 8: Four-way traffic in a hallway.

density of synthetic crowds affects the results of building layouts optimized with respect to flow. The patterning of optimal pillar placements and resulting flow increases reveals the benefits of designs that increase crowd order, such as lanes. Specifically, areas of high density, or crowd use, are of special interest for the optimization of placements. These results can be successfully used to develop informed approximate processes that reduce computation time whilst performing on par with exact offline methods.

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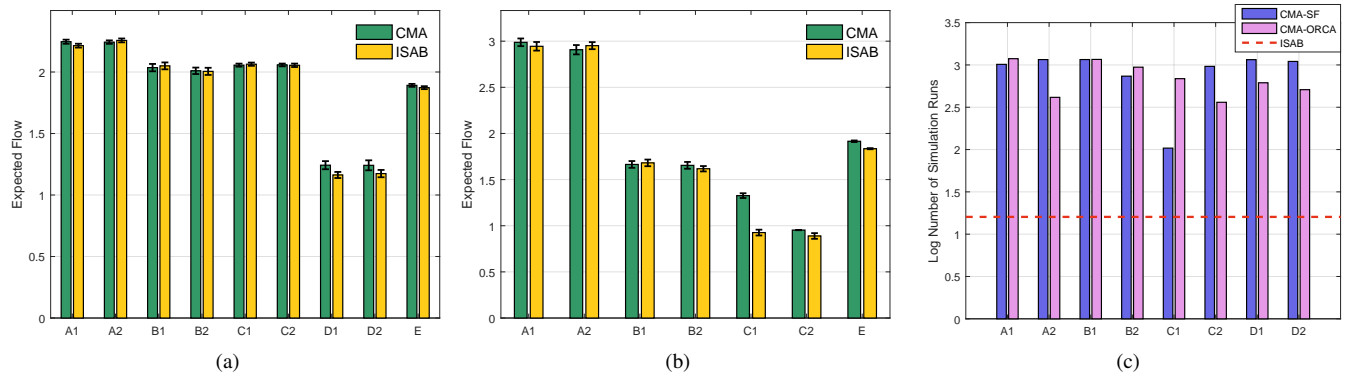


Figure 9: Comparison between ISAB and CMA-ES results, where each bar represents expected flow for each group, and the error bars show the 95% confidence intervals. A is the unidirectional-hallway scenario, B is the bidirectional-hallway scenario, C is the bi-directional hallway side-egress scenario, D is the four-way-hallway and E is over all scenarios, and numbers 1 and 2 correspond to single and two pillar placement respectively. (a) Expected flow results obtained based on SF algorithm (higher flow is better). (b) Expected flow results obtained based on ORCA. (c) Log number of simulation runs till convergence (best fitness value).

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