Comparing different metrics quantifying pedestrian safety

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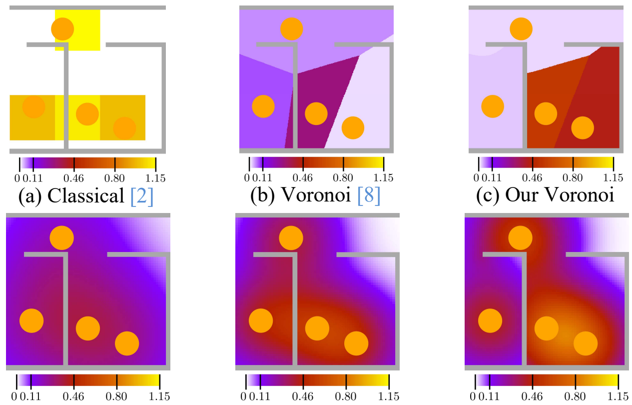
At the 2010 Love Parade [3][6], 21 people were crushed to death and hundreds got injured. In 2006 and 2015, hundreds of pilgrims died during the Hajj to Mecca due to dangerously overcrowded situations [4]. Motivated by such disasters, researchers study ways of preventing these from happening again. Some researchers use crowd simulation techniques to make predictions about safety. By studying metrics like density, velocity, flow and pressure, early warning signs for potentially dangerous situations can be found.

Metrics can be used to classify safety in different ways. One way is to divide the range of possible values in bins. An example of this is Fruin's concept of *Level of Service* (LoS) [2]. Different densities, velocities and flows are mapped to 6 different categories of "safety", labeled A through F, where A means that everyone can move freely, and F means that there is a possibly dangerous situation.

However, the values for the metrics can be determined by using different methods, and each one gives different results. A list and analysis of different density methods is given in [1]. In the paper by van Wageningen-Kessels et al. [10], they show that the density, velocity and flow are related. Pressure can be derived from a given density and velocity fields [4]. Because of these interdependencies, a wide range of possible outcomes exists for any metric and different conclusions about pedestrian safety can be drawn from the same data.

In addition, it is not clear which metric for evaluating pedestrian safety is the best. Duives et al. [1] try to resolve this problem by comparing different metrics of crowdedness. This is done by plotting the velocity/density relationship, giving a *fundamental diagram*. For different situations, Duives et al. formulate what "trends" they expect to see in the fundamental diagram for different situations, and visually look for them. Furthermore, the authors propose an objective way of comparing the different metrics. They do this by determining the average scatter for each measure. The higher the scatter, the less suitable a measure is.

In this paper, we propose a methodology for comparing different metrics that compute density, velocity, flow and pressure fields, without the need for fundamental diagrams or visual inspection of these fields. Furthermore, we refine existing metrics to include obstacles in these fields by replacing the Euclidean distance by the geodesic (walking) distance [5].



(a) Classical [2] (b) Voronoi [8] (c) Our Voronoi
(d) Gaussian [4] (e) Gaussian [7] (f) Our Gaussian

Figure 1: Different density fields. The orange disks represent pedestrians. (a): Fruin's classical density [2]. The cells measure 1×1m. (b) and (c): The Voronoi diagram as used by Steffen and Seyfried [8] and the geodesic Voronoi diagram. (d),(e) and (f): The Gaussian-based density measure by Helbing et al. [4] with $\sigma = 1$m, the measure proposed by Plaue et al. [7] and a Gaussian density measure using the geodesic distance.

In our experimental analysis, we see a wide range of possible values while the flows are similar. This confirms the need for calibrating the LoS for each individual metric and scenario.

Metrics for Safety

We compare six methods of computing density, velocity, flow and pressure fields, including the methods by Fruin [2], Steffen and Seyfried [8], Helbing et al. [4] and Plaue et al. [7]. The remaining two (new) methods are adaptations of the Voronoi-based [8] and Gaussian-based method [7] to better account for obstacles in the environment by using the geodesic distance instead of the Euclidean distance. The resulting density fields are shown in Figure 1.

Comparing Metrics

When analyzing a metric M, we will look at a region of interest R within the studied environment. This area is divided in a set of cells C_i for $1 \leq i \leq N$. The value for such a cell is given by $v(C_i, M)$.

When comparing the metrics, we consider the following values. First, we look at the maximal value for M within R, which enables us to compare measured peak densities, velocities, flows and pressures. We also look at the maximal difference between two metrics.

$$\max(M) = \max_{1 \le i \le N} v(C_i, M) \quad (1)$$

$$\max_{\delta}(M_1, M_2) = \max_{1 \le i \le N} v(C_i, M_1) - v(C_i, M_2) \quad (2)$$

The above two methods do not offer much more information than a simple visual inspection of two images. The extreme differences are accented, but other information is lost.

For that reason, we also introduce two other methods for comparing the different fields. For these methods it is important that R is centered on the area we want to study. This, however, should not be a problem since we are interested in local values in this study, and not in global values. We call the first one the *quadratic score*. This is defined as follows:

$$qs(M) = \frac{1}{A_R} \sum_{i=1}^{N} \left(\frac{v(C_i, M)}{\max(M)} \right)^2 \times A_i \quad (3)$$

Here, A_i is the obstacle-free area of cell C_i and A_R is the obstacle-free area of R, which is the same as $\sum_{i=1}^{N} A_i$. The resulting value is a number in the range of 0 to 1. A value of 1 denotes that all N cells are at the maximal value. The closer the quadratic score is to 0, the smaller the area of R that is at the maximal recorded value.

The last method we discuss is a comparison based on how the industry often uses the values from the metrics. Usually, a certain threshold value is used or categories are specified. An example is the LoS concept [2]. Expression (4) calculates the difference in categorization between two different metrics.

$$\mathrm{bd}(M_1, M_2) = \frac{1}{A_R} \sum_{i=1}^{N} (b(C_i, M_1) - b(C_i, M_2))^2 \times A_i \quad (4)$$

Here, $b(C_{i,}M)$ is a function that maps $\mathrm{v}(C_{i,}M)$ to the category's number. For example, when a threshold t is given, a value $\mathrm{v}(C_{i,}M) < t$ maps to 0 and all other values to 1.

Experiments

We performed experiments to test whether there are statistical differences between the metrics. The experiments were performed with the ECM simulation framework [9]. This framework enables us to generate pedestrian trajectories for different scenarios.

We performed the simulations in a U-turn, corner and T-junction environment. The hallways had a width of 1.5m and all experiments had a unidirectional flow. For the T-junction environment, we performed experiments with one and two entrances. The rate at which pedestrians were added to the simulation was varied from 0.5/s through 5/s. This resulted in flows in the range of $\frac{1}{3}$ /m/s to $1\frac{2}{3}$ /m/s.

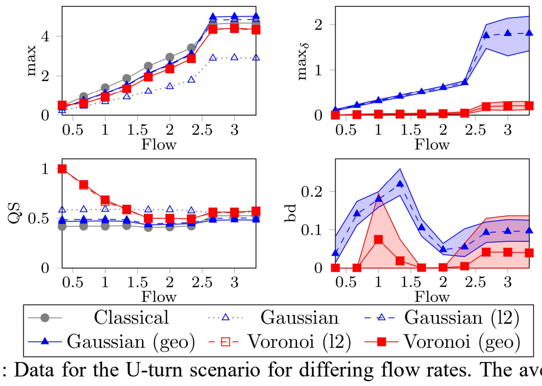
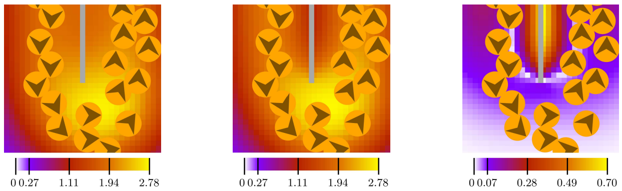


Figure 3: Data for the U-turn scenario for differing flow rates. The averaging window is set to 10 seconds. From left to right we show the maximum density, maximal difference, quadratic score and bin difference. Upper and lower borders show the 5^{th} and 95^{th} percentile.



(a) Density (b) Density (geo) (c) Difference

Figure 2: The absolute difference between a field calculated using Plaue et al. [7] using the Euclidean distance and the geodesic distance. The shown images correspond to a spawn rate of 7 pedestrians / s, which corresponds to a flow of $2\frac{1}{3}$ pedestrians / s. The size of the averaging window is 10s.

We recorded the location and velocity of the pedestrians every tenth of a second for 10 minutes, starting 2 minutes after the first pedestrian reached the other side of the environment. We used this data to calculate the fields. We also calculated the time-average fields over a timespan of 1s, 10s and 60s. The instantaneous information is usually considered too volatile to draw any conclusion.

Results

In Figure 2, an example is given that shows the difference between two density metrics. Using visual inspection, we can see that there is a difference between the two fields. The maximal difference in Figure 3 confirms this. When we compare the Voronoi metrics or the Gaussian metrics using the quadratic score, we see that there is a difference in scale. When these values were compared using an ANOVA with Tukey HSD post-hoc analyses, these differences were found to be significant at a 95% confidence level. In case of the U-turn scenario, the biggest difference in quadratic score for density was found at a flow rate of 1.6 pedestrians/m/s. The difference was 0.15. Our methods showed higher maximal densities and pressure compared to the previously existing methods.

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