

How to Monitor and Ensure ‘Physical Distancing’ in Crowded Spaces

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Abstract

We show how real-time people flow data can be used to assess and ensure the safety of pedestrian facilities in presence of a contagious disease. We derive indicators that identify and monitor areas prone to contagion (such as packed queues caused by too narrow pedestrian routing), and to identify spontaneous gatherings of people that result from problematic behavior (such as people standing too close). Such knowledge is of key importance to facility operators in their quest to re-open essential facilities, as well as to surveillance personnel in guaranteeing everyone’s safety. Our approach is based on two premises: basic knowledge of the type of contagion risk and availability of a high-precision people flow monitoring system.

Person-to-person spreading of an infectious disease – referred to as contagion – poses a major threat to public facilities. Often, it is assumed that the risk of contagion depends on person-person distances (Wells; 1934). While the details of this relationship are case-specific and often unclear (Salathé et al.; 2010), the contagion risk generally reduces with increasing person-person distances (Fig. 1).

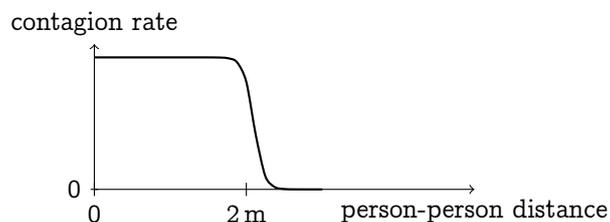


Figure 1: Larger person-person distances reduce risk of contagion (illustration).

To quantify distances between people, high-precision people flow monitoring systems are key. Optical sensors mounted on ceilings may be used to track each person’s position in real-time, with sub-meter accuracy and without privacy intrusion.

Based on the above-mentioned relationship between distance and contagion rate and high-precision people flow data, we discuss in the following three indicators that quantify the contagion risk resulting either from inadequate crowd management, or from individual misbehavior.

1 Crowd density

One may consider crowd density as a prior in the assessment of contagion risk. Let $\mathcal{P}(t)$ denote the set of people present at time t , and let the two-dimensional coordinates of person $i \in \mathcal{P}(t)$ at time t be denoted by $\mathbf{x}_i(t) \in \mathbb{R}^2$. Assuming a Gaussian distribution with parameter σ , a smooth density field can be constructed, i.e., crowd density at point \mathbf{x} and time t may be expressed as

$$d(\mathbf{x}, t) = \sum_{i \in \mathcal{P}(t)} \frac{1}{2\pi\sigma^2} \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}_i\|_2^2}{2\sigma^2}\right). \quad (1)$$

Density, at least as defined by Eq. (1), is of limited use in assessing person-person distances. For instance, to guarantee a minimum distance d , one can show that density may not exceed $\sqrt{3}\pi/(6d^2)$ (Chang and Wang; 2010). For a minimum distance of $d = 2$ m, the corresponding maximum density would be 0.23 pax/m². However, this assumes a perfect packing of people, and therefore represents a rather unrealistic upper bound.

2 Contagion map

To show hot spots of potential person-to-person infection, a dedicated *contagion map* is required. Contagion hot spots may emerge unexpectedly (e.g. from queues growing in an uncontrolled way), and knowledge thereof allows facility operators to react quickly (e.g. by increasing lane spacing).

As discussed at the example of Fig. 1, each pair of pedestrians gives rise to a potential contagion whose likelihood changes as they move closer or farther apart. Assuming a logistic relationship, we may define the mutual contagion rate at time t between people $i, j \in \mathcal{P}(t)$, $i \neq j$, as

$$r_{i,j}^{\text{pair}}(t) = \frac{r_0}{1 + \exp(k(\|\mathbf{x}_i - \mathbf{x}_j\|_2 - \ell))}. \quad (2)$$

Parameters k , r_0 and ℓ capture aspects such as efficiency of indoor ventilation or whether people wear masks, and should be based on epidemiological evidence.

To generate a contagion map, we locate the potential point of contagion between two people at the center point between them. By aggregating over all pairs of people, and by applying some ‘smoothing’ (e.g. Gaussian), we can build a ‘surface’ of contagion points. Doing so, we obtain a ‘heat map’ representing

the instantaneous rate of contagion over space, i.e.,

$$r^{\text{tot}}(\mathbf{x}, t) = \sum_{i \in \mathcal{P}(t)} \sum_{\substack{j \in \mathcal{P}(t) \\ i \neq j}} \frac{r_{i,j}^{\text{pair}}(t)}{2\pi\sigma^2} \exp\left(-\frac{\|\mathbf{x} - \frac{\mathbf{x}_i + \mathbf{x}_j}{2}\|_2^2}{2\sigma^2}\right). \quad (3)$$

If we further aggregate over time, we gradually build up a topology of contagious areas – i.e., the desired *contagion map*. Specifically, we distinguish two types of contagion maps:

- The *absolute contagion map*, which is given by

$$c^{\text{abs}}(\mathbf{x}, t) = \frac{1}{\tau} \int_{\tilde{t}=-\infty}^t \exp\left(-\frac{t-\tilde{t}}{\tau}\right) r^{\text{tot}}(\mathbf{x}, \tilde{t}) d\tilde{t}, \quad (4)$$

where an exponential filter with parameter τ has been assumed. The absolute contagion map shows where person-to-person infection is most likely to happen, typically ranking highly frequented places first.

- The *relative contagion map*, which is obtained by additionally normalizing with crowd density, i.e.,

$$c^{\text{rel}}(\mathbf{x}, t) = \frac{1}{\tau} \int_{\tilde{t}=-\infty}^t \exp\left(-\frac{t-\tilde{t}}{\tau}\right) \frac{r^{\text{tot}}(\mathbf{x}, \tilde{t})}{d(\mathbf{x}, \tilde{t})} d\tilde{t}. \quad (5)$$

The relative contagion map shows where the contagion risk is highest for an individual. For instance, in a little used, narrow corridor, the overall rate of contagion may be low, but the individual contagion risk is high.

We note that, as contagion pathways are better understood, more detailed models may be used. For instance, Eq. (2) may incorporate viewing direction, a feature that some people flow monitoring systems already measure. Similarly, interval-based instead of exponential filtering may be desirable for off-line instead of real-time contagion analysis.

3 Identification of ‘contagious groups’

The contagion map allows to spot systematic contagion risks and is, as such, a highly valuable instrument for facility operators. However, it provides only little information about individual threats – the kind of information most useful to surveillance personnel.

Individual contagion risks may arise from spontaneous gatherings exceeding a maximum permitted group size, or with individuals standing too close to each other. We refer to such gatherings as ‘contagious groups.’

Machine learning tools can be used to identify contagious groups. Advanced people flow monitoring systems already make use of appropriate clustering mechanisms, e.g. for conversion rate estimation in the retail sector. With little modification, they can be used to monitor undesired grouping activities, and to target surveillance actions on a case-by-case basis.

Of course, real-time identification of contagious groups will still require human judgment – large families for instance shall still have the right to stand close together – but it helps using available resources in the most efficient way, keeping everyone as safe as possible.

4 Illustration

We illustrate the use of the proposed contagion indicators at the example of an airport departure hall: Prospective passengers enter from below, check in at one of the automated desks located on the left, and join the security queue (Fig. 2a). Generous person-person spacing is visible in most parts of the queue, except at its tail, which is rather crowded. While self-service check-in machines are currently not too busy, their close configuration is striking. In the lower right corner, there is a group of travelers standing close to each other.

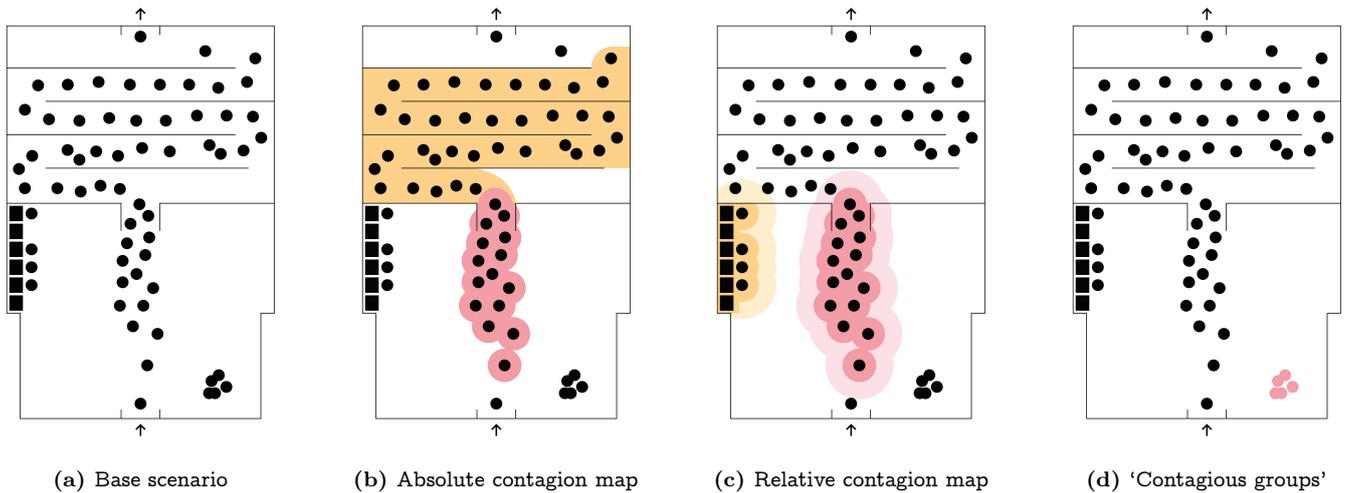


Figure 2: Contagion indicators at the example of an airport departure hall.

- Absolute contagion levels are moderate to high in busy areas, i.e., within the queue and especially at its tail (Fig. 2b). Areas with high absolute contagion levels are the ones that should be surveyed most carefully. In this case, facility operators may consider extending barrier tapes at the queue tail, or installing ‘keep distance’-signs.
- The relative contagion risk, i.e., the contagion risk corrected for density, is high at the tail of the queue, and moderate around self-service check-in machines (Fig. 2c). The relative contagion map reaffirms the need to take action at the queue entrance, and suggests a closer look at the check-in area. Closing every other self-service machine, or pulling them apart, may reduce the risk of contagion.

- ‘Contagious groups’ are shown in Fig. 2d, i.e., groups that violate physical distancing in that they are too packed, or too big in size. Detected is one group in the lower right corner, which surveillance personnel may be asked to investigate, and if needed, disperse.

5 Conclusion

We have outlined how the combination of an epidemiological ‘distance vs. contagion risk’-curve and a high-precision people flow monitoring system can help identify systematic contagion risks as well as individual risks caused by spontaneous, uncontrolled group formation. We have conceptually defined two powerful tools – the contagion map and an identification measure for contagious groups – that will help facility owners and surveillance teams re-open and operate crowded public spaces safely.

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About the author



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