Inferring crowd conditions from pedestrians' location traces for real-time crowd monitoring during city-scale mass gatherings

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***Abstract*—There is a need for event organizers and emergency response personnel to detect emerging, potentially critical crowd situations at an early stage during city-wide mass gatherings. In this work, we introduce and describe mathematical methods based on pedestrian-behavior models to infer and visualize crowd conditions from pedestrians' GPS location traces. We tested our approach during the 2011 Lord Mayors Show in London by deploying a system able to infer and visualize in real-time *crowd density*, *crowd turbulence*, *crowd velocity* and *crowd pressure*. To collection location updates from festival visitors, a mobile phone app that supplies the user with event-related information and periodically logs the device's location was distributed. We collected around four million location updates from over 800 visitors. The City of London Police consulted the crowd condition visualization to monitor the event. As an evaluation of the usefulness of our approach, we learned through interviews with police officers that our approach helps to assess occurring crowd conditions and to spot critical situations faster compared to the traditional video-based methods. With that, appropriate measure can be deployed quickly helping to resolve a critical situation at an early stage.**

I. Introduction

Festivals and city-wide mass events are popular gatherings and commonplace in human societies all over the world. Such events range from concerts with a few dozen attendees to events of massive scale like the Olympic Games with millions of spectators. It is a top priority for every organizer of such an event to be able to maintain a high standard of safety and to minimize the risk of incidents. Hence, establishing adequate safety measures is important. In the past few years, efforts have increased to derive pedestrian behavior models and to use them in simulations to measure the effect of architectural configurations on crowd behaviors [1]. This approach has been followed to identify critical locations where dangerous crowd behaviors may emerge. This helps to design and proactively deploy crowd control mechanisms before an event to mitigate the risk of a fatal crowd incident. Models and parameter calibration can be obtained through experiments under controlled conditions [2] or by evaluating video footage from comparable events [3]. By generalizing the obtained findings, a set of safety regulations and procedures can be defined aiming to help optimally planning future events [4]. Despite these efforts, deploying optimized emergency strategies for city-scale mass gatherings, however, remains challenging due to different limitations coming along with the nature of such events: They often take place in urban spaces, pedestrian areas or cultural places not designed for the number of visitors of such events and often operate at the capacity limit or even exceed it. Existing pedestrian flow control mechanisms are not adequately designed for big crowds or are missing completely. Designing a temporary solution for the specific event is not an easy task either as the number of attendees is often unknown and can only be estimated based on assumptions derived from experience of previous years. The actual number, however, may greatly deviate from these estimations as it depends on factors like the festival program, weather conditions, alternative events, etc. Yet, the biggest challenge of all is that the behavior of the crowd during an event remains highly unpredictable. All these challenges foster the need to detect critical crowd situations like overcrowding at an early stage in order to rapidly deploy adequate safety measures to mitigate the impact of a potentially dangerous situation. To do so, real-time information about the behavior of the crowd is required. At present, mostly video-based monitoring systems come into operation for this task. Recent research has focused on developing computer-based methods to automatically analyze the recorded scenes and to detect abnormal and potentially dangerous crowd situations [5], [6]. Vision-based approaches face several limitations: Cameras can not capture elements outside their fields of view or occluded by other obstacles and it is still difficult to fuse information from many cameras to obtain global situational awareness [7]. Another drawback is the need for good lighting conditions. As many events happen during the night, the application of a vision based approach is limited.

As an alternative to vision-based approaches, we see a big potential in monitoring crowd behaviors by tracking the locations of the attendees via their mobile phone. We believe that the high distribution of location-aware mobile phones in our society and the acceptance to share personal context information enables such an approach.

In this work we present methods to infer crowd conditions in real-time from location information collected on mobile phones of attendees of a mass gathering. This information is made instantaneously available to event organizers and emergency response personnel through intuitive visualizations. Our approach relies on participatory sensing paradigms by offering incentives to users to deliberately share their location information. We deployed and tested our framework during a the Lord Mayor's Show in London in 2011. By interviewing personnel from the City of London Police's Emergency Planning team, we evaluated the usefulness of this approach.

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II. Crowd conditions hinting at potentially critical situations

To improve pedestrians' safety, much research has been devoted to understanding crowd behaviors and to identify critical crowd conditions by conducting lab experiments and evaluating empirical data from real mass gatherings. An obvious, yet important crowd characteristic to assess the criticality of a situation is the density of a crowd. For example, most stampedes occur in high-density crowds [8]. Different methods to measure crowd density and to identify dangerous overcrowding have been proposed [6]. Density, however, is not the only relevant characteristic; movement velocity and the flow direction of a crowd also have been identified as important indicators of critical situations [3], [9]. Methods for automatically measuring these conditions from location traces have been proposed in [2]. Johansson et al. identified a relation between flow and density of a crowd [3]. They measured a critical crowd density as soon as a breakdown of the flow occurred. They also identified crowd turbulence (irregular flows characterized by random displacement into all possible directions) occurring in high density crowds as especially dangerous, since the involved individuals are unable to control their motion and are pushed forwards and backwards by others [10]. In general, Helbing and Johansson [10], [3] suggest quantifying the hazard to the crowd (and with this the criticality of a situation in the crowd) by a measure they call *crowd pressure*, defined as the local pedestrian density multiplied by the variance of the local velocity of the crowd. We have interviewed officers from the City of London Police Emergency Planning team to learn which crowd characteristics may be monitored during mass gatherings and which may give an early indication of crowd control issues. The City of London Police has a long history of policing and considerable experience in managing large scale events, often attended by thousands of people, in the City of London area. The interviewees reported that the main methods of gathering this information is through the monitoring of CCTV footage by Control Room staff and reports received from strategically deployed personnel on the ground. These methods cannot necessarily provide an overview of a large crowd that covers a widespread area as the section of the crowd that is monitored is limited to that which can be seen by the CCTV operator and/or the person(s) deployed and can be quite resource intensive. Crowd density information can be an important parameter when assessing the potential seriousness of an incident and can be relatively easily inferred by observation. Other information of use in a crowd control situation or emergency is the crowd's movement velocity and its direction which can assist in determining where resources could be deployed. Crowd turbulence can be useful as an early indicator of potential crowd control situations, but can be hard to infer from observation. In the case of an actual crowd control situation or emergency, information about jammed exits or passageways is crucial to the deployment of appropriate counter-measures. As stated by the interviewees, the ability to identify potential crowd management issues from CCTV footage requires that the CCTV operator is able to recognise the possible indicators of these issues and has a high level of concentration during the event. Based on these findings, in this work we use location traces collected on mobile phones to infer the *crowd density*, *movement velocity*, *turbulent movement*, and *crowd pressure*.

III. Real-time sensor data collection

To infer crowd conditions, we require the location of festival attendees. We use attendees' mobile phones to obtain their location as most of today's mobile phones are situation and location aware. Methods to obtain location information include GPS positioning and WiFi/GSM-fingerprinting [11]. Collecting location updates on user's mobile devices requires users to install and run a dedicated application on their mobile phones. At first sight, such an approach may appear undesirable, as it can be assumed that people are not willing to install such an application. In the case of a mass gathering, this may mean that only a fraction of all attendees would run such an application and many would opt for not having their location tracked for various reasons, including privacy concerns and energy considerations. Nevertheless, we believe this approach is still viable and promising by following a participatory sensing approach where users themselves are motivated to deliberately share their location information by offering them a set of attractive incentives. In a preceding study, we have verified that people are willing to share privacy-sensitive location information if they receive some benefits or if they realize that sharing such information is for their own good and safety [12]. Also, our approach offers users full control of the recordings and allow them to disable it at anytime.

To collect location information of festival attendees, we developed a generic festival app for mobile devices which can be tailored to a specific event and provides the users with relevant, event-related information such as the festival program, a map indicating points of interest and background information. These features are designed to be attractive and useful during the event to reach a large user base. While a user is running the app, GPS location is regularly sampled with a frequency of $1Hz$ on the device and periodically sent to our servers running the CoenoSense framework (www.coenosense.com). CoenoSense acts as a centralized repository to store the location updates received from many mobile devices simultaneously and allows for real-time processing of the collected data. Our app offers users full control over the shared data and at anytime, data recording can be disabled.

IV. Inferring and visualizing crowd conditions

We want to provide emergency response personnel with the means to instantaneously assess the current crowd situation during mass gatherings. Displaying information as an overlay over a map is a common approach to present spatial information and allows for a quick assessment of the situation. In this section we elaborate on our methods to infer crowd conditions. We are going to show how, given the location updates from the users, an estimation of *crowd density*, *crowd velocity*, *crowd*

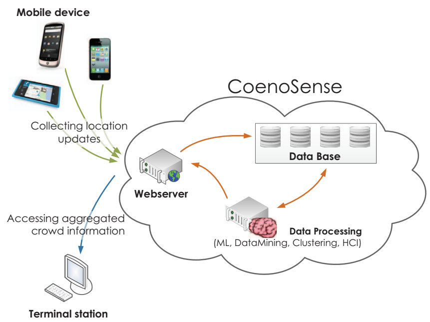

Fig. 1: Overview of the CoenoSense data collection platform. Location updates are collected on mobile phones and periodically sent to a centralized server infrastructure where they are being stored in a data base. The collected data can be aggregated and processed in real-time to infer crowd characteristics. A terminal client can access this information via the web server.

turbulence and *crowd pressure* can be obtained and how this information can be visualized as heat maps. A heat map is a graphical representation of spatial data where regions are colored according to measurement values found at the specific location. Heat map visualizations have been used in different applications to convey various types of spatial information.

A. Data preprocessing

We want to infer occurring crowd conditions at a specific point in time (for real-time applications). Hence, to determine the crowd conditions at time t, location updates received within $[t-\delta, t]$ are considered. If, for one user, multiple location updates have been collected within this time frame, the most recent one is considered as the user's current position. To calculate the walking speed of a user, we determine the distance traveled within $[t-\delta, t]$ and divided it by δ. We use the Haversine function to calculate the distance between the GPS location points. To obtain a user's heading direction θ, we calculate the final bearing by determining the angle between consecutive location updates of the subject's most recent location updates. With this, at time t, we obtain a set U of active users $u_1, \ldots, u_N$ and each user u_i has an associated location $X_{i,t}$, velocity $v_{i,t}$ and heading direction $\theta_{i,t}$. These are the basic measures we need to infer the crowd conditions of interest.

B. Crowd Density Estimation

To visualize density information, we calculate a density estimation by applying a Kernel Density Estimation (KDE) [13] from the active users' location updates at a given time. KDE is a non-parametric way of creating a smooth map of density values in which the density at each location reflects the concentration of sample points. Hereby, each sample point contributes to the density estimation based on the distance from it. By using a Gaussian kernel K, the density estimation $\hat{d}$ at each location X is given by:

$$\hat{d}(X,t) = \frac{1}{N \cdot h} \sum_{i=1}^{N} K\left(\frac{X - X_{i,t}}{h}\right) \tag{1}$$

with h the Bandwidth (an application dependent smoothing parameter), and $X_{1,t}, \ldots, X_{N,t}$ the users' current location. The Gaussian kernel function K is given by

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right) \tag{2}$$

By determining the density values $\hat{d}(X,t)$ for each location and mapping each density value to a color using a color gradient, a heat map representing the participant density estimation is obtained. Figure 3a shows an example of such a heat map. The visualization can be read in the following way: The warmer the color, the higher the crowd density at that location.

C. Visualizing Behavior Dynamics

The previously introduced approach is suitable to visualize the concentration of data samples as a density representation. It is in the nature of our data that we have areas with many active app users and by contrast, areas with very few; also large parts with no users. We are only able to infer crowd conditions in areas where location updates have been recorded. By calculating crowd conditions in an area, the amount of active users (and hence available location updates) is relevant: Information from areas where many location updates were recorded might be more important as this region seems to be more popular than in regions with only a few individuals. To visualize the crowd conditions and to also include the importance, we adjust the heat map generation method in the following way: We use a color gradient to indicate the crowd conditions at a location with a varying opacity level that corresponds to density at the location. The calculation of the density is identical to the approach presented in Section IV-B by performing a KDE using Equation 1. The obtained density estimation for a location is then directly mapped to the opacity value of the point. A very low density value will result in an almost transparent point, while a high density value will result in a fully opaque point. Hence, the more users are situated around a location, the more intense the location color. Regions where no data is available remain transparent. The coloring is then determined by calculating the crowd conditions at the specific location and mapping this value to a color value using a color gradient. With this, for each point in space, we obtain an opacity value representing the density together with a color value for the crowd condition at that location. Figure 2 illustrates this process.

Next, we introduce the methodology to calculate the three remaining crowd conditions.

D. Crowd Velocity

The local crowd velocity can be seen as the weighted average velocity of each user at a given location by weighting the speed values of each user depending on the distance to

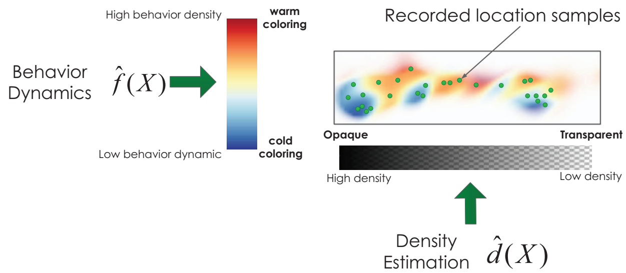

Fig. 2: Heat map of the crowd characteristics are generated by considering the density distribution of the recorded samples as an opacity value. the more users are situated around a location, the more intense the location color. Regions where no data is available remain transparent. The coloring is then determined by calculating the crowd conditions at the specific location and mapping this value to a color value using a color gradient.

that location with a Gaussian weighting scheme. With this, the formula to calculate the crowd movement velocity estimation $\hat{v}(X,t)$ at the location X and time t is given by:

$$\hat{v}(X,t) = \frac{\sum_{i=1}^{N} v_{i,t} K\left(\frac{X-X_{i,t}}{h}\right)}{\sum_{i=1}^{N} K\left(\frac{X-X_{i,t}}{h}\right)} \tag{3}$$

where $K(u)$ is the Gaussian kernel according to Equation 2 to determine the weight for each speed value $v_{i,t}$ and $X_{1,t}, X_{2,t}, \ldots, X_{N,t}$ the locations of the active users. For the heat map generation, the user density value is considered as the opacity and the crowd movement velocity estimation is mapped to a color gradient. Figure 3b shows an example of such a heat map. This heat map now conveys the following information: the warmer the color, the higher the movement dynamics and the more intense the color, the more users are to be found in this region.

E. Crowd Turbulence

To determine the crowd turbulence $\hat{c}(X)$ at location X, we calculate the variance of the heading direction of the users at that location. We use the heading direction θ of each user to calculate the weighted circular variance introduced by Brundson et al. in [14] which is given as

$$\hat{c}(X,t) = 1 - \left| \frac{\sum_{i=1}^{N} z_{i,t} K\left(\frac{X-X_{i,t}}{h}\right)}{\sum_{i=1}^{N} K\left(\frac{X-X_{i,t}}{h}\right)} \right| \tag{4}$$

where $z_{i,t} = e^{i\theta_{i,t}}$, and $\theta_{i,t}$ is the heading angle of subject i at location X_i at time t. $K(u)$ is the Gaussian kernel according to Equation 2 to determine the weight for each sample. A heat map representation is now generated in the same way as previously by mapping the crowd turbulence values to colors using a color gradient and considering the user density values as opacity values. Figure 3c shows an example of such a heat map. The hotter the color, the larger the heading direction variance at this location, and thus the higher the turbulence. The more intense the color is, the higher the density of users in that spot.

F. Crowd Pressure

According to [10], the crowd pressure is given as

$$P(X) = \rho(X) \cdot \mathrm{Var}_X(\vec{v}) \tag{5}$$

where ρ is the local pedestrian density and $\mathrm{Var}_X(\vec{v})$ the local velocity variance. In our case, we can obtain a density measure using Formula 1 and can calculate the velocity variance as

$$\hat{\mathrm{Var}}_{X,t}(\vec{v}) = \frac{\sum_{i=1}^{N} \left|\vec{v}_{X_{i,t}} - \langle\vec{v}\rangle_{X,t}\right|^2 \cdot K\left(\frac{X-X_{i,t}}{h}\right)}{\sum_{i=1}^{N} K\left(\frac{X-X_{i,t}}{h}\right)} \tag{6}$$

where $\langle\vec{v}\rangle_{X,t}$ simply is $\hat{v}(X,t)$. $K(u)$ is the Gaussian kernel according to Equation 2 to determine the weight $X_1, X_2, \ldots, X_N$ the locations of the active users. With this, the formula to calculate the crowd pressure estimation $\hat{P}(X,t)$ at the location X at time t is given by:

$$\hat{P}(X,t) = \hat{d}(X,t) * \hat{\mathrm{Var}}_{X,t}(\vec{v}) \tag{7}$$

The heat map is generated analogously to the other crowd conditions by mapping the crowd pressure to a color and combining it with the opacity obtained from the crowd density. Figure 3d shows an example of such a heat map.

V. System Trial, Lord Mayor's Show 2011

To understand the usefulness of a real-time visualization of crowd conditions during mass gatherings, we deployed the system during the Lord Mayor's Show 2011 in London on November 12th. The Lord Mayor's Show is a street parade in the City of London, the historic core of London. A new Lord Mayor, mayor of the City of London, is appointed every year and this public parade is organized to celebrate his inauguration. The annual one-day event attracts about half a million spectators each year and is one of the City's longest established and best known annual events. The event starts at 11:00am and the processional route goes from the Mansion House via Bank, St. Paul's Cathedral and Fleet Street to the Aldwych. Then the whole procession sets off again at 1pm to take the new Lord Mayor back to Mansion House. The procession finally ends at about 2.30pm when the last floats reach the City. In collaboration with the event organizers, we tailored our festival app to the event and distributed it for free as the festival's official app. It was advertised on the Lord Mayor's Show website and available through Apple's iTunes app store. Data collection was active between 00:01am and 11:59pm on November 12, but only if the user was in a specific geographical area around the festival venue. Over the whole day, we collected a total of $3'903'425$ location updates from 827 different users. During the parade, location updates from up to 244 users were received simultaneously, at any one time.

(a) (b) (c) (d)

Fig. 3: Visualization of: (a) Density distribution, (b) Crowd movement velocity, (c) Turbulence, and (d) Crowd pressure

A. Information from the visualization

It is not the aim of this work to discuss the occurring crowd situations during the event, but to understand the usefulness of the crowd condition detection and visualization method. Hence, at this stage, we will not provide an in-depth analysis of the occurring crowd behaviors during the Lord Mayor's Show but will describe how our visualizations can be read and interpreted on one specific example. Afterwards we are going to report on feedback received from emergency response personnel using the tool during the parade. Figure 3 shows the heat map visualization of the four crowd conditions at 5:21pm. This point in time is right after the end of the firework display as people are leaving the festival venue. It is clearly visible that there are high densities of users around train, Subway and bus stations. These are locations pedestrians find public transportation to travel home. The heat maps also reveal that the movement velocity is lower in regions around the river Thames. This might indicate that visitors are still standing around. However, by looking at crowd turbulence we see that the movement velocity is higher in regions with less crowd turbulence. Hence, we can assume a high density of people who want to walk in opposite directions. This slows down the flow as pedestrians have to cut through the crowd. Visualization of the crowd pressure indicates several high-pressure situations around areas where pedestrians can catch public transportation.

B. Feedback on the system

Security aspects of the Lord Mayor's Show 2011 were managed by the City of London Police. Together with the event organizers, they operated out of a Control Centre to monitor the event, from where they had access to the CCTV camera network and could communicate with strategically deployed personnel on the ground. Additionally, we provided access to a web interface displaying the heat map visualization of the density information. In the following we will report on feedback received from the City of London Police Emergency Planning team after the event, on the advantages and limitations of our system. By asking the interviewees to compare our system to existing approaches, they reported that currently, mostly visual obtained information gathered from CCTV cameras and officers on the ground is used for crowd monitoring and management. Additionally, experience gained from policing the same event over several years, leads to a buildup of knowledge of where crowds gather, which routes are often jammed, etc. Such information is used to optimally distribute policing resources and event stewards over the event footprint. Additional crowd information could be obtained, if required, from the deployment of a police helicopter which has equipment that can give an overview of the crowd from a higher vantage point during both day and night time. All these methods can be used in conjunction to obtain an overall picture of the situation. A minimum of one person is required to monitor the CCTV footage in the Control Room and several people are needed on the ground especially in areas not covered by CCTV or at night when CCTV systems without infra-red capability may be ineffective. The time required to detect a crowd problem (e.g. critical density, clogging of narrow pathways, etc.) is less when CCTV is available, but it is still difficult to build an overall picture of the whole situation. Those viewing the heat map visualization during the Lord Mayor's Show 2011 found interpretation of it was intuitive, with little explanation required. The heat map was seen as very helpful in obtaining an overview of the current crowd conditions at a glance. The police reported that the heat map provides an easier method of gaining an overview of crowds than from purely manual observation and/or CCTV system monitoring. The provided spatial resolution was perceived to be sufficient for the nature of city streets. While more precise location information would be useful, it was stated that it was possible to get a sufficient overview of what was happening during the Show based on the visualization. The police reported that the density measure is only an estimate based on an expectation of the location information of the app users. Having an estimated number of the actual crowd density, would be preferred. Such a value would provide information on how many people may be involved in any incident that may occur and could help to enhance the response to that incident by deploying sufficient resources in the right place.

VI. Conclusion

Traditionally, emergency response personnel rely on vision-based technologies or observations from personnel deployed on the ground to monitor crowd conditions during mass gatherings. The widespread usage of location-aware mobile devices in our society motivates us to investigate the potential of tracking people's movement traces via their mobile phone to infer crowd conditions. In this paper we introduce methods to infer various crowd conditions. By visualizing this information as heat maps, we can offer emergency response personnel an intuitive way to obtain a global view of the crowd situation and to assess different crowd conditions instantaneously throughout an event. We deployed the system during a city wide festival where over 800 people shared their location information. We learned from the City of London Police Emergency Planning team that our system provides useful information that can be used together with the information gained from other existing monitoring systems, to rapidly assess the current crowd conditions and identify potential crowd management issues. The collected data together with the visualization offers a unique insight into crowd conditions that is not possible with traditional methods.

However, there are also some challenges coming along with our approach. Mainly, due to the nature of our participatory sensing approach, our system can only collect data from the users of the mobile phone app. This is usually only a subset of all attendees. Keeping this in mind, two aspects are crucial: (a) **Ensuring a large user base:** Providing attractive incentives is important to reach a large user base. We reach this by offering festival attendees an enhanced experience by using our festival app. Hereby, a user study has revealed a set of attractive features and helped us to design the app accordingly [12]. Advertising the app in an appropriate way is key. Recently, big events started to offer their own app. Our tools can easily be integrated into their existing solution. (b) **Seeing users as probes:** By designing robust crowd condition measures that are robust with respect to the ratio of the app users, it is possible to extract accurate crowd condition measures, even when not all attendees are being tracked. To do so, we have to consider the users as probes and conclude from their behavior the overall crowd situation. This can be achieved e.g. through calibration of the data. While the ratio of app users to festival attendees remains unknown, we assume that the spatio-temporal distribution of users reflects the distribution of attendees at any one time during the event. With this assumption in mind, an actual crowd density estimation can still be obtained by determining the ratio of mobile app users to festival users in a given area e.g. by inspecting CCTV recordings. This ratio has to be updated periodically throughout the event.

We believe a participatory sensing approach by collecting location updates from users' mobile devices is suitable to infer crowd characteristics. In the absence of GPS reception, WiFi-based positioning methods offer an adequate resolution to also obtain relevant information especially in urban areas [11]. With our approach, the user is in full control of the data being shared and can opt to switch off data recording at anytime.

In this work, we presented a framework to collect location traces and visualize crowd conditions and reported on feedback received from security personnel accessing this information. In a next step we will continue developing our methods to infer crowd conditions and develop and evaluate models to map the information obtained from the app users to real crowd measures. We see a huge potential in inferring crowd characteristics from location traces collected with people's mobile devices. It offers a simple way to instantaneously obtain a global view of various different crowd conditions which cannot easily be captured with state-of-the-art vision based approaches. This approach can be used to rapidly spot critical crowd situations, which can then be further inspected with a CCTV system or ground officers. The usefulness of our approach has also been realized by a member of the City of London Police who stated that "'This is one of those pieces of kit that you do not realize its true potential until you use it."'

During the Lord Mayor's Show 2011, only the emergency response personnel and security personnel had access to the real-time visualization of the crowd conditions. It will be of further interest to investigate the dynamics evolving when festival attendees themselves are given access to such crowd information. It would then be of interest to study how the available information is considered in their decision making process and what kind of co-evolutionary dynamics will emerge. Ultimately, we would like to understand if such information can help to lower the number of overcrowded situations, while decreasing turbulence and crowd pressure.

VII. ACKNOLEDGEMENT

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