Crowd density estimation from Wi-Fi positioning data in the Amsterdam Arena

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Abstract

1 Introduction

*********************************From Sonja. nb: the text will be polished in the final phases, first I care only about putting all ideas on paper***************

Crowd disasters have taken many human lives. The Love Parade disaster (Duisburg, 2010), the Ellis Park Stadium disaster (Johannesburg, 2001), the PhilSports Stadium stampede (Manila, 2006) are just a few recent examples. One of the reasons that disasters happen is a "lack of overview of everybody" [cite paper on love parade EPJ DS], that is, a lack of macroscopic overview of the crowd. Critical crowd density (cite paper 8/m2, find it in e-mails)) is a contributing factor to crowd disasters; yet, it is still challenging to determine timely when it occurs, so that a disaster can be prevented before it happens, by e.g. navigating the rest of the crowd away from the congestion.

In our work we are interested in estimating crowd density during concerts in indoor spaces. A lot of research on estimating crowd density has been done using video processing from security cameras (cite papers (1), (2), (3) from proposal?). However, this approach does not apply in our case, because 1) it is difficult to obtain macroscopic overview ; 2) the lighting conditions during concert hours are not sufficient for video-based crowd analysis; and 3) the error of video-based density estimation increases with the increase of the actual crowd density.

In our approach, we combat the three above mentioned issues by exploiting the ubiquity of smart phones, as in ((4) (5), (6) from proposal?). Our living laboratory is the Amsterdam Arena(citation). First, we are estimating in real-time anonymously the positions of the visitors via the signal strengths of their phones to the Wi-Fi routers in the venue. This technique has been presented in (cite Jan's slides), and is similar to trilateration. However, due to signal interference, irregular internet packet rates and systematic errors, this methodology is imprecise as well. Thus, second, we apply the law of the large numbers to obtain an estimation of the crowd density, also in real-time. With the first step, we are dealing with issues 1) and 2) mentioned above. With the second step, which is the main contribution of this paper, we are handling issue 3) - that is, with our method the precision of estimation actually increases as the crowd density increases.

n.b. in related work section put all that use wi-fi tracking, for those that use GPS tracking only mention that this does not work in indoor spaces and that it requires participation. Not necessary to put work on video tracking in related work - it is already mentioned in intro. Mention also bluetooth tracking, but bluetooth is not so ubiquitous and our principles apply also if bluetooth was used (right?)

Finally, none of the mentioned work uses our approach of modeling the position of an individual as a probability distribution; our method is designed to attack the problem of having a dense crowd; we are not interested in precise estimations for freely moving crowds; rather, we are interested in obtaining precise estimation when the concert crowds is dense and static due to this. blah blah (sonja: explain better)

***********************************end from Sonja

2 Positioning of visitors using Wi-Fi sensors and smart phones

3 From positioning to estimation of density

3.1 Issues with positioning (title to reconsider)

3.2 Addressing the issues: real-time crowd density estimation

- The method we use is similar to Kernel Density Estimation, but what we are doing is not actual smoothing (?).

To construct two-dimensional probability density functions we apply non-parametric density estimation. To make density histograms we consider a two-dimensional binned region of space, and count the number of positions that fall into each bin. For each bin location X, in the time interval t, we apply the kernel density estimation (KDE) method [4][5] given by

$$\hat{d}(X,t) = \frac{1}{N}\sum_{i=1}^{N} K_{h_x}(x - x_i)K_{h_y}(y - y_i) \tag{1}$$

where K_{h_u} is the kernel function $K_h(u) = K(u/h)/h$, h is the smoothing parameter, or bandwidth, and N is the number of data points (positions) in the time interval t.

The bandwith parameter h is crucial for the accuracy of the density estimate. Several theoretical approaches are possible. Here we base our choice of kernel bandwidth values h on the error values (σ_x, σ_y) provided by the positioning methods (see Section).

3.3 Real-time data analysis

To process positioning data in real-time during events, we consider data within a specific moving time window. To take in account that visitors are moving, we subdivide the time window in multiple sub-windows and attach more weight to measurements in later sub-windows. The weighting scheme is given by

$$\hat{d}(X,t) = \frac{w_1\hat{f}(X,t_1) + w_2\hat{f}(X,t_2) + ... + w_m\hat{f}(X,t_m)}{w_1N_1 + w_2N_2 + ... + w_mN_m} \tag{2}$$

where $\hat{f}(X,t)$ is the non-normalized sum of smoothed counts $(N \times \hat{d}(X,t))$ in Equation 1, w_k is the weight value given to sub-window k, and m is the number of sub-windows.

3.4 Validation

- Simulation?
  Do we include simulation of the positioning process, i.e. the toy Monte Carlo simulation, or do we generate fitted positions with error values, and only test the density estimation methods?

4 Related work

Wirz *et al.* (2012) [9] infer crowd density from GPS location traces of people who use an App during the 2011 Lord Mayor Show in London. They visualize the data in real-time, and generate heat maps (dynamically) using the kernel density estimation (KDE) method. In (Wirz *et al.* 2013) [10] the methodology is presented more elaborately, using a real-world data set collected during the same festival. The relation between the number of App users and the crowd density is calibrated (using linear regression), which forms the basis of their participatory sensing method. The accuracy of the smoothing method is assessed using ground truth crowd density information obtained from video footage recorded by CCTV cameras. The influence of the kernel radius on the correlation between the actual density and the density of App is analysed.

The Gaussian weight function used in (Wirz *et al.* 2012; 2013) [9][10] is introduced in Helbing *et al.* (2007) [2] to estimate local densities in an area captured by video cameras during the Hajj in

Mina/Makkah in 1426H on January 12, 2006.

A number of studies use Bluetooth to estimate crowd densities at a wide range of places and events. In these studies the position of a mobile phone is approximated to the location of the sensor by which it is detected.

Schauer *et al.* (2014) [3] count unique MAC addresses detected by two sensors (nodes) at both sides (public and security) of a security check inside a major German airport, to estimate pedestrian densities and pedestrian flow. They consider time information, to determine the direction of a person's movement, and at least one RSSI value, to reduce the number of false positives in case devices are captured by both sensors. They compare Bluetooth and Wi-Fi based methods, and compare their methods to a known ground truth provided by the number of security checks.

Versichele *et al.* (2012) [6] use Bluetooth scanners at strategic locations during the 10-day Ghent Festivities, to analyze spatio-temporal dynamics of pedestrians.

Yoshimura *et al.* (2016) [11] use Bluetooth detection to analyze visitors' behavior at the Louvre museum in Paris.

Delafontaine *et al.* (2012) [1] use a similar approach (of Bluetooth tracking) and apply (genetic) sequence alignment methods to analyze the resulting data which consists of different sequences of sensors (nodes) for detected mobile devices.

Weppner and Lukowicz (2013) [7] estimate crowd densities during a soccer European championship public viewing event and during the Oktoberfest, by distributing volunteers in the crowd, who are carrying smart phones scanning for Bluetooth devices. They then use statistics to combine the different measurements in space and time.

In Weppner *et al.* (2014) [8] similar methods are applied to a city-wide festival in Zurich 2013, now supported by GPS data.

5 Conclusion

References

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