HOW TO MEASURE STATIC CROWDS?
- Monitoring the number of pedestrians at large open areas by means of Wi-Fi sensors

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INTRODUCTION

In order to effectively apply crowd management measures, knowledge on the state of the crowd is essential. If one knows when and where large crowds are expected and how these crowds feel and behave at that moment in time, one can better assess which measure will most effectively guide the dynamics of the crowd in the intended direction. Yet, current crowd management solutions provide a limited qualitative assessment of the situation.

Crowd monitoring systems provide a state-of-the-art solution to objectively and accurately manage large crowds (e.g. *1-8*). Many other studies are currently identifying the opportunities of digital sensor systems for traffic state estimation regarding other modalities (e.g. *9– 17*).

Even though crowd monitoring systems are already readily applied to current crowd management challenges, the validity of the sensor information is often not yet determined. Consequently, it is currently unknown whether Wi-Fi sensors can be used to identify the amount of pedestrians within a certain region with certain accuracy.

The objective of this study is to determine to what extent Wi-Fi sensors can be used to provide an indication with respect to the amount of pedestrians that is present at an open area. An operational field study is performed at a large-scale event in the Netherlands in order to assess this new application of Wi-Fi sensors. During this event Wi-Fi sensors, counting systems and cameras were used to identify the amount of pedestrians nearby the main attraction point of the event.

MEASURING CROWD DENSITIES BY MEANS OF WI-FI SENSORS

The Wi-Fi sensors used in this research are passively listening to the wireless signals in their direct environment and determine some characteristics of the devices that send out these signals. For each signal, the Wi-Fi sensor that is used for this study determines several pieces of information, among other things, a hashed MAC-address of the Wi-Fi enabled device and a timestamp.

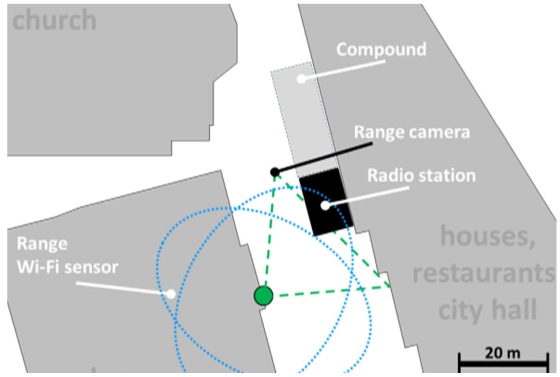
The list of hashed MAC-addresses, in combination with the timestamp at which these addresses were received, is used to determine the number of number of that were present in the vicinity of a certain Wi-Fi sensor. Several actions have to be undertaken to ensure the best possible count of the number of Wi-Fi devices in the area, namely:

1. Select the MAC-addresses in the database within a certain time interval (3 minutes).
2. Exclude stationary devices based on often reoccurring MAC-addresses.
3. Filter the MAC-addresses using the hashed bssid.
4. Determine the total amount of Wi-Fi devices based on the clean list

CASE-STUDY AND VALIDATION MEASUREMENTS

Each year, in the week before Christmas a large (music) event is organized by radio stations all across Europe, named 3FM Serious Request (www.seriousrequest.3fm.nl). In 2016 the radio studio was located on the Grote Markt (large market square) in Breda, the Netherlands, opposite to the Grote Kerk (church) in front of the city hall, which was approachable for the crowd from Sunday 18th of December till 24th of December.

During this time period, two Wi-Fi sensors and a camera system were attached to the same pole which was located opposite to the radio station that recorded the number of pedestrians just in front of the radio station for all days that the event was ongoing (see FIGURE 1.a). FIGURE 1.b show an example of the images that were captured by means of this camera.



A) Location of the sensors used in the benchmark

B) Impression of crowd during a busy period

C) Impression of no. of people during a busy period.

FIGURE 1 Visualization the counting systems in the vicinity of the radio station during Serious Request 2016, a) the locations of the sensors on the Grote Markt in Breda, b) impression of the camera image c) the estimated number of people at certain locations (green - low, red-high).

For the entire run time of the event, by means of manual identification, the amount and location of pedestrians in front of the camera have been determined using snapshots from the camera each 15 minutes, which serves as the ground truth for the comparison of the Wi-Fi sensor data. The unique number of Wi-Fi enabled devices is determined for the three minutes just before the snapshot was taken.

RESULTS OF THE OPERATIONAL FIELD TEST

From the onset of the event visitors have been present in front of the radio station. FIGURE 1.d visualizes the spread of the pedestrians in front of the radio station, as recorded by the camera.

The market loaded with pedestrians from 7 AM in the morning onwards until approximately 9.30 PM in the evening, afterwards the market slowly unloaded until 6 AM the next morning. The number of spectators in the evening fluctuates heavily. Depending on the activities that were announced during the day, the peak of the demand lasts longer or shorter in the evening. Within the vision field of the camera in front of the radio station at maximum 659 people were counted.

In general, the crowding starts nearby the fences in front of the radio station. FIGURE 2.a and b illustrate that the highest density region (i.e. the region indicated in red) expands backwards throughout the day and has a reasonably uniform distribution of spectators over space. When approximately 400 or more visitors are counted in an image, the options to move through the crowd at the back of the crowd decreases.

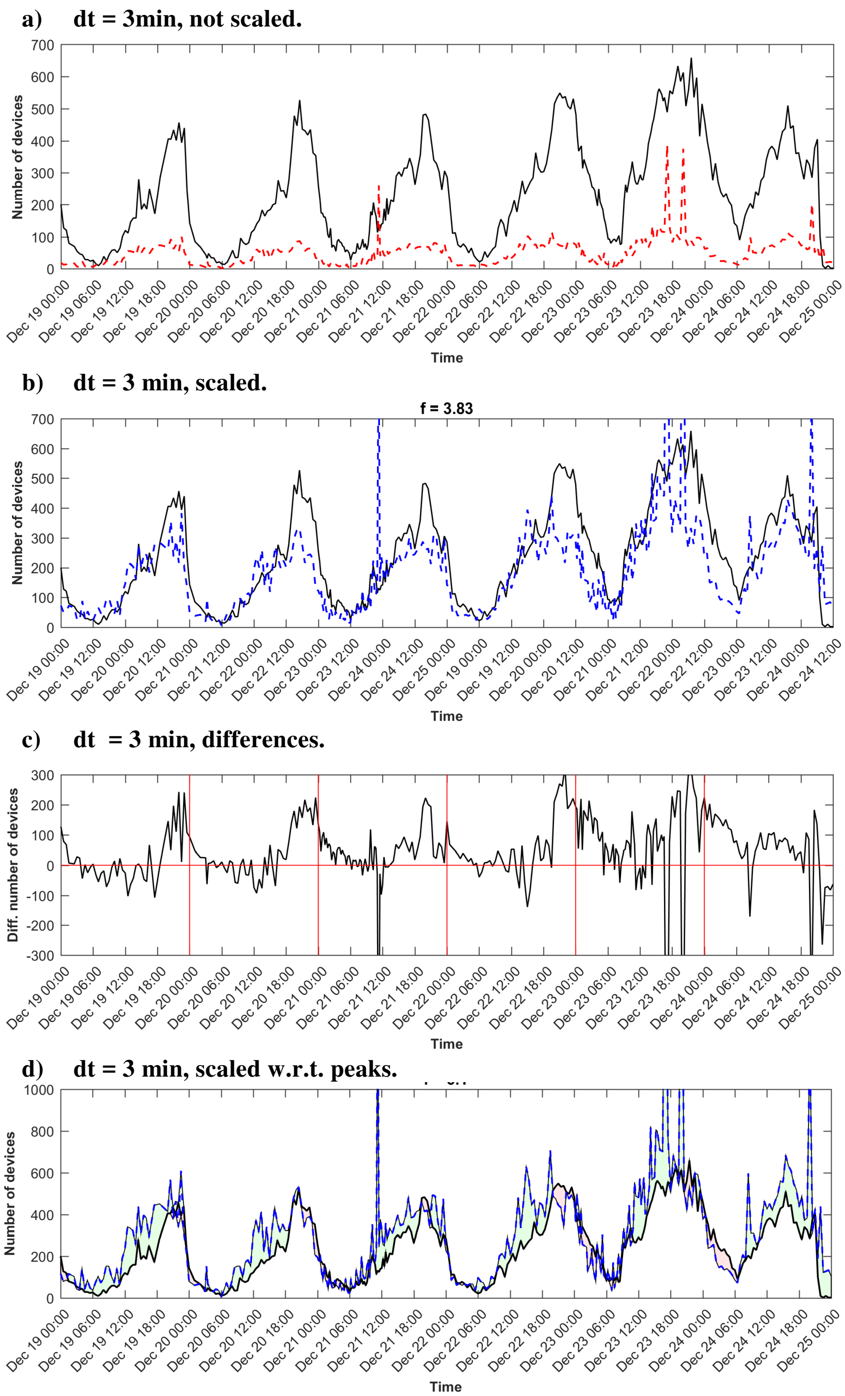


FIGURE 2 Comparison between camera counts and number of unique Wi-Fi devices, A) comparison between normalized Wi-Fi count (solid black line) and the camera count derived from the counting camera (dashed red line), B) the scaled number of unique Wi-Fi devices (dashed blue line) and C) the difference between the camera count and the scaled number of unique Wi-Fi devices and D) the scaled number of unique Wi-Fi devices while taking into account the correlation between the two types of data, where *f* identifies the conversion factor that is used to scale the data.

In FIGURE 2 several comparisons are shown between the manual counts based on the camera data and the number of unique Wi-Fi enabled devices registered by the Wi-Fi sensor. FIGURE 2.a illustrates that there is a large quantitative difference between the camera counts and the amount of unique Wi-Fi devices that are identified by the Wi-Fi sensors. The fact that the sensor does not receive signals from all smartphones might be at the root of this issue. A conversion factor (3.83) is determined as the factor that minimized the squared sum of residuals between the camera counts and the scaled version of the amount of unique Wi-Fi devices. The resulting scaled curve (FIGURE 2.b) is accordingly compared with the camera counts.

An analysis of the residuals (FIGURE 2.c) illustrates that the scaled curve mostly underestimates the amount of people on the square. Early in the morning the residuals are small and the two trends seem to coincide. Yet, during the more busy moments of the day, the scaled unique number of Wi-Fi enabled devices flattens while the camera count increases further. Given that the number of unique Wi-Fi devices during the peaks differs per day, the authors assume that the shape of the sensing area of the Wi-Fi sensors is at the root of this issue.

By means of a scatter plot the correlation between the two curves is analyzed. This analysis illustrates that a higher number of unique Wi-Fi devices correlates with a higher number of spectators on the square. The correlation coefficient ($\rho = 0.6782$, $p \ll 0.01$) of the two curves (i.e. camera counts and the scaled number of unique Wi-Fi devices) corroborates this fact.

The existence of the over/underrepresentation error is taken into account in FIGURE 2.d, which shows an approximation that takes into account both the conversion factor as well as the correlation coefficient. In this graph the green areas represent the times at which the information from the Wi-Fi sensor overestimates the number of pedestrians, while the red areas represent the times at which the information from the Wi-Fi sensor underestimates the number of pedestrians. The figure illustrates that the number of spectators on the market square is indeed better captured when incorporating the over/underrepresentation error.

CONCLUSION & FUTURE RESEARCH

This paper studied the application of Wi-Fi sensors to monitor the number of pedestrians that are present at an open area during an event. The analyses show that the number of unique Wi-Fi enabled devices that send out a signal in the vicinity of the Wi-Fi sensor is indeed a good indicator for the amount of pedestrians that are present in an open area. Next to that, this study illustrates that Wi-Fi sensors can be used to quantitatively determine the amount of pedestrians within a certain area. Moreover, Wi-Fi sensors can, given that these sensors are calibrated and validated for the situation in which they are being used, provide a quantitative estimation of the number of people that reside within a certain area.

This study, however, also indicates that there are limits with respect to the inferences that can be made using this indicator. Most importantly, this study reveals that a good filtering algorithm is essential in order to filter out the noise. Moreover, it is essential, to reevaluate the conversion factor and over/underrepresentation error for every new instance where the Wi-Fi sensors are used. Next to that, the authors expect that shifts in population between weekdays and weekends will influence the conversion factor and the over/underrepresentation errors.

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