Exploiting Density to Track Human Behavior in Crowded Environments

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Abstract

For the Internet of Things to be people-centered, *things* need to identify when people and their things are nearby. In this paper, we present the design, implementation, and deployment of a positioning system based on mobile and fixed inexpensive proximity sensors that we use to track when individuals are close to an instrumented object or placed at certain points of interest. To overcome loss of data between mobile and fixed sensors due to crowd density, traditional approaches are extended with mobile-to-mobile proximity information. We tested our system in a museum crowded with thousands of visitors, showing that measurement accuracy increases in the presence of more individuals wearing a proximity sensor. Furthermore, we show that density information can be leveraged to study the behavior of the visitors, for example, to track the popularity of points of interest, and the flow and distribution of visitors across floors.

1 Introduction

Measuring and tracking the behavior of individuals is central to the implementation of an Internet of Things (IoT) that is *people*-centered. To this end, it must be possible to identify when an individual is positioned in proximity to an object, at a point-of-interest, or in front of another person [1].

We analyze the use case of a museum. In a museum, people proximity-aware applications could enable museum staff to make sure that visitors can approach all exhibits and information without congestions and clogging, that they have access to all resources such as restaurants, restrooms and lockers when needed, and that they do not experience queues and waits that are too long, as well as to understand which artworks individuals stop at.

A common approach to monitoring visitor behavior is to compute the *positioning* of visitors at exhibits and points of interest [2]. Here, positioning is *relative* to a point of interest, and not absolute in the coordinate space (i.e., as provided by indoor localization systems). However, as crowd density increases, sensors are known to provide more noisy, incomplete, and ambiguous data, problems that are exacerbated by complex indoor venues. Museum staff are thus left with instruments that operate unreliably in those conditions where they are most needed.

We present a MObile-Nodes-Assisted positioning system (`MONA`) that can operate at conditions of high crowd density by utilizing proximity sensing between mobile sensor nodes as well as between mobile and fixed sensors nodes. Our approach exploits the increased presence of mobile sensor nodes in the surrounding of each individual. In fact, positioning accuracy *increases* when more visitors wearing a sensor are present in the museum. `MONA` can position a visitor (i) when mobile-to-anchor proximity detections are missing and even (ii) at points of interest not instrumented with anchors.

2 Overview

2.1 Museum

The museum we study has half a million visitors per year and more than 3000 daily visitors during our experiment (we chose the day before Christmas). With a median visit duration of three hours, the museum can present crowded scenarios with peaks of nearly 3000 people

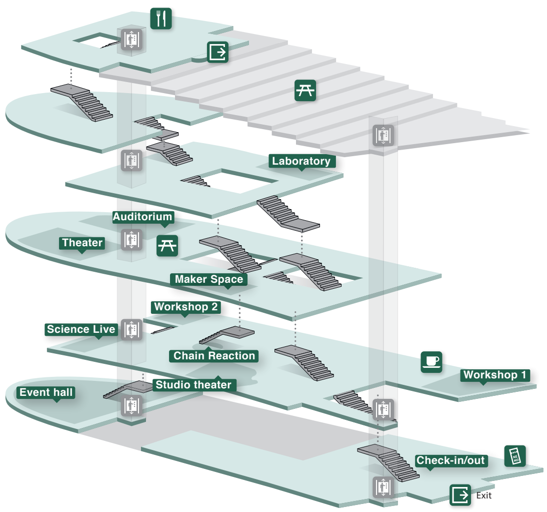


Figure 1: The map of the museum.

visiting at the same time. Approximately 25% of all visitors participated in our experiment, with a peak of around 600 participants at a single moment in time.

Our museum is an open six-story area. The first four stories share a large hall in the middle connected by several stairs, with floors 3 and 4 that are effectively balconies projected over the underlying stories. With this layout, network links spanning over multiple floors are common. Figure 1 shows the 3D map of the museum.

Exhibits can comprise multiple items within a radius of approximately 3-4 meters.

The museum curators were interested in three types of information: (i) the popularity of a set of points of interest and exhibits, (ii) the distribution of visitors across the floors, and (iii) the flows of people between floors.

2.2 Sensing infrastructure

To collect positioning information, visitors were asked to wear a *bracelet* equipped with a 2.4GHz transceiver and a microcontroller running a neighbor discovery protocol with a sampling rate of 1 Hz. Note that we used bracelets devices as they were most suitable solution to our prototype environment and setup, as opposed to mobile phones, but nothing of the technique presented in this work is bound to this particular device and, in principle, it could be implemented with BLE on mobile phones.

Anchors. For each point of interest (PoI), an *anchor* device was installed. These devices had the same hardware as the bracelets. They were externally powered so that it was possible to run the neighbor discovery algorithm with longer duty cycles, increasing the probability of a PoI to be discovered by bracelets. As a result we were able to discover bracelets in the range of a PoI in just a few seconds.

Every second, bracelets could receive broadcasts from anchors or other bracelets within a distance of some 5-7 meters. Such broadcasts contain the unique identifier (ID) of the sender, and we consider the reception of such broadcast as a *proximity detection* between the two nodes involved. Bracelets recorded together with the ID of the other node also signal strength information about the broadcast.

Sniffers. Once every second, bracelets reported the proximity detections collected during the previous second via a special packet sent on a dedicated channel to the backbone of the system consisting of the *sniffers*. Like anchors, sniffers used the same hardware as bracelets in addition to a single-board computer that used either wifi or ethernet to commit the packet to a central database hosted on a server. The sniffers were placed uniformly in the museum to cover all areas, with some overlap.

Due to packet size limitations at the MAC layer, each sniffed packet could report up to three detections, favoring two anchors and one bracelet when possible. The resulting dataset contained more than 6 million anchor-to-bracelet and bracelet-to-bracelet detections, together with timestamp and signal strength information.

3 Related Work

There is a large body of work regarding indoor localization and positioning with mobile sensors.

In the case of museums, earlier works focus on localizing visitors at very coarse-grained levels (room level) through technologies like Bluetooth [3] to support multimedia guides [4]. More recently, proximity sensors have been used together with "physiological" sensors to classify the behavior of visitors [5].

Computer-vision techniques are an alternative approach to tracking human mobility [6] and detecting anomalies in a crowd [7]. However, cameras can suffer from poor lighting, and temporary or permanent obstructions [8]. Also, fusing the views from multiple cameras in a highly dynamic indoor scenario is challenging [9]. Finally, the privacy issue of collecting large-scale footage of visitors often restricts researchers from accessing these sources of data.

Alternatively, we can localize the absolute position of an individual. While this technique is a feasible option in outdoor scenarios – where the GPS system can be exploited – for indoor conditions accurate localization is still an open problem.

Among the wide literature of radio-based localization techniques, only few [10, 11, 12] are accurate enough to be employed in museum scenarios. Unfortunately, none of these techniques perform consistently throughout the museum areas as localization error increases significantly at the edges of rooms and in hallways. By installing anchors specifically at exhibits and objects of interest, we limit this problem drastically. For our tracking application, this phenomenon can be even more problematic, since even small estimation errors could lead to visitors being associated to the wrong exhibit, positioned in the wrong room or placed on the wrong floor.

We borrow some ideas from the field of cooperative localization [13], in which nodes share measurement information in a peer-to-peer manner. We trade the advantages of deploying algorithms that can be computed in a distributed manner by the nodes "in-the-network" with the more global view provided by collecting and managing this data from a central repository. This aspect is particularly useful in high density scenarios, where packet loss increases, potentially hindering cooperative approaches.

Finally, many of these approaches are usually tested outside of the extreme conditions of high mobility and density of a complex real-world museum as the one subject to our study. For a more detailed discussion of related work, also in the specific context of museums, we refer the interested reader to previous work [2].

4 Model

We consider N visitors $V = \{v_1, v_2, \ldots, v_N\}$. While bracelets have their unique IDs and were re-used during the experiment, each element in V has a unique ID assigned at check-in, and we use these IDs for detections. The museum has O points of interest $I = \{i_1, i_2, \ldots, i_O\}$ and M anchors $A = \{a_1, a_2, \ldots, a_M\}$. In the simple case where each anchor is assigned to a PoI, $I \equiv A$. We consider S the set of proximity sensors $S = V \cup A = \{s_1, s_2, \ldots, s_{N+M}\}$, as the union of detectable anchors and visitors. We define the series of proximity detections for a visitor v as a $S \times T$ matrix D_v, where $D_v(i, j) = r$ if the proximity sensor of visitor v detected sensor s_i at time j with signal strength r. Note that D_v has $N+M$ rows, as it comprises all proximity sensors, either used as anchors or worn by other visitors. $D_v(*,t)$ refers to all detections collected at any time t, and $D_v(i,*)$ to all detections of sensor s_i. Moreover, we define a positioning matrix M_v as the $O \times T$ matrix where $M_v(i, j) = 1$ if the visitor was at a distance shorter than d from PoI i at time j. Note that there can be times where a visitor is not positioned at any PoI, and that a visitor cannot be positioned at more than one PoI at the same time (when a visitor is within d distance from multiple PoIs, we choose the closest).

Our goal is to produce the positioning matrix M_v starting from the series of detections in D_v. In principle, in the case of $I \equiv A$ and with perfectly working sensors (i.e., with signal strength correctly mapping to distance and no inter-floor detections) we could use D_v to generate directly M_v by assigning a visitor to the anchor detected with highest signal strength, and computed to be at distance shorted than d. As the visitor walks around the museum, we would generate contiguous series of "bits" in M_v reflecting the intervals of proximity with the anchors and PoIs. However, in real-world scenarios we need to take into account *missed* as well as *spurious* detections, caused for example by interferences, walls, people, and the nodes themselves.

5 Particle filter

We designed and implemented a particle filter that takes into account the topology of the museum, the location of anchors and PoIs, and the estimated location and movement of the visitors. Particle filters have been used in indoor localization to estimate the absolute position of individuals with unreliable sensors [14, 15]. For localization, usually a mobile sensor communicates with a few anchors installed at known locations. It is assumed that the sensor can communicate with all, or a majority of, anchors from all positions and directions, and that the sensor can measure distance from these anchors, for example, through signal strength or time-of-flight. Our setup is more complex, as we have a larger number of anchors that are detectable at shorter distance, and a number of detections from proximity sensors at *unknown* locations, i.e., the visitors, together with a multi-story venue.

The filter requires topology information about the museum, such as the sets of anchors A and PoIs I, each defined by a triple f,x,y with f being the floor number and x,y the coordinate within that floor, and a set of walls $W = \{w_1, w_2, \ldots, w_M\}$, each defined as a segment between two points. Every floor is modeled as a distinct two-dimensional space, with an independent origin. As floors are connected by a number of different stairs and elevators, it is difficult to model the transition spaces between floors reliably. Instead, we assume a visitor can "appear" at a certain floor and model this transition confidence in the filter, based on the measurement. For each visitor we define a set of particles $P = \{p_1, p_2, \ldots, p_K\}$, each defined by a tuple f,x,y and a weight w that models the likelihood of the visitor to be at that coordinate. Initially, particles are spread uniformly at random across the museum floors.

For each time of the day $0 \leq t < T$, the following four steps are executed for each visitor checked-in at that time, given the respective detection matrix D_v.

- **Estimation**: At each time, we estimate the floor the visitor is positioned at, if any, by computing the floor with the largest number of particles, given enough confidence is provided by the particles. Then, we compute the likelihood of each particle's estimate (i.e., its position) given the measurement at time t, that is the set of detections in D_v contained in the t-th column. For each particle p, the weight is updated using the likelihood function $\Phi(p, D_v(*,t))$. We return to details below.
- **Positioning**: We estimate the position of v by computing the weighted average among the floor's particles (i.e., *the centroid*) and find the closest PoI i_i on the floor within distance d. We then set $M_v(i,t) = 1$, unless the confidence of the estimate is smaller than a threshold δ.
- **Re-sampling**: We create a new set of particles by drawing with replacement from the current weighted set of particles. While drawing particles from the set, we favor particles proportionally to their weight (i.e., their likelihood). As a result, particles with higher likelihood are picked more often than particles with lower likelihood. Depending on the confidence in the current set of particles, we may choose to (i) pick only from the particles in the current floor, (ii) additionally spread particles with smaller likelihood across other floors, or (iii) re-distribute all particles across all floors (i.e., when we believe we have lost track of the visitor). More details follow below.
- **Movement**: We move particles at walking speed in random directions, avoiding illegal moves, such as walking through walls.

Compared to previous work on positioning [2], the two steps where we focused most of our efforts to tailor the filter for our use-case are the estimation and the re-sampling steps. Those steps were redesigned to (i) include mobile-to-mobile detections, (ii) consider multi-floor environments, (iii) support PoIs without anchors and anchors not associated to PoI, and (iv) omnidirectional sensing with signal strength.

In general, we can compute the confidence of the particles' centroid by measuring the dispersion of the particles and the amount of time spent without collecting any detection from a sensor located on the same floor as the visitor. We consider the visitor to be at the floor with the largest number of particles, normalized by floor sizes, given enough confidence. Note that having a visitor assigned to a floor does not mean we position the visitor at any PoI, as that depends on the position of the particles within the floor, their likelihood, and dispersion.

The likelihood function $\Phi(p, D_v(*,t))$ computes the likelihood of particle p given the set of sensors detected at time t that were positioned *on the same floor* as p. In Φ we consider both anchors, of which we know the location, and neighbor visitors, for which we use the centroid computed at time $t-1$. In other words, we use neighbor visitors as anchors. We consider neighbor visitors only if we are confident enough of their centroid.

Intuitively, the likelihood of a particle depends on the particle's distance from a reference point proportionally to the strength of the detections. This reference point can be a single sensor or an average across sensors. We first map signal strength values to the $(0,1]$ continuous interval by means of a Gaussian kernel[1]. Then, if multiple sensors were detected, we compute the average coordinate across these sensors' coordinates weighted by the respective signal strength, and use the particle's distance from this average coordinate. We use a linear kernel to map distances to $(0,1]$.

If only one sensor was detected, instead, we compute the difference between the signal strength value and the particle distance from the sensor (both mapped to $(0,1]$) and use this difference.

When we update particle weights and re-sample the particles, we proceed depending on the centroid confidence c as follows (the two thresholds δ and δ' to be chosen empirically).

[1]Signal strength decreases non-linearly with distance

- $c > \delta$: This means we know the visitor is on the floor. We ignore the likelihood of particles from other floors, practically "teleporting" these particles from other floors to the current one.
- $\delta' < c \leq \delta$: This means we are starting to believe the visitor may have left the floor. We spread particles with smaller likelihood from the current floor to other floors.
- $c \leq \delta'$: This means we have lost the visitor completely. We re-distribute particles uniformly at random across floors.

As a visitor moves around a floor, particles spread towards areas that are more likely to have produced the current measurement. As the visitor moves to a new floor, absence of detections on the previous floor causes particles to disperse until we start spreading particles on the other floors, including the new one.

Finally, we apply a density-based filter and a majority-voting filter to account for particles "jumping" between between PoIs and floors [2].

6 Evaluation: setup

Before the 3-days main experiment, we conducted a *controlled* experiment scripting a visit of the first floor while the complete sensing infrastructure in the museum was turned on. The script defined arrival and departure times at each PoI. Originally, the first floor had all PoIs associated with an anchor, and one additional anchor to improve positioning accuracy. To test the ability to position visitors at PoIs without anchors, we added to the script three "virtual" PoIs not associated with any particular exhibit or anchor (that is, solely defined by a coordinate in space). In addition, one PoI with an anchor was *not* used in the script, but the anchor was turned on and hence could affect accuracy.

Together with the scripted visit, we distributed 15 bracelets around each interested PoI area within a radius of some 15-20 meters from the respective anchor (or virtual PoI coordinate), at 1 meter of height, and moved them at random across the space for the whole duration of the stop. This setup allowed us to control bracelet density and movement, and at the same time minimize external factors like body shielding effects (which were tested during the real-world experiment). Each stop lasted eight minutes, divided in four periods of two minutes. During the first periods only the visitor's bracelet was on, while during the following 3 periods we turned on the additional bracelets, in groups of 5 per period.

To evaluate real-world accuracy, for the duration of the main experiment we positioned 5 bracelets at known locations at PoIs, and additionally scripted a visit of the whole museum of the duration of around one and a half hours with 14 stops of the duration of around 5 minutes each (hence, not all time was spent at PoIs). Also for this scripted visit, we added a number of "virtual" PoIs such that the visitor did not stop at PoIs associated with an anchor, except for the stops at the restaurant and the live attraction called "Chain Reaction".

For both experiments, we set filter parameters to the same values.

To measure the performance of our solution at the task of positioning visitors at PoIs, we compute the number of false/true positives and negatives, and with these we compute the *sensitivity* (or true positive rate, also known as recall) and *specificity* (or true negative rate, or negative class precision) for each PoI.

We implemented the filtering pipeline with less than 1000 lines of Python code. By implementing the filters with vectorized SIMD operations and leveraging linear algebra libraries like numpy[2] and a just-in-time compiler with numba[3], our pipeline can manage in real-time (i.e., sub-second compute time to process 1 second worth of data) peak-time data with a single thread executed on a ultra-low power laptop[4]. The pipeline can be easily ported to multi-cores and even GPUs for very large crowds.

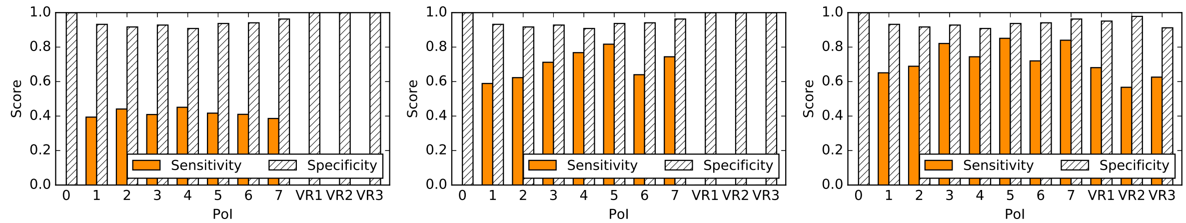
7 Results

7.1 Controlled experiment

We test our technique against an approach where we position the visitor at the anchor/PoI detected with strongest signal strength. As this technique is subject to missed detections and noise, we additionally extend it by making positioning decisions over a sliding window of 10 seconds. Figure 2 presents the sensitivity and specificity of each anchor/PoI for the two techniques as well as for `MONA`. Note that for this test, we compute values for `MONA` only for the first period, that is we position the visitor *solely based on anchor detections*.

One can notice that raw data suffers from missed detections, yielding an average sensitivity that is around

[2] http://www.numpy.org/
[3] http://numba.pydata.org/
[4] Provided with a mobile 1.2Ghz Intel Core M CPU



(a) Strongest RSSI (b) Smoothened Strongest RSSI (c) `MONA` (anchors only)

Figure 2: Positioning accuracy during the controlled experiment at the PoIs on the first floor and three additional "virtual" PoIs not instrumented with an anchor. We compare our technique (not using here mobile-to-mobile proximity) to a technique that positions the visitor at the anchor with strongest signal with and without a rolling window. The combined balanced accuracy, defined as the arithmetic mean between average sensitivity and specificity, for the two competing techniques and `MONA` (anchors only) were 0.62, 0.69, and 0.81 respectively.

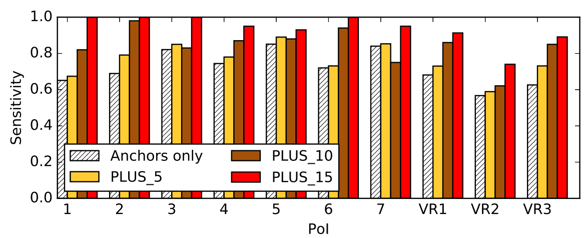


Figure 3: Impact of neighbor bracelets around a visitor on the first floor. We added 5 more bracelets in the surrounding of the visitor every 2 minutes of each stop.

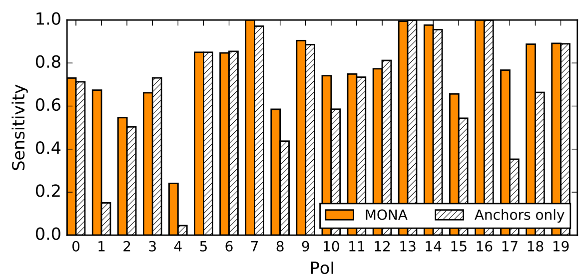
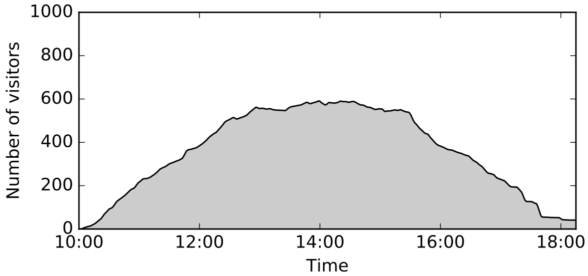


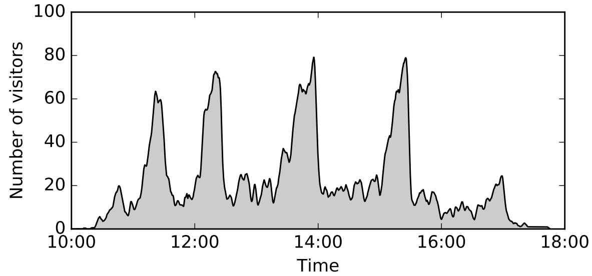
Figure 4: Positionings accuracy of our system with `MONA` and without it during the real-world experiment. Only PoIs 7, 9, 13, 14, 16, 19 were instrumented with an anchor. The average sensitivity was 0.68 and 0.77 respectively.

40% the sensitivity obtained when smoothening the decisions over a window (0.42 and 0.68). As expected, specificity is close to the maximum value of 1, as it is difficult to wrongly position a visitor at a PoI far away with a controlled transmission range. Looking at the results of `MONA` (anchors only) one can notice a relative improvement in average sensitivity of over 5% (from 0.68 std. 0.34 to 0.72 std. 0.26), compared to the smoothened technique, but the most interesting result is the impact on positioning at virtual PoIs (impossible with the other techniques). This is due to the spatial nature of the filter and it is one of the main contributions of the filter compared to the smoothed filter.

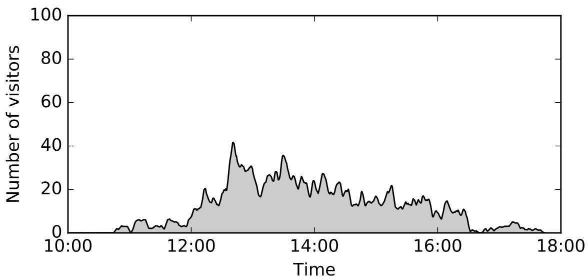
Figure 3(a) presents the sensitivity results when `MONA` takes into account also detections of neighbor bracelets to position both the visitor and the neighbor bracelets. We do not present specificity values here as they are consistently close to 1 as in Figure 2. One can notice that adding mobile node proximity information improves positioning ability reaching a value of (or close to) 1 when 15 additional neighbors are used, with an average relative improvement between using only anchors and including 15 neighbors of around 30% (from average sensitivity of 0.72 std. 0.09 to average sensitivity of 0.94 std. 0.08). The improvement is slightly worse in the case of virtual PoIs (in particular VR2), but note that here we leveraged the anchors used for the other PoIs (except for only an additional anchor). Moreover, more data points (i.e., visits) should yield more consistent results (e.g., for PoI 7 and 3 adding 10 bracelets yields worse results than using anchors only). Finally, one would expect a slightly lower impact in the real world, where body shielding effects and other irregularities would influence mobile-to-mobile detections.



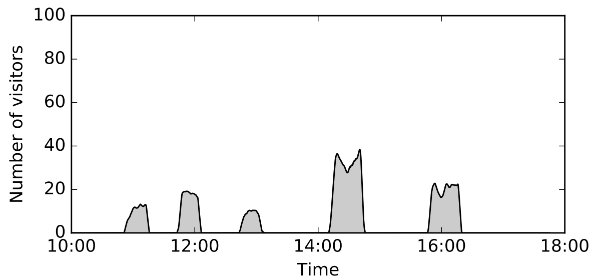
(a) Checked-in devices



(b) Chain Reaction



(c) Restaurant



(d) Auditorium

Figure 5: Number of individuals positioned at different PoIs over time. (a) The number of visitors wearing a bracelet during the day (experiment participation was around 25%). (b) The Chain Reaction PoI. Events started at 11:15AM, 12:15PM, 2:45PM, 3:15PM and 4:45PM for the duration of about 15 minutes. (c) The restaurant at the top floor. (d) An Auditorium open to the public only in 5 occasions during the day.

7.2 Real-world experiment

Figure 4 presents a comparison of sensitivity values, for both the stops of the scripted visit and for the 5 bracelets installed at PoIs, when mobile-to-mobile detections are used and ignored for positioning. Note that 13 out of 19 PoIs are virtual, hence they represent the hardest task for `MONA` (i.e., only PoIs 7, 9, 13, 14, 16, 19 represent stops at actual PoIs instrumented with a dedicated anchor). One can notice that `MONA` produces a relative improvement in average sensitivity of over 13% (from 0.68 to 0.77), though for a few virtual PoIs the performance is lower. Again, more data points should produce more consistent results.

A main reason why we do not always see a strong impact as presented in Figure 3(a) is due to the "sampling" effect of the real-world experiment. Considering that "only" 25% of the visitors were wearing a bracelet, the chances to leverage mobile-to-mobile proximity detections are reduced. This is aggravated by that fact that in the first and last part of the day crowd density is lower, as fewer visitors are in the museum. Most importantly, at each second bracelet often report only one neighbor visitor, as bracelets favor reporting two anchors out of three detections when possible. Combined with the fact that only 25% of the visitors were wearing the bracelet and not necessarily all the places in the museum were very dense at all times, we would expect a higher impact by increasing the number of reported neighbors (the current value of three was due to limitations to the packet size of the current implementation and can be increased in future versions).

8 Application

8.1 PoIs "popularity" over-time

Because at each time we know which visitors are positioned at which PoI, we can estimate how many individuals are visiting a PoI. In Figure 5(a) we present the number of checked-in devices during the day. One can notice that peak-time is between 1PM and 3:30PM, with around 600 visitors wearing a bracelet (and around 2400 individuals overall in the museum). Figure 5(b) shows

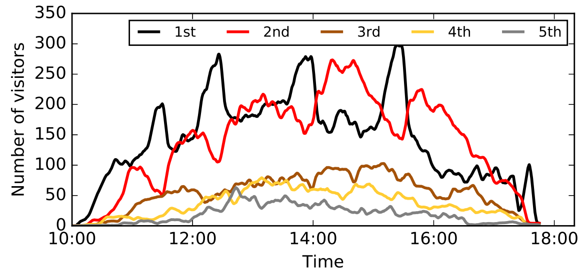


Figure 6: Distribution of visitors across floors over time.

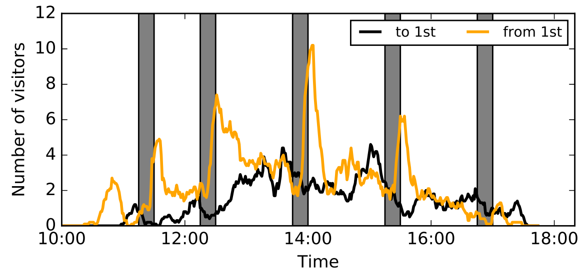


Figure 7: Flow of visitors *from* and *to* the first floor.

the number of individuals spending at least two minutes at the popular "Chain Reaction" (CR) events throughout the day. A CR event takes place in the middle of the museum hall and is widely announced. They took place at 11:15AM, 12:15PM, 2:45PM, 3:15PM and 4:45PM for the duration of about 15 minutes. One can notice that CR events have the typical footprints of crowded events. First, in the *build-up phase*, density gradually increases during the minutes before the event, as people either stop-by or approach the event location in advance. Then, the event takes place and density remains more or less constant. Finally, in the *break-up phase*, density decreases quicker, as all individuals leave the event location for another PoI.

Figure 5(c) shows data for the restaurant at the top floor. For this data, we aggregate positioning information for all the anchors at that floor, as the restaurant covers the whole space. Here, one can notice that lunch time peaks between 12:30PM and 1PM, but decreases gradually, as it is used by families for breaks at the end of the visit, enjoying the view from the rooftop. Figure 5(d) presents data for the Auditorium. The Auditorium is a closed theater space, that is open to the public only during scheduled events. For this reason, one can notice no visitors outside of scheduled shows and a less gradual build-up phase.

8.2 Crowd distribution across floors

Figure 6 shows the number of individuals at each floor throughout the day. First, one can notice how the CR event greatly influences the distribution of visitors across the first two floors and also at the third floor. When the CR event takes place, we can see corresponding peaks at the first floor and dips at second floor (and smaller dips even at third).

Second, one can notice that the "popularity" peak of floors happen at different times of the day depending on the floor. The first floor hosts more people during the first half of the day, while second floor peaks around 2PM, and third floor around 3PM (and the fourth floor has very few visitors at all before 12PM). This is because the building is built to be visited somehow in order floor after floor, though visitors are not obliged to do so. Again, the fifth floor hosts the restaurant and has a different pattern.

8.3 Flows between floors

Figure 7 shows the number of visitors moving per minute *from* and *to* the first floor in particular. We compute this by considering only visitors that remain on the floor for at least 10 minutes (hence filtering out visitors just passing by). One can notice again that CR events, in gray, dominate the pattern. Small peaks in the movement to the first floor appear at the minutes before CR events, while higher and more sudden peaks appear in the movement from the first floor right after the event (again, the footprints of build-up and break-up phases). As stairs to the second floor are positioned right besides the CR event location, visitors tend to move to the second floor right after the event finishes.

9 Conclusion

In this paper, we have presented the design and evaluation of a positioning system that leverages mobile-to-mobile proximity sensing to overcome missed mobile-to-anchor detections due to high crowd density. We have shown that our approach is able to increase positioning accuracy when more visitors wearing a proximity sensors are present in the museum. The museum where we conducted the study presented extreme conditions of density and challenging conditions due to a complex multi-story open space. We have tackled these challenges by tailoring a filtering pipeline to our use-case. Yet, the approach is general and applicable to any proximity sensing technology that is able to detect neighbor sensors with and an estimate of distance.

Moreover, we have used the data to gain insights about the behavior of the visitors during the experimentation days. The insights show a clear behavioral trend, opening new questions regarding how museum staff can integrate such an approach in their work. The work we presented is however not limited solely to the use-case of a museum, but it is applicable to the general problem of indoors crowd monitoring.

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Biographies

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MAARTEN VAN STEEN is professor at the University of Twente, where he is scientific director of the university's ICT Research Institute CTIT. He is specialized in large-scale distributed systems, now concentrating on very large wireless distributed systems, notably in the context of crowd monitoring using gossip-based protocols for information dissemination. Next to Internet-based systems, he has published extensively on distributed protocols, wireless (sensor) networks, and gossiping solutions. Maarten is associate editor for IEEE Internet Computing, field editor for Springer Computing, and section editor for Advances in Complex Systems. He authored and co-authored three textbooks, including a highly successful book on distributed systems, as well as an introduction to Graph Theory and Complex Networks.

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