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MODELLING MICROSCOPIC PEDESTRIAN MOBILITY USING BLUETOOTH

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Abstract: Emergence of Bluetooth tracking technology for event monitoring is currently applied to extract individual pathways, movement patterns or to rank popularity of locations by their visitor quantities. The next steps are to achieve short term movement predictions, to understand people's motivations and to come up with microscopic traffic values. This work proposes a solution for these questions, namely, the combination of recorded values with a microsimulation. In our presented framework, simulated pedestrians move from one decision area to the next one in a navigation graph. The graph is automatically generated from the facility based on the inter-visibility of the exits. Intermediate areas are inserted if needed. With the data obtained from the Bluetooth scanners, individual pathways of pedestrians are determined. The routing algorithm will then use those information to adjust the pathways of the agents in the simulation. An accurate reproduction of pedestrian route choice in a complex facility is expected.

1 INTRODUCTION

Major public events as concerts and soccer matches which attract thousands or billions of visitors are on one hand a great chance for street marketers and advertisement companies but on the other hand also a growing financial risk for the organizers and a safety hazard for the guests themselves, due to huge expenses and high visitor densities. Understanding the movement behaviour, identification of attractors and distractors, determination of waiting times, as well as localization of congestions and bottle-necks gives insights on visitor preferences and motivations during a particular event. Knowing such detailed information on visitor behaviour helps not just at the next similar event, but is also a location-based performance indicator for the event itself. Various locations and attractions can be ranked by their popularity, safety or frequency. Currently used technologies to measure these highly needed microscopic movement values are surveys and video surveillances. Whereas the first solution (surveys) is expensive and hardly representative due to the non-random sampling among all visitors the second one (video surveillance) depends on weather, brightness and density of the people and does not seldom require special scaffoldings to carry the cameras.

Within this work we propose a novel four stage approach to monitor microscopic pedestrian movement during events. Our system is cheap, fast deployable and it is independent from the pre-existing technical infrastructure. The sensor technology we use, can be applied seamlessly to monitor indoor and outdoor movement, which offers the chance to track peoples movement during their whole stay (e.g. starting at the arrival by car, during the event and leaving again by car after the event). We utilize recently evolved, Bluetooth-scanners (Bruno and Delmastro, 2003; Fuller, 2009) to record people's presence (step 1). This is basically a mesh of radio frequency sensors of certain diameters (depending on the used Bluetooth hardware 10 m, 20m or 100m). Whenever a person with a Bluetooth enabled device (e.g. a mobile phone or an intercom) passes the footprint of a sensor, an entry is attached to a data-log storing the time-stamp, the position and a unique id for this person. Each sensor itself generates pedestrian counts. By use of multiple sensors, movement patterns and transition times are recorded. Expected representativeness is about 7 percent of the people (Leitinger et al., 2010). The technology is already widely used for performance monitoring (Hagemann and Weinzerl, 2008) which just depends on macroscopic movement values. To extend this as well to microscopic features, we adjust and apply (step 2) an agent simulation to the recorded values. The analysis returns highly granular values on pedestrian speeds, duration of stay, direction of movement and pedestrian counts. We apply the proposed methods during a soccer match at Stade de Costière in Nîmes, the achieved results will be used later on by the local firefighters and forces.

The remainder of the paper is structured as follows: Section 2 gives a brief overview on event monitoring and Bluetooth tracking systems. In section 3 our use case and the empirical data collection is described. Based on this our novel microscopic modelling method is introduced and explained by means of the soccer match use case in section 4. The paper ends with a summary and outlook in section 5.

2 RELATED WORK

Existing indoor tracking technologies are surveys and video surveillances. Whereas the first solution (surveys) is expensive and hardly representative due to the non-random sampling among all visitors, the second one (video surveillance) depends on weather, brightness and density of the people and does not seldom require special scaffoldings to carry the cameras. The need for further robust passive localization technologies pushed development of sensors that are capable to monitor people's movement. First choice is to track most popular digital gadgets: mobile phones and intercoms. Analysis of mobile network GSM (Global System for Mobile Communications) log files (Giannotti and Pedreschi, 2008) causes strong privacy objections. Besides, Bluetooth technology is an emerging technology for monitoring tasks. Recently evolved Bluetooth based mobility sensors have been used for event monitoring at the Sziget festival in Budapest (Leitinger et al., 2010). There, a mesh of six sensors has been placed at carefully selected places, having an intermediate distance from 50m to 200m. This work extracts the route choices and number of people at particular locations but does not consider any extraction of microscopic values. Besides event monitoring, also other successful indoor applications of Bluetooth scanners are described in literature. In (Pels et al., 2005) various scanners were placed at Dutch train stations to record transit travellers. In (Hagemann and Weinzerl, 2008) not only the transit travellers are monitored but, by placing sensors in public busses, also the performance of the public transport network itself. Accurate locating and following of objects within complex facilities is as well an important research topic (Hallberg et al., 2003).

So far Bluetooth tracking is used to monitor a sample of visitors and extract their route choices. In few works time-geography and movement patterns are addressed. The next data mining step is to combine recorded values with a microsimulation to (1) achieve short term movement predictions, (2) to understand people's motivations and (3) to come up with microscopic traffic values. This challenge has not been addressed in mobility mining and Bluetooth tracking literature, yet. The next sections describe our novel approach to achieve these goals.

3 PEDESTRIAN MONITORING USE CASE

Arbitrary events require a flexible, robust and easy deployable monitoring technology as they are varying in space and time. Thus, we decide for recently evolved Bluetooth-scanners (Fuller, 2009). The particular real word scenario we focus within this work is a soccer match at Stade de Costière in Nîmes, France. The stadium has 18.364 seats and expects many visitors since the local football team happened to play in the second league. We deploy a mesh of 17 sensors at the stadium in order to monitor people's behaviour and route choices. Afterwards, see section 4, we are going to build a pedestrian model using the collected data, which represents accurately route choices and pedestrian behaviour.

For microscopic event monitoring we propose a four stage process (figure 1). In step 1, *Survey Design*, basic parameters and decisions (e.g. number of sensors, sensor placement, sensor form factor and antennas) are made according to the particular application needs. Step 2 is the *Data Collection* phase during the event. Afterwards, step 3, *Data Preparation* is required. In this step recorded values become temporally aggregated to compensate asynchronous data entries. During the final step 4, *Microscopic Pedestrian Modelling* the pedestrian simulation, which is capable of route choice representation (see section 4), becomes adjusted by the recorded values.

Figure 1: Workflow for microscopic event monitoring.

3.1 Sensorplacement and Data Collection

The sensors we use contain multiple Bluetooth antennas which search simultaneously for visible Bluetooth devices within the sensor footprint. Thus, a complete scan of the frequency band is accelerated and moving people are more likely to become detected while they are crossing the footprint. Each time a Bluetooth device (e.g. smartphone or intercom) is seen a data entry is stored in a file. This log-entry consists of timestamp, sensor identifier, unique scrambled device identifier and the signal strength. The need to scramble the device identifier results from the fact that Bluetooth sensors collect privacy sensitive data. Every Bluetooth chip is identifiable by its unique Media-Access-Control-address (MAC). Hence, a Bluetooth device (respectively a person) is detectable (and therefore trackable) beyond the spatial-temporal boundaries of an event. Hence, our Bluetooth-scanners save just an anonymized identifier, valid for the time of the monitored event. To scramble the MAC-address, we embed the irreversible SHA-256 encryption algorithm (National Institute of Standards and Technology, 2002) with an event specific random seed into the sensor software. Thus, privacy of the monitored pedestrians is preserved from the very first data recording.

We use multiple of these Bluetooth-sensors, which allow re-identification of the persons at various locations. This allows recording of transition times, stay times, movement patterns and movement preferences. The sensor locations were chosen carefully. We placed one sensor at each entrance in order to record visitors at their arrival and leaving of the stadium. Additionally, sensors were place at the shops in the uppermost floor. In intermediate floor levels, we placed sensors as well at junctions. Finally, sensors which monitor people's presence during the match were place in the corridors of the tribunes. In total we placed 17 sensors but before the start of the match, two sensors were removed by vandalism. The three-dimensional sensor placement strategy is depicted in figure 2.

3.2 Data Preparation

Every single sensor runs asynchronous and the maximum time for each Bluetooth scan may easily exceed the theoretical upper bound of 10.24s (Woodings et al., 2001; Bruno and Delmastro, 2003). One reason is the noisy environment during the event. Thus, temporal filtering and spatial aggregation is necessary to get a pure dataset. Duplicate entries are removed

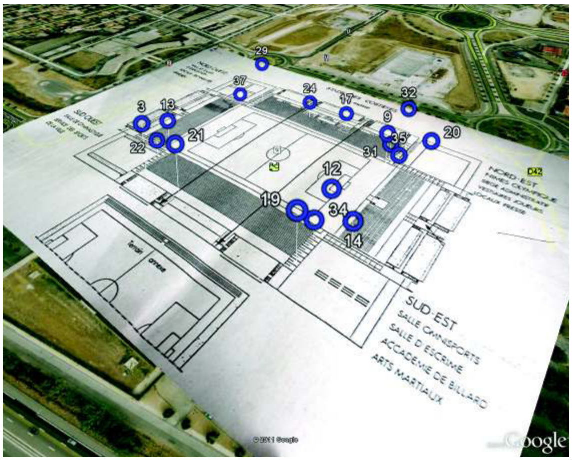

Figure 2: Three-dimensional sensorplacement at Stade de Costière in Nîmes, France.

from the dataset as well as devices which were only detected once (spot readings). The sensors also record by chance devices of non-interest (e.g. navigation systems of passing cars or pedestrians at the border of the event area). These artifacts are removed by vendor filtering as well as spatial-temporal filtering. Finally, arbitrary jumps among sensor locations, resulting from overlapping sensors are also removed. For this action, the spatial distances between sensor footprints, time-stamp and duration of the stay are taken into account to calculate speed and position changes per time.

After the data has been purified the dataset contains sequences of positions visited per device enriched with the time-stamp and stay-time duration. Thus, for every sensor location quantity of detected visitors can be determined within a particular time-interval. Additionally, movement patterns and dynamic information on popularity of footprint transitions remained preserved in the data. These empirical recordings are utilized in the subsequent micro simulation step (section 4) for accurate route choice modelling.

4 MICROSCOPIC PEDESTRIAN MODELLING

The framework used for describing pedestrian traffic can be divided in a three-tier structure. One distinguishes between the strategic, the tactical and the operational level (Hoogendoorn et al., 2002). The start and the end trip for each pedestrian is usually known in advance. At the strategic level pedestrians choose their self estimated best route, among a collection of different alternatives. This can be done based on experience. Examples could be the global shortest path or the familiar path to a given destination. Short-terms decisions are taken at the tactical level, avoiding jams or switching to a faster route for instance. Basic rules for motions are defined at the tactical level, these include accelerating, decelerating, stopping. The different tiers have local interactions with each others.

There are mainly three different classes of models for pedestrian dynamic at the operational level: cellular automata models (Blue and Adler, 2001; Kirchner and Schadschneider, 2002), rule based models (Thompson, 1994; Galea et al., 2004; Korhonen et al., 2008; Raney and Nagel, 2006) and force based models (Helbing and Molnár, 1995; Yu et al., 2005). Cellular automata have the advantage of being computationally efficient, but the resolution of the simulated geometry is limited by the size of the cells. Force based models usually operate on a continuous geometry. They need more computations. For more about the advantages and disadvantages of the individual models we refer to (Schadschneider et al., 2009).

4.1 Force based model

In our simulation the operational level of the pedestrian walking is described by the Generalized Centrifugal Force Model (GCFM) (Chraibi et al., 2011) which operates in continuous space. In the GCFM at the operational level pedestrians are described with ellipses with velocity dependent semi-axes. Faster ellipses (pedestrians) need more space in the moving direction. The motion is ruled by the social forces (Helbing and Molnár, 1995; Molnár, 1995). At each simulation step the forces between the pedestrians and the obstacles (e.g. walls) are computed. Given a pedestrian i with coordinates $\vec{R_i}$, the equation of motion is:

$$m_i\ddot{\vec{R_i}} = \vec{F_i} = \overrightarrow{F_i^{\mathrm{drv}}} + \sum_{j\in\mathcal{N}_i}\overrightarrow{F_{ij}^{\mathrm{rep}}} + \sum_{w\in\mathcal{W}_i}\overrightarrow{F_{iw}^{\mathrm{rep}}}, \qquad (1)$$

where $\overrightarrow{F_{ij}^{\mathrm{rep}}}$ denotes the repulsive force from pedestrian j acting on pedestrian i, $\overrightarrow{F_{iw}^{\mathrm{rep}}}$ is the repulsive force emerging from the obstacle w and $\overrightarrow{F_i^{\mathrm{drv}}}$ is a driving force. m_i is the mass of pedestrian i. $\mathcal{N}_i$ is the set of all pedestrians that influences pedestrian i and $\mathcal{W}_i$ the set of walls or borders that acts on pedestrian i. They are within a certain cut-off radius $r_c = 2m$. This model has been validated in corridors and bottlenecks using the fundamental diagram. This model has already been used to perform simulations of a multipurpose arena (Holl and Seyfried, 2009; Seyfried et al., 2010).

4.2 Pedestrians Route Choice

The route choice for pedestrians can be done using navigation field (Hartmann, 2010; Guo and Huang, 2011). This approach is spread in the cellular automata area. Continuous models usually work on a visibility graph, where the driven force of the simulated agent points towards a node of the graph. The strategies used are usually the shortest path combined with the quickest path (Kretz, 2009; Kirik et al., 2009; Helivaara et al., 2011; Kemloh Wagoum and Seyfried, 2011). These strategies are in most of the case validated using a visual assessment on some screenshots taken from the simulation. Some experiments have been conducted to determine pedestrians route choice using video surveillance, but only on simple scenarios, reducing the problem to an exit selection problem (Guo and Huang, 2011; Helivaara et al., 2011; Lo et al., 2006). This is partially due to the fact that in complex facilities pedestrians have to be tracked across many rooms.

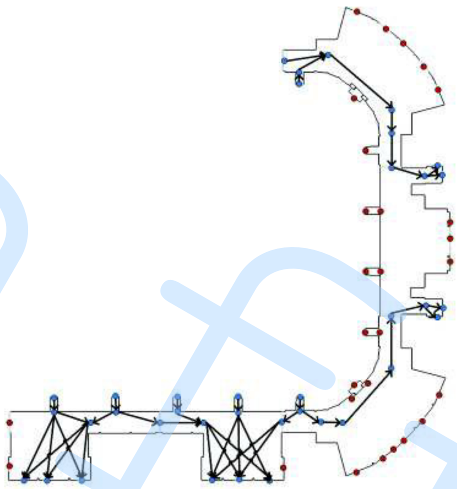

Figure 3: Example of a navigation graph generated from a section of a stadium considering which exits are closed.

In the framework used here, pedestrians move from one decision area to the next one. A decision area is a place where the pedestrian decides which way to go or change the current destination. Ideally the decision areas are around the exits, which might be relevant for an evacuation scenario. The navigation network is automatically generated from the facility based on the inter-visibility of the exits, intermediates areas are inserted if needed. Visibility graphs can be constructed using different algorithms (de Berg et al., 2008; Höcker et al., 2010). In the case of an evacuation scenario, the navigation graph can be limited to a visibility graph. A sample navigation graph for a section of a stadium is presented in Fig. 3. Pedestrians are routed to the outside in this graph using four algorithms: the local shortest path, the global shortest path and a combination with the the quickest path (Kemloh Wagoum and Seyfried, 2011). This example is suitable for an evacuation scenario where the pedestrians might prefer the shortest or quickest path to reach the outside. This approach is insufficient for normal day life situations, where the individual trips of pedestrians are subjected to other motivations. Some pedestrians might choose to go out the shortest way, whereas others might feel more comfortable walking along the promenade to get to some other points.

With the data obtained from the Bluetooth-tracking system, it is possible to assign individual destination and to calibrate the complete process of the route choice. The routing algorithm will then use the provided information to adjust the pathway of the agents in the simulation. Accurate reproduction of pedestrian route choice in complex facilities is expected.

5 CONCLUSION AND FUTURE WORK

In this contribution Bluetooth tracking was applied at events to monitor a sample of visitors and extract their route choices. Individual pathways could be tracked across many rooms. By sensor-design, the whole process is at any time privacy preserving.

As part of the spatial knowledge discovery process related works, analysing Bluetooth based mobility data, focussed on time-geography and movement pattern analysis. Driven by major goals of mobility data analysis (to achieve short term movement predictions, to understand people's motivations and to come up with microscopic traffic values), we proposed a solution for the next step, namely, the combination of the recorded values with a microsimulation. The routing algorithm in the microsimulation will then use the recorded information to adjust the pathways of the simulated pedestrians. An accurate reproduction of pedestrian route choice patterns in complex facilities is expected. As Bluetooth-scanners work seamlessly indoors and outdoors, further research needs to focus on outdoor models and the integration with existing mobility models. We conclude that use of Bluetooth-scanners for event monitoring is not just feasible for pattern extraction but by utilizing our novel approach also for understanding microscopic movement behaviour and to expose people's motivation.

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