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Analysing the Effectiveness of Wearable Wireless Sensors in Controlling Crowd Disasters

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Abstract
The Love Parade disaster in Duisberg, Germany lead to several deaths and injuries. Disasters like this occur due to the existence of high densities in a limited area. We propose a wearable electronic device that helps reduce such disasters by directing people and thus controlling the density of the crowd. We investigate the design and effectiveness of such a device through an agent based simulation using social force. We also investigate the effect of device failure and participants not paying attention in order to determine the critical number of devices and attentive participants required for the device to be effective.

Keywords: Crowd Simulation, Disaster Management, Wearable Electronics, Wireless Sensors, Agent Based Simulation

1 Introduction

The Love Parade was a popular festival and parade in Germany that used to be held periodically till 2010. In 2010 a crowd rush in the festival area lead to 21 deaths and injuries to more than 500 people resulting in the cancellation of all further Love Parade events. Helbing and Mukerji [5] concluded that the major reason for the death and destruction was the inadequate capacity of the holding area and the fact that the parade area could only be entered and exited through one tunnel. This lead to highly dangerous levels of crowding which in turn lead to high crowd pressures and eventually death and injuries.

The Love Parade disaster may have been preventable if the people entering through the tunnel had some way of knowing that it was too crowded in the festival area. In the case of a tunnel, or the entrance to most major auditoriums this is difficult because the participants generally have limited visibility because of crowding and structural design. One way to solve this problem is by providing an indication of global safety (or density) to the relevant individuals so they can take appropriate action. Low power wearable sensors with basic communication facilities (as in wireless sensor networks) could be one way of automatically estimating density

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of the surroundings and then provide a means of relaying information back to people. We assume that it would be possible to develop a simple device that individuals would wear (i.e., a small wristband). This device would be able to communicate with other devices within a fixed distance and then change colour based on the information received. Given such a device it would, in principle, be possible to develop local information algorithms that would guide individual's behavior, e.g., to stop moving. Finally, assuming that it is possible to manufacture a device and given an effective algorithm for density measurement and information propagation, there is still an open question regarding how many devices are necessary (i.e., fraction of the crowd wearing the device) and a further question regarding the impact of people's attention (i.e., whether they follow the instructions from the device).

There are several possible algorithms and settings that could be used for such a device, and to evaluate these in the real world would be prohibitively costly and possibly dangerous. Thus, we choose to investigate the design and effectiveness of such a device through an agent based simulation of the crowd [11]. In this paper, we develop a model of a device which is built into an existing agent based crowd simulation [9, 10] system. Using the model we evaluate different algorithms to gauge the effectiveness that such a system might have in real world crowd scenarios. We go on to understand the impact that the fraction of individuals wearing the device has on the system and also the role that a person's perception has on the overall safety.

The organization of paper is as follows: Section 2 starts with a review of the relevant literature. Following this, Section 3 describes the models used for implementation and Section 5 presents the results and analysis of the designed simulation models for a number of different scenarios. Finally we conclude the paper and propose directions for future work.

2 Literature Review

Still [7] studied several crowd disasters and analyzed the effects of crowd densities in moving crowds. He determined that more than 4 people per square meter for a moving crowd is dangerous and likely to cause some disaster. Wireless sensors have been used before as a means of estimating crowd density. In [12], the authors develop a system which uses wireless sensors and k-means clustering to provide good estimation of density. The authors also highlight issues related to signal strength and the critical role it plays in obtaining accurate density measures. Others have used wireless devices and human crowds to create interactive art pieces; in [2] the authors use wireless sensors to create a crowd generated interactive musical environment.

Zia et al. [3] proposed the LifeBelt which is a wearable navigation and directional guidance system. This device aims at improving the efficiency of evacuation by using its ability to sense its neighbourhood, extract the spatial relationship of detected neighbours and instructing the person wearing the LifeBelt on the recommended best course of action. This device has two mechanisms for working: At the local level, it helps the wearer move according to neighbour locations to reduce congestions; At a global level, the LifeBelt is controlled by a central control unit that directs each LifeBelt to an appropriate exit. However, the details of how the global control is done aren't explained. Also the testing of the LifeBelt was done using a CA model whose discrete space inherently limits the analysis that can be done. By using a continuous 2 dimensional space we believe the situation can be studied more accurately. We also use a local decision mechanism instead of a global one since we believe this is a more practical approach.

3 Device

The basic premise in our modeling of the device is that each device is able to send simple messages to other devices that are within the device's sensing range. We assume that the devices are reliable and have a fixed communication range r. We also assume that devices have some basic processing power and are able to aggregate incoming messages and that information can be relayed to other devices through broadcasting to devices within range. With the information that is received the devices can change into one of two states: *green* indicating it is safe to proceed and *red* indicating stop. We divide the working of device into three distinct phases: *Neighbour Counting*, *Density Propagation* and *Information Display*.

3.1 Neighbour counting

The first way in which a device determines the density around it is by simply counting the number of devices that it can directly sense around it. If this is greater than a predetermined threshold (N_τ) it concludes that it is in an *unsafe* situation. In principle there are a number of ways that the device may fail during this phase. If the sensing range of the device isn't consistent, e.g., decays with power or has a large error, the device will not be reliable in its density estimation. In this paper, for all experiments, we assume that the device is reliable and has a fixed sensor range. In practice, it should be possible to reduce the range of communication by effectively limiting it below the maximum possible range. This should in principle reduce error and negate any effect due to battery discharge.

3.2 Density propagation

By a device only knowing about its own density situation we do not gain much more than a human could do alone, so it is vital that there is a method of message propagation among the devices. When a device determines it is a unsafe (dense) situation, a device broadcasts an unsafe message to all other devices in range. The message m is a tuple (i, h) where i is the unique device ID (where the message originated) and h is a hop count indicating how many devices have relayed this particular message (initialised to 1).

When a device receives an unsafe message $m = (i, h)$, the receiver relays a new message $m' = (i, h + 1)$ to all its own neighbours. If a device receives a message $m_a = (i, h_a)$ the device will ignore any another incoming message $m_b = (i, h_b)$ if $h_b >= h_a$. This effectively provides a shortest path from the unsafe device to all other devices in the environment. This in turn means that a device will know all reachable (via hops) unsafe devices and the shortest distance to those devices. Thus each device knows approximately how far it is from a dense situation through both the number of reachable devices and the total (or average) hop counts. A transmission threshold is defined h_τ which specifies the maximum number of hops that a message is transmitted. In the simulation this is done by simply not relaying any message $m_f = (i, h_f)$ such that $h_f = h_\tau$. In reality this could be ignored and all devices would receive all information. This would require more logic on the receiver to determine how close is close enough when considering nearby unsafe devices. However, by adding this logic in the relay process we reduce the power used during the message propagation phase. In all experiments of this paper we define $h_\tau = 3$, so each unsafe message can reach a maximum of three hops away. Figure 1 illustrates the situation with $h_\tau = 2$ where device 4 does not receive the unsafe message from device 1, but devices 2 and 3 do.

At any point in time we can consider that the devices form a *propagation network*, where nodes are devices and an edge between two nodes indicates the devices are within range of

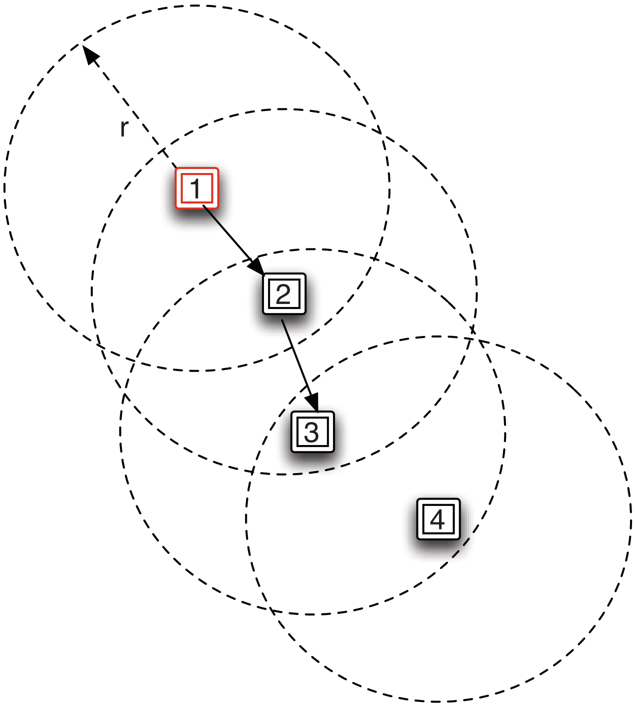


Figure 1: Information propagation of 2 hops: device 4 does not receive the unsafe message emanating from device 1, but devices 2 and 3 do.

one another. As the devices (or humans) move, the size of this network, specifically the giant component will change, and clearly as the density of people increases the fraction of individuals inside that giant component will also increase. The fraction of individuals inside the giant component will also depend on the communication range (see r in Figure 1) of the devices. In the limit of $r \to \infty$, the propagation network will be a fully connected network (i.e., it will have $\frac{N(N-1)}{2}$ edges) and the fraction of devices in the giant component will be one. An important issue, in respect to the system, is understanding the fraction of individuals in the crowd that must wear working devices in order to ensure safety. In order for information to propagate throughout the crowd the giant component must cover a *sufficient* fraction of the entire crowd. This type of question is well studied in the wireless sensor network literature [8]. However, the giant component of the network, while important, does not address the issue of sufficiency. We do not need the density information to propagate to all members of the crowd, only to the correct group of individuals, with the correct group being those that are in danger. To understand this we analyse how the fraction of users wearing the device[1] impacts the size of the giant component and how that in turn leads to the emergence of dangerous densities.

3.3 Information display

Once the density propagation phase completes each device in the system will know if it is in an unsafe situation or if it is *close* to a number of other devices that are in an unsafe situation.

[1]The idea of failed devices we consider the same as an individual not wearing a device

Critical to the entire system is how a device determines when the wearer is safe to proceed, i.e., once it receives all the information from other devices how it should calculate the danger level. If the device detects some notion of danger it then needs to instruct the wearer, in some simple way, how to change their behaviour.

In this paper, we model a device that simply instructs the user to stop moving when it detects a dense situation and instructs the user to start moving again when the situation clears up. This device would work in relatively simple environments (e.g., a tunnel like in the Love parade disaster [5]). The benefit of such a device is that it requires a very simple design where an LED can switch on or off (or change colour) depending on the device state- safe or unsafe.

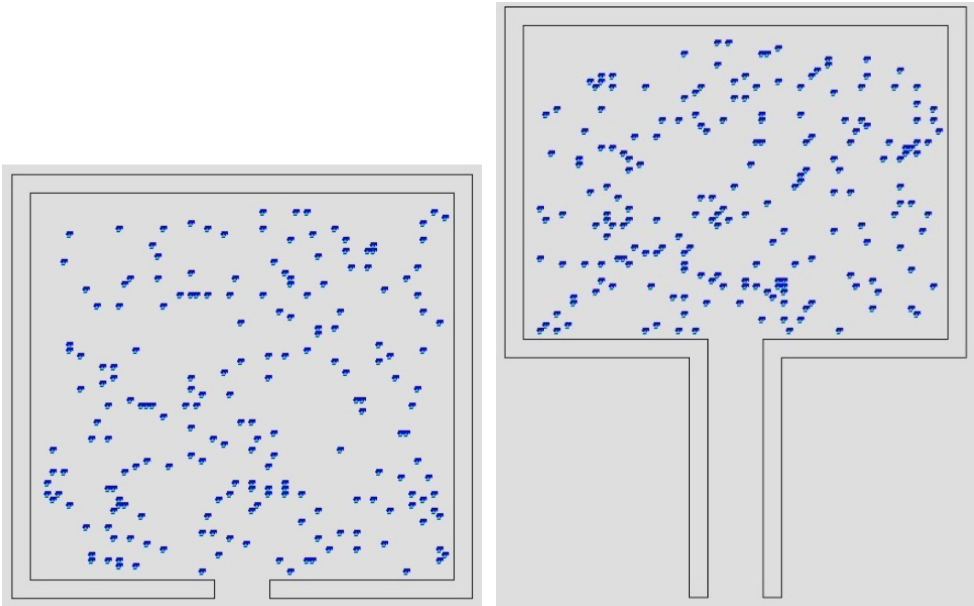
Our hypothesis is that even with a simple and relatively inexpensive device we can significantly reduce the number and magnitude of dangerous situations. Each device can appear in two states safe or unsafe. As described in Section 3.1 this can be done *locally* by a device simply counting the number of devices it sees and determining if this is greater than the threshold N_{tau}. A device can also become unsafe if it receives a number of unsafe messages as described in Section 3.2. We again use a parameter to specify a threshold M_τ that specifies the number of unique unsafe messages (i.e., messages emanating from different devices) a device must receive to mark itself as unsafe. The key distinction here is when a device becomes unsafe via message receipt it does not broadcast this fact to its neighbours. For the experiments here we define $M_\tau = 5$ and $N_\tau = 7$.

4 Experiments

In this paper we present two sets of experiments that are intended to investigate the ability of the device to prevent overcrowding and dangerous situations. In the first set of experiments (Experiment 1 and 2) we assume a perfect device and complete coverage (i.e., all individuals are wearing a device). We look at two different scenarios, a simple single room exit situation (see Figure 2a) and a corridor (narrowing) scenario (see Figure 2b).

The second set of experiments (experiments 3 and 4) is intended to show how the propagation network, and overall system performance, is affected by the fraction of individuals wearing the device and the fraction of individuals listening (or paying attention to the device). Note that experiment 3 and 4 assess two very different aspects of the system. With fewer people wearing working devices the underlying propagation network is impacted and so this can severely impact the level of information transmitted through the crowd. If some portion of people ignore the device (i.e., don't stop when told) then this doesn't impact the information that is transmitted, only the behavior of individuals.

The simulation was implemented in Java using the popular MASON [6] library which provides most of the tools necessary for agent-based discrete event simulation. A continuous 2D environment is used for the simulation with the area being divided into open areas and polygonal obstacles that define the boundaries of rooms or tunnels to simulate different scenarios. A pre-specified exit path is created for each scenario such that from every point in the environment, at least one waypoint is visible. Each waypoint is numbered with the starting point having the lowest and the final destination the highest value. Each autonomous agent has a simple behavior whereby they proceed towards the highest value waypoint that is currently visible. In proceeding to this point each agent must avoid collisions with the other agents. The simulation uses the Social Force model [4] to avoid collisions with other moving human agents and any obstacles. The social force model was chosen because it is one of the most popular and has been calibrated [1] and shown to agree best with real world data [10]. All experiments are repeated twenty times using different initial configurations of the agents. Each experiment ends

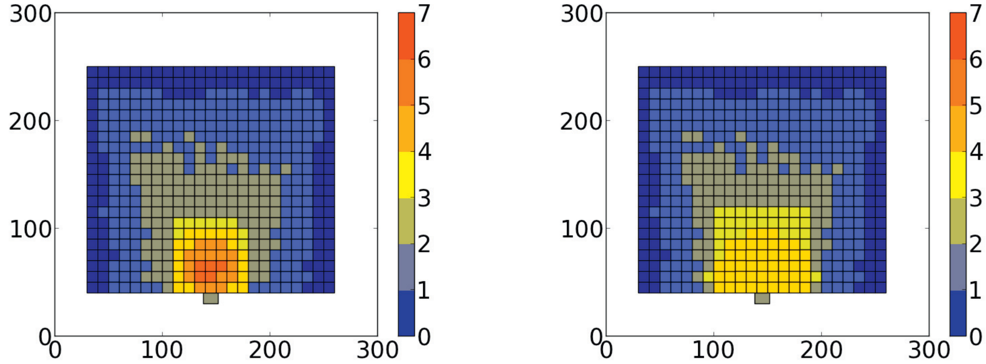


(a) Layout for Scenario 1 (b) Layout for Scenario 2

Figure 2: The layouts used for the two scenarios in the experiments

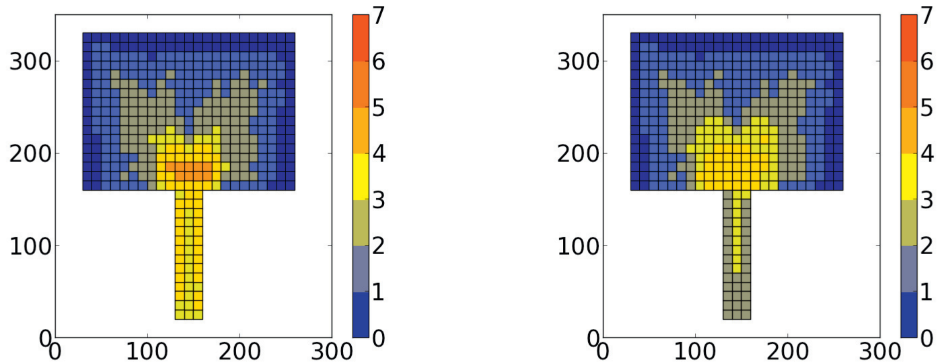
when all agents exit the environment. At each time step the agents and devices are executed. Executing the agent involves, first the agent choosing the appropriate way point, and secondly determining a velocity using the social force model (with a preferred velocity towards the next way point). Once the agent has calculated it's new velocity, and prior to actually moving, the agent checks its device. If the agent's device indicates unsafe (e.g., turns red) then the agent tries to stop moving by setting its *preferred* velocity to zero; the effective velocity is decided by the social force calculation. Once all the agents are executed, the devices are updated. This involves the density calculation and propagation procedures described in sections 3.1 and 3.2. The time step δ_t, of the simulation is chosen based on the requirements for the Social Force model, for all experiments $\delta_t = 0.05s$. Currently we assume that all the device procedures (i.e., density calculation and propagation) can occur within a single timestep. This may be somewhat unrealistic, but we aim for a best case scenario in the paper, fully aware that extra latency may perturb the information distribution, which in turn may limit the effectiveness of the device. The number of agents holding a device is determined by a device holding probability p_h and the number of agents following the device they wear is determined by a follow probability p_f.

To assess safety we measure the density distribution of individuals in the environment, this forms a longitudinal density distribution of the entire environment. This density map is obtained over a 1m x 1m grid across the entire environment. From this density distribution we can calculate, along time, the number of *unsafe regions*. A region (a 1m x 1m cell) is defined as unsafe if the density reaches a certain density threshold ρ_τ in terms of the number of people in that region. We currently define $\rho_\tau = 5$ [7], so a 1m x 1m space is unsafe (or dangerous) if it contains 5 or more people. We then calculate the number of unsafe regions that develop as a function of simulation time, we can also measure the average number of unsafe regions across an entire simulation.



(a) Without Device (b) With Device

Figure 3: Density Maps for Scenario 1



(a) Without Device (b) With Device

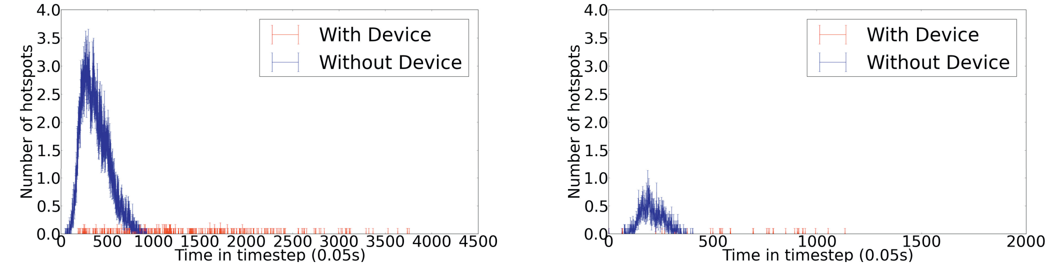
Figure 4: Density Maps for Scenario 2

5 Results

5.1 Experiment 1: density map

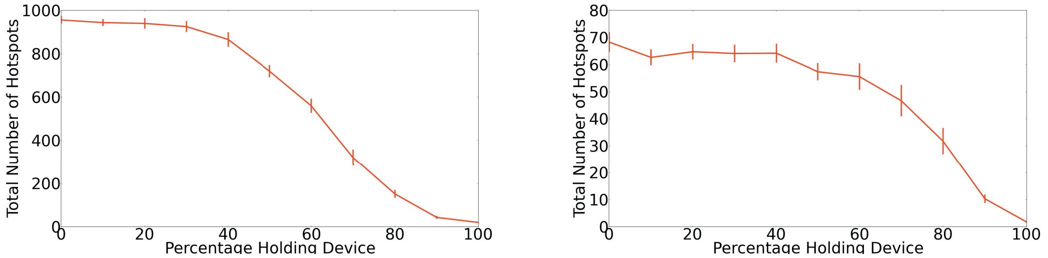
In the first experiment, we calculate the *maximum density map* for each scenario. We record the *maximum density map* for a particular run, that is each cell in the density map stores the maximum density seen at that cell over during the entire (single) simulation run. The density maps in Figure 3 and Figure 4 show the maximum density map averaged over all twenty repititions.

Figure 3 shows that for scenario one the device manages to reduce the maximum density seen in the simulation. This is most noticeable around the door way, where most people are pushing to the exit. Figure 4 also shows that the device manages to reduce the *unsafe regions* in scenario two, especially near the corridor entrance and along the corridor itself. These results indicate that the device would provide a feasible approach to reducing risk in crowded



(a) Scenario 1 (b) Scenario 2

Figure 5: unsafe regions as a function of time



(a) Scenario 1 (b) Scenario 2

Figure 6: Effect of p_h on safety

situations. Scenario two is perhaps the most interesting of the two as this closely reflects the types of scenarios we had described in the introduction, where many of the individuals would be unable to see the congestion ahead.

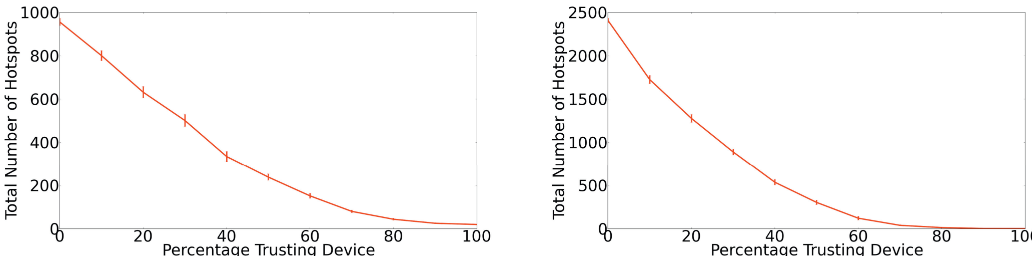
5.2 Experiment 2: unsafe regions as a function time

In the next experiment, we measure the number of unsafe regions (areas with more than 5 people per square meter) as a function of time. These are areas which could lead to dangerous conditions and so should be avoided. Figure 5 shows this for both scenarios. There are almost no unsafe regions in either scenario when the device is used.

5.3 Experiment 3: effect of more participants than devices

Next we measure the number of devices that are required for the device to have an effect on safety. We do this by plotting the total number of unsafe regions that develop as a function of the probability that an agent holds a device (p_h) in Figure 6.

Figure 6a shows that in scenario one the relationship between the fraction of individuals wearing a device and the number of unsafe regions follows a reverse sigmoid function. The graph also shows that with less than half of the individuals wearing a device the reduction in the number of unsafe regions is negligible. Once 70% of individuals wear the device we see the number of unsafe regions dropping to around 30% of the no device case (960 to 320). With all individuals wearing the device the number of unsafe regions reduces to almost zero.



(a) Scenario 1 (b) Scenario 2

Figure 7: Effect of attention on safety

Figure 6a shows that scenario two generates fewer unsafe regions, but also that is necessary to have a higher number of individuals wearing the device in order to reduce the number of unsafe regions. In this case to reduce the number of unsafe regions to around 30% we need approximately 85% of individuals to wear a device. This makes sense when one considers the critical places of information transmission. It is important that the devices in the corridor can transmit information back along the corridor to the entrance ensuring people wait before entering the corridor. As we randomly assign the devices to individuals we need a high fraction of p_h in order to ensure sufficient density along the corridor, which in turn ensures that sufficient hops can be made to transmit the information.

5.4 Experiment 4: effect of attention

Finally, we measure the effect of attention (or following) on safety. Figure 7 shows how the fraction of people that pay attention to their device (follow the device instructions) affects overall safety, with safety again measured as the number of unsafe regions. Recall that despite individuals not paying attention to their devices, the devices can still act as a repeater in the wireless sensor network and therefore still contribute to safety. The relationship between the fraction of users following the device and unsafe regions seems to be much more linear (slight exponential decay) than the fraction of individuals wearing the device. In both scenarios as long as 50% of individuals pay attention to the device we see the number of unsafe regions drop to around 30% of the no device case (see Figure 7a and see Figure 7b).

6 Conclusions And Future Work

In this paper we have investigated the feasibility of using low power wearable sensors with basic communication facilities (as in wireless sensor networks) as a means of ensuring crowd safety in high density situations. We have shown that in principle such devices could reduce the frequency at which dangerous situations occur. Our approach was to use known models from crowd simulation to investigate the interplay between the human dynamics and the propagation of information between devices. We identified two critical issues that would determine the success of such a system, firstly the number of individuals that must wear the device in order to have some impact and secondly how important it is that individuals follow the instructions of the device. For the two scenarios we investigated it is clear that it is necessary to ensure a high number of individuals wear the device (more that 50%), this was especially the case in situations where bottlenecks occur (e.g., corridors). Perhaps less critical, but sill important, is the need for individuals to follow the guidance of the device. If such devices could be manufactured cheaply, a system such as this could be integrated into event wristbands (often used at events like the Love Parade) that could be given to every individual. With carefully designed lighting (or vibrations) the device should provide an excellent warning system for crowd members.

In future it may be possible to investigate a second device that is slightly more sophisticated and instructs the user to avoid a particular direction. This would be particularly helpful for indoor scenarios where multiple exits may exist. The user could use this information to avoid the dense region and move towards a safer exit. To do so each device would divide its sensor range into quadrants. When a device receives a valid unsafe message (i.e., with minimum hop count) it can mark that message, indicating which neighbour it came from and in which quadrant that neighbour resides. The quadrant(s) with a high number of devices indicating an unsafe situation are assumed to be forbidden These forbidden quadrants will be displayed clearly to the user, so as to influence them to avoid the dense region.

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