How Crowded is the Crowd? - Visualizing Turbulence of Movement

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***Abstract*—Despite many technological and strategic advances made in recent years, problems relating to poorly managed crowd and population movement remain prominent throughout the world. This paper focuses on two key areas- traffic control and security management. While relatively uncommon now in many developed countries, traffic congestion remains a complex and persistent problem in much of the world. Additionally, with the increasing complexity of our infrastructure, coupled with the growing threat of natural disasters and human acts of violence in densely populated areas, it has become more vital than ever for security personnel to have a comprehensive understanding of the spatiotemporal nature of a crowd. A major part of this is predicting the areas that are most likely to be at risk. Since the advent of multiple disciplines across data science and machine learning, this can be made possible. Our project aims to help solve both the aforementioned problems by giving personnel responsible for infrastructure and security a tool through which they can understand and infer crowd and vehicular movement. This is done through a series of visualizations that will serve not only to highlight areas of deep congestion or lack of security but also to study human behavior in relation to environment. The solution will include a heatmap for determining population pressure in a given area and a temporal-based line-graph to understand the direction of crowd movement. Both methods aim to help in understanding the overall patterns and rhythms of the movement presented by a population, despite the trajectory of each individual being unique.**

***Index Terms*—**

I. Introduction

Festivals, large concerts, and religious gatherings regularly attract large crowds, with the Kumbh Mela pilgrimage in India even being visible from space. Providing security for these people is a major priority. This is no small feat. However, in the past few years, significant measures have been taken to improve security. Building on the expanding technologies of machine learning and deep learning, multiple techniques have been developed in data visualization, generating more and more proven methods lead to decreasing the security nightmare. These include pedestrian flow control. Unfortunately, these VA systems are still in their infancy and cannot be fully relied upon in visualizing large crowd movements. They are held back by issues such as early crowding where multiple people gather in a small area rather early (before a huge even to find a good viewing spot), thus making security for these people a potential challenge (Zeng, W. et al., 2016). We are thus establishing a novel method that will not only provide an "efficient" visualization, based partially on the work done by Wirz. et al., (2012)- using a heatmap to not only show the density of the population but also the 'pressure' at any given area, derived by the density, speed, and direction of the people there. We also provide a view of the overall direction of the crowd or clusters of individuals through a temporal visualization. These techniques combine to create a display of more cohesive results then are typically found in similar visualization methods. In crowd movement visualization the volume per area of a group of people insufficient to fully understand the nature of their movement. By also visualizing their direction, we are able to infer a more complex set of patterns. This plays a vital role in proving the required data to make complete and rational decisions regarding security and saving time in terms of traffic congestion. In this work we first took, some drone surveillance footage in the campus where we can see huge crowd movement and applied it to a program we modified based on the existing tracking algorithm that detected the moving trajectory of each person in the footage and calculated their moving directions and speeds by comparing their exact positions in two consecutive video frames. Therefore, for each individual video frame, we can always obtain complete information about people's movement at some specific moments. In this paper, we define the concept of pressure to measure the level of the disorder of people's movement. A mathematical formula consisting of the distance, speed and direction information is built to calculate the overall pressure value for each video frame. The major contributions in this work: Providing a temporal visualization layering it on top of existing heatmaps. Expanding on population pressure as developed by its respective models. Developed an improvised technique by tracking the movement of people in the video at receiving a high quality track. Merging the movement of people with iconic landmarks to calculate the rhythm and pattern in respect to architecture using a mathematical model.

II. Literature Review

In this section, we will be talking about the complex phenomenon known as crowd movement visualization. Many investigations and research have been carried out to simulate proper visualization of crowd behavior and crowd movement. Mathematical modeling, simulation techniques, empirical approached, etc, have been tried and tested to gain the most efficient and optimal method for visualizing crowds. The mathematical modeling procedures can be further classified into microscopic (so small as to be visible only with a microscope), mesoscopic (nanoscale size of a quantity of atoms and of materials measuring micrometers.) and macroscopic (visible to the naked eye; not microscopic.) depending on the level of detail and the algorithm being used. Many datasets are required to test the theoretical models quantitatively to provide the visualization that is required. Since the validity and reliability of these models needs to be tested an experimental study was done solely on human subjects to check their trajectories using the optical flow algorithm. The experiments with human crowds are mainly aimed at providing security which also provide insight into the behavior and characteristics of the subjects themselves as well as a pedestrian flow under congested and non-emergency situations. Since human subjects are being dealt with, the possibility of there being contingencies and emergency situations will arise and cannot be accounted for.

There are some studies which show that non-human organisms under stressed conditions (Altshuler et al., 2005; Burd et al., 2010; Shiwakoti et al., 2011; Soria et al., 2012; Shiwakoti and Sarvi, 2013) have the potential to provide an alternative means of empirically testing and verifying human pedestrian models, especially in the case of humans where ethical practices come into play. Using different organisms characteristics, similarities and dissimilarities may assist us to unlock certain physical and emotional behavioral patterns that would aid in understanding the complexities that cannot be fully captured by mathematical models. Other empirical approaches used for crowd behavior monitoring such as turning, crossing and weaving was used to understand the complexities of human nature and their behavior. However, there seems to be a few literatures pertaining to the experimental studies regarding crowd merging and crowd flow dynamics.

To simulate and understand pedestrian merging flows in a T-shaped channel(Tajima et al, 2002) a lattice-gas model of biased random walkers(A random walk is a mathematical object, known as a stochastic or random process, that describes a path that consists of a succession of random steps on some mathematical space such as the integers. An elementary example of a random walk is the random walk on the integer number line, which starts at 0 and at each step moves +1 or 1 with equal probability.) that can search for and find any clogging by using a procedure called cellular automata with multi-floor fields. Congestion seems to be highest at a merging "T" intersection regardless of which organism. Similarly, many computer simulations have been used to demonstrate the effectiveness of the merging process using the floor-stairs interface (Galea et al., 2008). In empirical testing (Zhang et al., 2012) focused on human subjects in closed corridors which established a base to monitor the performance of human test subjects and other biological organisms. The change in the complexity of the architecture established that the organisms had a potential inefficiency in turning, crossing and merging on the collective egress. Thus architectural complexities gave rise to inefficient egress for non-human organisms on a merging angle in a dense crowd.

Visualizing the crowd for congestion is not the only important aspect for simulating crowd movement but also to improve pedestrian security. There has been a lot of research in regards to identifying crowd conditions by conducting experiments but also by gathering empirical data. One of the most important aspects of crowd movement is to critically assess the density of the crowds to segregate potential threats or overcrowding. Not only density but velocity flow, turbulence and movement velocity have also been identified to be vital.

Being able to send emergency requests almost immediately will require an instantaneous assessment of the crowd gathering especially at religious events. Displaying information with an overlay map is a very common approach to presenting spatial information which allows for a quick assessment of the situation. In the following sections we provide detailed explanations regarding how the information will be visualized especially the crowd density and pressure. This can be easily obtained using the heatmap and overlaying it with a temporal visualization of tracking the direction in which they will be walking in. Pedestrian safety is and will always be a major concern for any researcher in the field of crowd movement. Providing a safe place for large events or gatherings like religious events, concerts etc is only a basic rule for improving the crow safety measures. This serves as an important characteristic to critically assess the many situations that may arise due to large crowd gatherings. The most common type of commotion is stampedes which are generally caused in large gatherings and high-density areas. There has been huge research in this area of measuring crowd density or crowd pressure which will lead to the identification of dangerous overcrowding. Destiny is not the only important characteristic as mentioned above, movement velocity, flow direction and turbulent movement also play a main role in the same. To solve this issue, quantification of the crowd was thought to be the answer where they measured crowd pressure which is the local pedestrian density multiplied by the variance of the local velocity of the crowd. Although this seems to be a complex problem with multiple answers and scenarios, there are multiple ways to visualise the pressure density of the large crowds. A heat map is a good way to be able to display crowd pressure. It is a graphical representation of spatial data and since the crowd density uses spatial data to locate the mass of the crowd, having a visualization that is able to display this is suitable especially when measuring specific locations. A very popular method to measure the density is the Kernel Density Estimation(KDE) of a local user in a given time. The KDE is reliant on ordinal datasets and so the focus is not on the numbers itself and so creates a smooth map based on density values each location which reflects the concentration of sample points. Based on the distance between each point the density is estimated using a Gaussian kernel. Each density value from a location is then mapped to a color using a color gradient and a heat map is obtained from the density estimation.

Each individual has their own movement in space and time which are called trajectories, these are time-ordered collection of the traces of these individuals. The movement of these individuals from one location to another are called pathways. Although calculating the pathways are important, extracting the information is equally important too, the process used for this is called Aggregation. However this is not the only way to calculate a trajectory, using C++ algorithm including the OpenCV library for low-level image processing this helps in establishing the velocity vector which is the difference between each position vector.

The KDE as mentioned above is a classical method for displaying densities for the sample by using the Gaussian filter model or the Gaussian kernel. Each kernel has a defined search radius around each positional point. The size of this readius is deeply impacted by the density surface of the point. This is typically more of an art rather than a science, there is an alternative approach to the selection process called the adaptive selection. "Density is not a xed concept with an objective denition," Batty (2009), "states that density is a point measure dened as the mass of some entity, such as a population of individuals or a collection of buildings described by their size, but normalized by some measure of the area they occupy." Density values may vary hugely depending on the datasets especially they are not intertwined together, if the dataset is different, it is arduous to perform the density calculations as the area size may differ immensely. The main focus in this area becomes to influence the parameters for the calculations and results. This is where KDE becomes the focus as to display the colors of a density map a color value has to be given to a specific point which is highly dependent on the z-value of the 3D kernel data point. The clustering technique of the KDE is used for grouping data on dissimilar patterns.

Heatmaps are often used to visualize density, an example being one created by Blanke et. all (2014) where brighter areas denote locations with a greater density of people. Building on ideas like this however, Wirz et. all (2012) used this model to create a more nuanced portrait of crowd behaviour by applying it to crowd 'pressure'. Crowd pressure represents a measurement of chaos and confusion that would correlate with the evacuation time of a given area should there be an emergency. The higher the pressure level of an area, the higher the probability that not everyone in that area will be able to escape in time and thus, it would require more attention from security personnel. This pressure value was made up of a combination of three different features- crowd density, crowd movement velocity (the average velocity of each person at a given location), and crowd turbulence (a measure of the variance of each person's heading direction at this location). This last feature is of particular importance- in a crowded area where people are moving quickly, there is going to be substantially more chaos and confusion if everyone is moving in completely random directions, rather then in the same one. Using a complex algorithm, the three values were combined into the final pressure value.

In their paper, Blanke et. all (2014) also proposed a novel set of methods for displaying speed and direction. Using a top down map, every pedestrian was visualized as an individual dot, and these dots were color-coded based on these respective values. In the case of speed, a rainbow scale was used, with red denoting the fastest speed while blue denoted someone who was standing still. For direction of travel, a different color was used to represent north, south, east and west.. For this visualization to work however, people's directions needed to be 'rounded' to the nearest 90 degree angle. As such, many important nuances in human movement become lost in this model.

While the majority of research into crowd behaviour visualisations focus on large areas, Shiwakoti, et. all (2014) chose to tailor their investigation to a more micro scale- specifically, a connected set of hallways. After putting their test subjects through a set of hallways that merged together from different angles, they drew up the results by tracing the trajectory of each participant with a line. Some of these results can be seen in Figure X To show in detail how angle of movement impacts change in velocity, they also visualized the temporal data for the movement of the participants by plotting a line graph of speed against distance, specifying the points at which the two groups merged together. To better visualize trajectory information, sometimes it helps to simplify the direction of movements by rounding it to the closest set number of degrees. This is what Chau et. all (2015) did in their analysis of tourist movement in Cilento. Placing a grid over a map of the area, they rounded the location of each tourist to the nearest point on the grid and the direction of their movement to the nearest 45 degrees. Thus, they plotted the rounded trajectories of these tourists from point to point on the grid via arrows. The width and color of each arrow was determined by the number of people who followed that trajectory. Using this data, they also plotted the total number of visitors who's locations are rounded to each cell on the grid, creating a mutli-coloured checkerboard. These visualizations are both aesthetically appealing and easy to understand. Like with the direction visualization by Blanke et. all (2014), people's directions of movement are simplified by combining them together in a set of qualitative groups. However, by using 8 directions instead of 4, a significantly larger portion of the information is maintained, and coming far closer to finding a 'happy medium' between visual elegance and preventing data loss. Additionally, the temporal information for the overall number of people in the region was recorded, with these people divided into groups of locals, domestic tourists, and forgion tourists.

While most of the research has treated human movement as independent, Leonard et. all (2012) attempted to analyse how the movement of one person can influence that of another. To do this, they observed a group of dancers performing an improvised routine that had to adhere to a set list of instructions. These instructions required each dancer to have a given number of other dancers at arms length from them at any given time, while no dancers were allowed to be closer than that. As such, the movement of each dancer was constantly influencing the movement of other dancers in their area. To visualize this, the coordinates for every dancer for a given moment were plotted on a plane, with arrows and lines drawn between them. For every set of dancersA and B, an arrow drawn from coordinate A to coordinate B indicates that the movement of dancer A at that moment was influencing that of dancer B. An undirected line means that both dancers were influencing each-other.

Using these diagrams, a timeline was then constructed charting the fluctuating level of influence of each dancer across the entire routine. From this, the researchers were able to extrapolate an overall level of influence for each dancer-indicating that some typically acted as leaders while others were often followers.

III. Methodology

Our work is based upon accurately detecting human movement from a top down video which we took using a drone. However, while there are a wealth of deep learning algorithms for object detection and tracking available, many of them are not suited for the task at hand. This is often due to a lack of data to train a neural network, or the fact that a top down view will obscure many of the human body features the algorithm is programmed to look for.

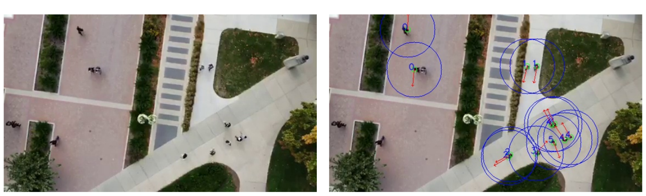

Fig. 1. Detection results using Optical Flow between frame 99 and frame 100

After comparing different object tracking algorithms, we believe that the Optical Flow algorithm is best suited to our purposes. In order to calculate the trajectory of each person, the Optical Flow algorithm requires a set of two consecutive video frames. A feature selection process is applied to the first of these frames. This looks at changes in color between adjacent sets of pixels and employs corner detection techniques to extract a set of key features (color, shape, adjacency, etc.). The algorithm then examines the next frame and searches for features in the video that match those that have been collected from the previous frame. If a similar set of features are found but in a different location to their position in the first frame, the algorithm can surmise that it has found a person who has moved between the two time intervals. Optical Flow will find the most matching features between observed patterns and a given scene. Therefore, for each video frame, we should in theory always get the position, velocity and moving direction of each person by comparing the corresponding features between two frames. Figure 1 shows the detection results using Optical Flow between frame number 99 and frame number 100. We can track the majority of people shown in this video frame, however, one person may be missing (at the left-bottom corner) in the results. After running the test on multiple video frames, we found that on average we the algorithm cannot detect 1 out of 5 people. As such, the algorithm bares significant room for improvement, and this issue would need to be taken into consideration when applying it to real world scenarios in it's current form. However, when visualizing a dense crowd, the algorithm is still accurate enough to be suitable for testing and demonstration purposes. For each individual, we can also draw the trajectories as shown in Figure 2.

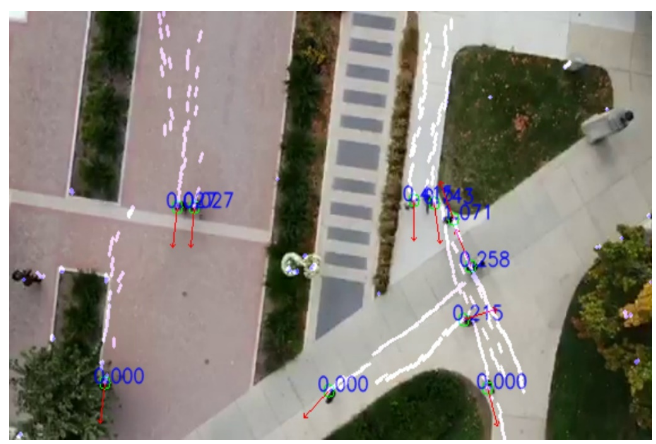

Fig. 2. Trajectories for each individual

In this paper, we proposed a new mathematical model for describing the level of disorder of the crowd. The formula is mentioned below:

$$Preassure = \sum_{i=1}^{n}\sum_{j=1}^{m}(\frac{|v_{ij}|}{d_{ij}})$$

1. n denotes the total number of people in the frame.
2. m denotes the total number of people within certain distance to person i.
3. v_{ij} is the subtraction result using vector v_i and vector v_j.
4. d_{ij} is the distance between person i and person j.

is the result of stacking different heatmaps on top of each other over the change of time. The brightness of the red color represents the pressure level. Figure 4 shows a 13 sec video clip and the pressure map result.

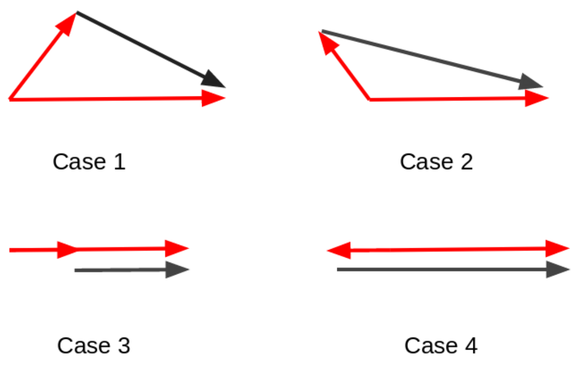

Fig. 3. Illustration of the rationale of using vector subtraction.

In Figure 3, we show four different cases to explain the design rationale. For each case, the red vectors represent the moving directions of person i and person j in the formula above. The length of the vector signifies the speed value. The vectors in black color are the results from subtracting from the red color vectors. When people are moving in a relatively similar pattern or direction (Case 1 and Case 3), the indication would be that the turbulence of the crowd movement will be comparatively low. On the contrary, if there exists a huge difference in moving directions or patterns, the turbulence of the moving crowd will be relatively high (Case 2 and Case 4).

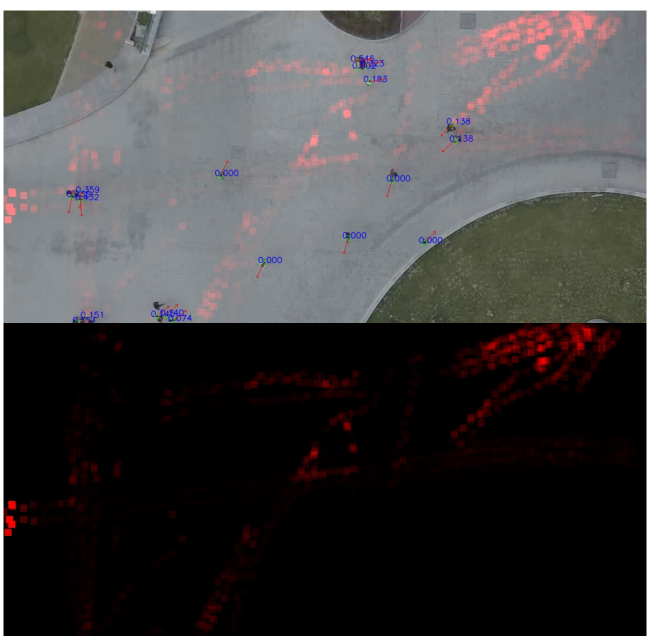

Fig. 4. Pressure Map of the Moving Crowd

Based on the formula we have for computing the pressure value, we can assign each individual a specific pressure measurement. To better visualize the geospatial pattern of the moving crowd, a pressure map is created. The pressure map

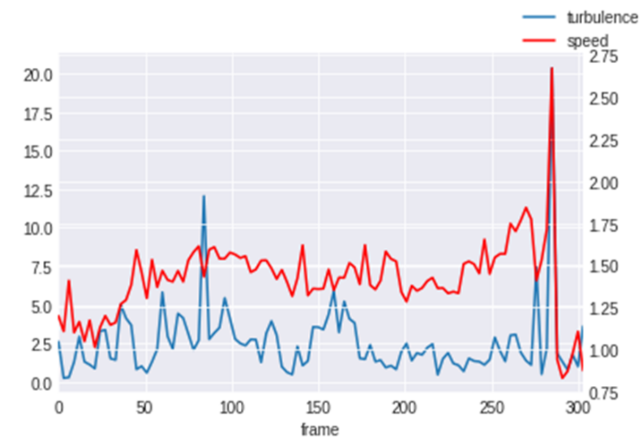

Fig. 5. Illustration of the rationale of using vector subtraction.

Tension Detection Unpredictable objects observation. By labeling moving objects such as people, animals, and bionic subjects in the video, the efficient algorithm we discovered and developed could be able to summarize the density of the crowd, the speed, and direction of a single element, and therefore, detect the suspicions movements. Furthermore, consistent monitoring of the labeled data will allow the system to categorize the movable objects into groups whose patterns can be expressed numerically. Due to the collection of numerical data of duration, space distribution, and the speed justification, the study is able to learn about transit and crowd behavior and possibly simulate it in a virtual environment. Nevertheless, the reduction of the real scene in a 3D modeling would not be our primary goal, the accuracy and realistic digital data sets allow us to easily simulate the urban space and draw individuals' movement. Rudomin (2007) acknowledged that the objective of observing and analyzing the crowded is to identify a triggering "symptom". Thus, consistent harvested observations of flow of people, target landmarks and nodes, social networking monitoring will be important methods for density measuring and crowd insight. Rudomin is using existing temporal-Geo located observations such as public cams and GPS data for tracking the users. However, Drones have been promoted as special future development features that could obtain the targeted zones and areas. This refers to our research focus when drone data will be our initiative data inlet. The naive crowd patterns include casual crowd for the strangers, conventional crowd representing the norms, expressive crowd refer to an event base, and an acting crowd inside the friends or colleagues circle where people know each other well. This kind of categorization of the crowd will help the study to decompose the groups of people and learn their behavior in a predictable range.(initialization, tracking, pose estimation and recognition), A movement model could be generated by AI that should predict the location of moving objects and possibly detect the potential collisions. This branch of data set will provide extra information to the auto-driving system and therefore drop the threat rate of the random objects.

We also used a 160 degree line of sight of the user to disregard and remove all unwanted incoming people so as to remove the condition of feeling pressure from unwanted areas. This essentially means that we are only considering the users field of view which is in their line of sight to a limit of a 160 degree angle and disregarding what the user cannot perceive.

IV. Evaluation

A. Heuristic Evaluation

Emphasis on evaluating the accuracy and efficiency of visualization outcomes is growing. However, not many of these cover the usability of the visualization from the user's perspective. Here in this paper, to get countable feedback from targets with minimum involvement of participants, heuristic evaluation method is conducted. This usability engineering method has been widely accepted in Human-Computer Interaction (HCI) as an alternative evaluation technique, which "involves having a small set of evaluators examine the interface and judge its compliance with recognized usability principles (the "heuristics")" (Nielsen, 1995). The experts will be offering a list of heuristics based on visualization and usability guidelines accompanying our final dashboard. A 0 to 4 rating system, as well as a comment area, will be attached to each of the heuristics with an oral explanation. The ratings will help us to identify the most pressing issues while comments can provide further detail. To keep the evaluation independent and away from bias, an evaluator will only be allowed to communicate and aggregate their findings after finishing all the tasks. In terms of summarizing the record efficiently, accurately, and comprehensively, a hands-off observation will be added to oversee and record the verbalized comments and actions of the participant. This is not only because the observer could transcribe the oral information into text that is relevant to the heuristics instantly, but also a written report as an option will only take advantage when the online evaluation is unavoidable.

1) The participants: The participants: Nielsen (1995) indicated in his experiment that 5 expert evaluators are able to determine three quarters of the usability problems when the ratio of the benefits (financial value of the projects) to the costs (the down payment for the evaluation process) is slightly below the peak. Therefore, five professionals with expertise in informative data visualization and on-site security monitoring are volunteered.

2) Procedures: The evaluators should have the freedom to decide how they would like to proceed with the interface. It will be recommended to them to go through the interface at least twice, with the first round being a warm-up session. Following this, the second pass will allow the evaluators to be more familiar with specific details of the interface that fit into the categories of usability principles. One of the observers will transcribe the comments during the evaluation.

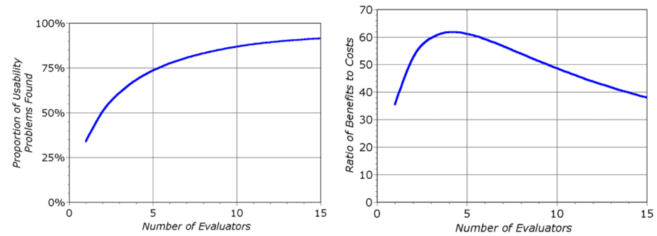

Fig. 6. (Nielsen, 1995)

3) Tasks: The evaluators will be signed with following tasks in terms of better experience the heuristics. 1) Based on Fig.4, please tell the area with high level of conflict 2) and what does these areas mean to a security person; 3) please tell the trail with high level of traffic flow and low level of turbulence, 4) and what does this mean; 5) please tell the busiest intersection.

4) Heuristic forms: Table 1 represents the heuristics that reflects data visualization methods and the tasks signed to the evaluators along with descriptional questions, while table 2 shows the framework that has been conducted in the evaluation.

TABLE I

Heuristics	**Sub-Heuristics**	**Questions**
Attractiveness	Aesthetics, reliable	Does the visualization map include appropriate color and sign? Does the visualization include reasonable information and reliable representation?
Affordance	Speak user's language, inclusive	Is the content easy to be understood? Does the visualization require pre-training?
Effectiveness	Organization, multiple functions	Does the information easy to be managed? Does the visualization represent multiple approaches?
Efficientness	Feedback, stimulation, interactive, adaptability	Whether it has relevant functions to motivate users and enhance the user's sense of self-efficacy? Does the interface offer a problem-solving respond? Could the interface adapter to all security field?

TABLE II

Heuristics	**Sub-Heuristics**	**Questions**	**Rates**	**Notes and Comments**	**Discussion**
Attractiveness	Aesthetics,	...	0 - 4	Transcripted	Only conduct after evaluation

B. Interview Evaluation

In addition to the Heuristic evaluation, we decided to conduct a separate set of informal interviews to gain extra insight into our program. We transcribed the responses we received and summarized their key points.

V. Results

A. Heuristic Results

In the University Security Department, 5 of the security sectaries have been signed with the tasks and able to comment and rank the heuristics based on their acknowledgement and experience. the aesthetics and organization are the two sub-heuristics, which have more complain with. It will be hard for the evaluators to see the information in a comprehensive way. Also, the interface is quite original that color of contrast, fade of background, and size of the dot should be discussed in the advanced version. However, reliability, novelty, multiple function, and stimulation stands on a satisfactory position that the mathematical model we created speaks out an understandable and flexible language of crowed data. It creatively describe the crowed and is applicable to different approaches not only in security but business.

B. Interview Results

1) Purdue Police Department: We were fortunate to be able to get feedback on the project from members of the Purdue Police Department. Three members in total were interviewed-consisting of the local captain, the IT, Communications Equipment and fleet manager, and an intern studying for a masters degree in Computer Science. While they were not without their criticisms of the the project, they reacted to it enthusiastically. They expressed that they could see themselves using this technology to monitor entrances and exits in a building or stadium, thus seeing which ones are not being used and thus know to direct people towards them to ease congestion. They also noted that this tool could be used to spot friction points in a space- small 'pockets' where pressure increases due to bins, stairwells, planters, and other everyday items that might be in the way. Something key that all three agreed on was that the tool might in fact be better suited for vehicle tracking then human crowds. They suggested using it to monitor traffic speeds in particular (as apposed to traffic 'pressure')- saying it would be a great way to find out 'what the traffic is actually doing as apposed to what it is supposed to be doing'. Surprisingly, the members of the Purdue Police Department also suggested that the tool might have great value in the commercial sector, which reflects on our early discussion of the implementation value towards the commercial. They proposed that our visualization could be used to gouge what areas people tend to gravitate towards in shopping malls. This could be used by owners of the shopping mall to more accurately price their locations based on the amount of traffic they get. In addition, store owners could use the visualization to measure how much time people spend around their store, where in store they tend to gravitate, etc. They did note however, that as the program currently only works with drone footage, this limits it's applications somewhat. They made particular note that realistically, the program could only be used to monitor vehicular traffic if it is able to work with footage from traffic cameras.

2) Purdue University Professors: As per the discussion with Dr. Tim McGraw and Dr. Paul Parsons it was clear that there were a lot of limitations regarding the UI and the significance itself. Excluding the fact that the importance of this visualization is catered towards a more commercial approach which has been elucidated above. The UI was the main topic of discussion among the professors, especially in providing a more robust framework in terms of using this application is real time as currently, we have the algorithm and code which has to be run continuously but a VA system would bring it all together. A VA system will also help us in determining whether the code can be implemented in a cohesive manner that non-technical personnel can make use of it in emergency situations, thus a UI which can produce effective results quickly as well as be simple enough that a non-technical mind can grasp the essentials will be required. This can also be part of a potential limitation. A secondary point that was raised was that a VR system will not be a rational option if attempting to measure any bio-metrics of the human body to determine pressure. As this may help establish a baseline unfortunately it will not be objective enough nor will it be quantifiable enough to accurately display the requirements of what is being achieved.

Including the points mentioned above, the visualization itself needed clarification as the colors being displayed seemed to misconstrue what needed to be communicated. The normal circumstances of crowding seemed to have a more "reddish" color than required and it was suggested that it should be separated out for more exaggerated scenarios and thus a peak or a threshold value was mentioned to be set so as to cut off some extremely high outliers or low outliers.

VI. Limitations

The main crux of the paper was the design and implementation of the algorithm to enhance and optimize the efficiency of crowd movement and the respective turbulence between each individual point. The algorithm is using an optical flow technique which based of Machine Learning algorithms which uses training and testing data-sets to achieve the output. Just like other algorithms this had its own limitations as well. Firstly, while using the algorithm it was learned that the tracking does not work for each individual, i.e., the algorithm does not seem to establish each individual separately in the given frame but takes it as a whole. In this case, if an individual trajectory suddenly changes the algorithm will not be respond as efficiently as it should. Secondly, not only the individual but also each individual or element must be moving in the video for the algorithm initiate the tracking process. In other words, any stationary individual will not be tracked. Lastly, in the implementation of the algorithm seems to be sub-optimal as there seems to be a threshold on the amount of individuals being tracked, in other words not all the moving individuals are being tracked this seems to be on average around 90 percent. A reason for this could be heavy distortion or an unstable video which is making it difficult for the tracking to calculate.

VII. Future Work

There are a couple of things need to be discovered, not only the algorithm, the technical part, but also the user interaction, which is the usability part. Due to the limitation of the existing formula, the executable improvement would offer a wider coverage of the data that can be accessed. The advanced version of data collection methods should include the features of 1) tracking any individual's movement on the map, 2) tracking vehicles separately, 3) avoiding the identification of the area base as a moving object when the camera shaking. 4) Using 3d simulations for extreme cases such as violent attacks as getting the information using a drone may not always be approachable.

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