Privacy-preserving and IoT-capable Crowd Analysis and Detection of Flow Disturbances for Enhancing Public Safety

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Abstract: This paper describes a solution for monitoring and detection of crowds and analysis of density structures and movement characteristics, to enhance safety of citizens and security of critical infrastructures. The system leverages the Internet of Things concept and heterogenous, energy efficient, networked sensors, with support for wireless communication. Privacy protection, instant deployability and auto configuration are hereby underlying core objectives. The solution, which will be described, comprises two novel distributed crowd analysis algorithms, allowing on the one hand the localisation of critical areas within large crowds and on the other hand the recognition of counter streams, which can cause severe impacts on the crowd flow and movement velocity and which can transform crowding scenarios into threatening situations.

1 INTRODUCTION

Crowd analysis and modelling is a research area with a long history involving a variety of disciplines. Different types of surveillance systems have been proposed in the past and analysis of person streams and crowd densities are ongoing research topics. However crowd surveillance for identification of critical situations is a complex problem and establishing a solution, taking into account the majority of obtainable information (e.g. velocity, density, movement directions, flow), can be difficult. To process all the data a global solution is necessary with an appropriate set of rules defined and with observation in an integrated manner. There seems to be still a lack of solutions, which take most obtainable crowd parameters into account and reason about the information in a comprehensive way. Defining rules for identifying critical states of dynamic crowds, which evolve over time and can change their location, size, density structure, direction composition and velocity properties within a short time period, is difficult and requires detailed information about the crowd. For example a density analysis rule, which initiates an alert when a critical density value is reached, will not be activated if the average crowd density is low and only a small area of the crowd exceeds the critical threshold. Information about the intrinsic structure of the crowd is needed here.

Video surveillance is a concerning topic in the general public and societal acceptance and perception of surveillance are delicate topics. Thus it is of importance to develop solutions that have privacy protection as an underlying objective, aiming at respecting privacy of individuals as far as possible.

The main part of this paper is dedicated to crowd analysis mechanisms, with the capability to perform a density structure analysis to localise critical areas inside of crowds and moreover to identify counter streams, which were the main causes for related mass disasters in the past. The mechanisms focus on robust analysis of density structures and movement patterns and are principal parts of a safety and security solution, which was developed in the context of the French-German research project SAFEST (Baccelli et al., 2014). Additional objectives of the developed system are intrusion detection, identification of critical situations and provision of crucial information to security personnel using lightweight and networking-capable sensors and devices. Privacy preservation is addressed via specific cameras (e.g. infrared), providing less information about persons, application of a vertical camera perspective and early-stage anonymisation in the data processing.

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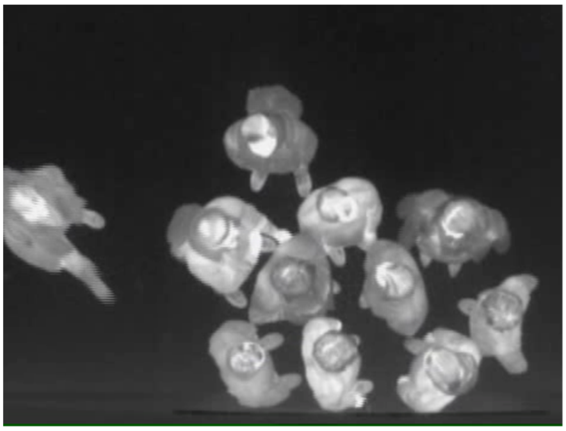

Figure 1: Infrared overhead camera recording.

2 RELATED WORK

In a wider sense on the one hand previous work addressing pedestrian flow analysis, crowd dynamics, modelling and simulation of pedestrians (Helbing et al., 2000, Helbing et al., 1995, Hoogendoorn et al., 2005, Schadschneider et al., 2009) is related to this work, but also crowd density estimation (Eiselein et al., 2013, Rahmalan et al., 2006, Ma et al., 2004) and identification of crowd anomalies (Mahadevan et al., 2010, Mehran et al., 2009). More closely related are the concept by Krausz and Bauckhage for realtime detection of threatening situations in crowds (Krausz et al., 2011, 2012), the work for crowd anomaly recognition based on the social-force model and video-analysis and also the adoption of concepts from pedestrian dynamics, which were used for the design of visual tracking systems (Mehran et al., 2009).

Detection of dense crowds can be covered for instance by anomaly recognition algorithms. However analysis of inner density structures and detection of flow disturbances were not covered yet in previous work to the authors knowledge.

3 SOFTWARE PLATFORM

The requirements for the software platform in the Safest-project includes the capability of processing significant amounts of data from video and audio monitoring devices with a low energy footprint and the support for adding and connecting substantial numbers of nodes to the system. In addition to the video monitoring nodes, which require powerful hardware, also light-weight nodes for intrusion detection have to be supported by the system. The support for heterogenous hardware is therefore a requirement. To fulfil these requirements a specific IoT middleware (RIOT) has been applied to ensure reliable communication and connectability for heterogenous sensing hardware.

The crowd analysis software is realised as a component-based architecture, in which each analysis functionality is encapsulated in its own component. Each software component contains a middleware for asynchronous communication with other components, using the publish-subscribe principle, and additionally encompasses a rule engine with data stream analysis and reasoning capabilities, inherited from temporal modal logic. For each component a set of rules, such as thresholds for critical density values, is defined and observed by the respective rule engine. Critical situations detected by components are communicated and published as events to message queues, to which other components can subscribe in order to receive the events instantly. The underlying component-based framework applied is the Fraunhofer Knowledgefusion Toolkit (Kriegel et al., 2013) and the communication platform is realised using a Redis-infrastruture.

4 CROWD ANALYSIS

The crowd analysis components address the following functionalities:

- **Density** thresholds and value ranges, which are predefined in the system, are applied to measured values to detect critical or unexpected situations.
- **Movement Directions** of people are measured and analysed via frequency distribution. The distribution values are then compared with expected values for respective directions. The directions covered are the four cardinal directions and the four inter-cardinal directions.
- **Counter Streams** which can cause severe disturbances in pedestrian flows and tend to have a significant velocity-decreasing effect are identified and located and as corresponding event information made available.
- **Velocities** of moving people are determined and compared with expected values, allowing to detect escape scenarios or unexpected velocity distributions in general.
- **Flow** density and velocity values are compared to a density-velocity graph by definition of an

integral in the surrounding of the graph, to assess flow characteristics.

Due to the extent only density analysis and counter streams will be covered here.

5 DENSITY STRUCTURE ANALYSIS

In this section a comparison of two technical approaches will be described, which was performed in order to determine an appropriate algorithm for accurate identification of crowds and for analysis of intrinsic structures. The two approaches are data clustering and image contouring. The density structure is important to assess crowds with respect to criticalness. The capability to localise a crowd is important, however to detect threatening high-density areas inside of low-average-density crowds, knowledge about the composition is needed.

5.1 Clustering Algorithms

The datasets that were constructed for comparing and applying clustering algorithms represent density-centric, arc-shaped and homogenous low-density crowds.

The first crowd type has a centric structure (Fig. 2) and has been chosen, since crowds with high-density values towards the center and lower density in the outer area tend to appear often in real life with significantly varying sizes, often with only small high-density regions, sometimes with larger regions in relation to the overall area size. To detect low-density areas as separate clusters is an important requirement to make judgments. Pedestrians

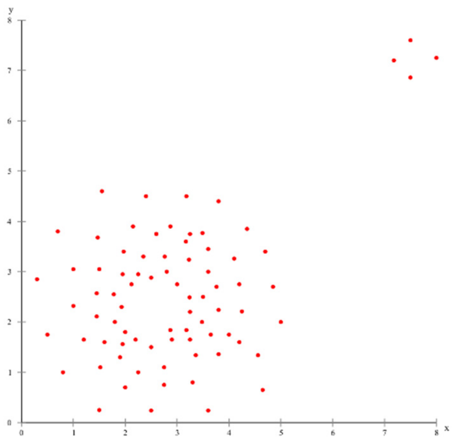

Figure 2: Centric formation.

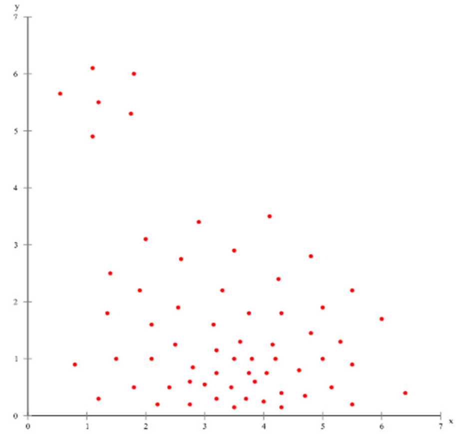

Figure 3: Arc-shaped formation.

standing near to the crowd but not belonging to it also need to be recognised as such. Often crowds are formed around columns, obstacles or barred areas and appear in the pedestrian coordinate data as holes.

The second crowd type is arc-shaped (Fig. 3) and contains a high-density region, opposed to the previous example, in the outer area. Hence the high-density area is not fully surrounded by a lower density structure. This type of crowd also appears often in real life, such as in front of blocked exits, narrow pathways or doors with insufficient flow capacities. The difficulty here is to detect the low-density area together with the high-density area as one single crowd. Moreover algorithms that look for certain distributions, such as Gaussian, now face the difficulty that the distribution is not continuous at one side.

In the third formation three homogenous low-density pedestrian groups of the same shape and geometry were chosen. These were defined, as here the density distribution is flat, which might be relevant for distribution-based algorithms. Also due to the flat density distribution neither dense areas nor any density transitions do exist, which might be of relevance for density-based algorithms.

The types of clustering algorithms that were considered include partitioning methods, density-based clustering, hierarchical density-based clustering and distribution models. Thus a broad range of conventional clustering algorithms as well as advanced algorithms are applied. For each clustering type a representative algorithm was chosen. The respective selections are KMeans (MacQueen, 1967), DBSCAN (Ester et al., 1996), Expectation-Maximization (Moon, 1996) and OPTICS (Ankerst, 1999), which will be described briefly in the following. KMeans is an conventional partitioning algorithm, which calculates iteratively cluster means and associates data to the cluster with the closest mean. Data are assigned to Voronoi cells. The algorithm DBSCAN is based on the density of data points and is especially for density-based clustering problems appropriate. It requires for each point p a cluster $\mathcal{C}$ to have at least a minimum number *MinPts* of points q within its neighbourhood of radius ϵ. DBSCAN utilizes the concept of density-reachability. The algorithm Expectation-Maximization determines maximum likelihood values for models involving latent variables. It is an iterative method which can be applied to different mathematical models, however is computationally expensive. In the context of this work it will be applied to a Gaussian mixture model. The fourth algorithm investigated is called OPTICS, which is a hierarchical density-based clustering algorithm that creates an ordering of the data and determines information about intrinsic cluster structures.

In the following the results of the analysis will be described.

1. Centric Crowd: For the first dataset, which involves a centric crowd structure, the following results were obtained: KMeans did not detect the two clusters correctly. This is due to the fact that it partitions the data into Voronoi cells based on the centroids, which however did not move to the location to represent a correct data assignment to the clusters. DBSCAN and Expectation-Maximization in contrast detected the clusters correctly. The missing data points in the center did not cause difficulties here. OPTICS recognised clusters and inner density structures however not with the required accurateness. The two main clusters here were not separated sufficiently.

2. Arc-Shaped Formation: For the arc-shaped dataset KMeans did not identify the clusters in a sufficient way. DBSCAN and Expectation-Maximization detected the clusters appropriately. As shown in the illustration for the EM-clustering the number of clusters k was set to 3, resulting in three clusters with different densities. If k is set to 2, EM returns the same clusters as DBSCAN. OPTICS created a cluster hierarchy however the results are not satisfying by means of density structures. In the figures 4-7 the results are illustrated for this scenario.

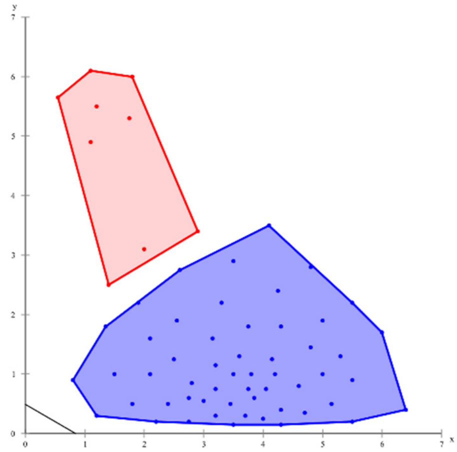

Figure 4: KMeans.

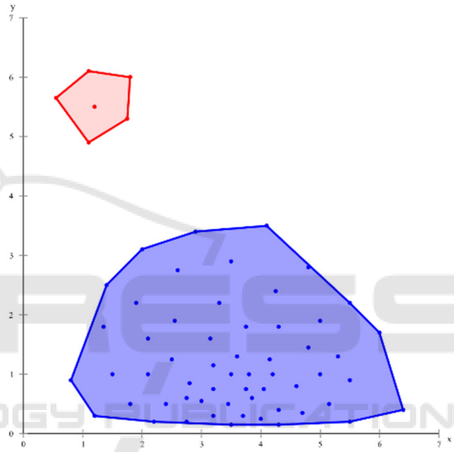

Figure 5: DBScan.

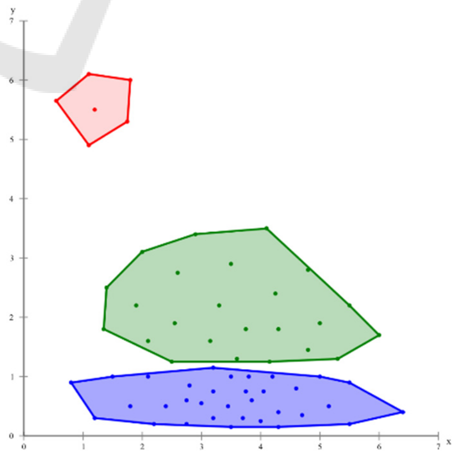

Figure 6: Expectation-Maximization.

Algorithm 1 Extended Marching Squares

Require:
Matrix $\mathcal{I}$, granularity γ, lower/upper density μ_l/μ_u, crowd k, eventlist E, clusters $\mathcal{C}$, perimter p

function ANALYSE($\mu_l, \mu_u, \gamma, \mathcal{I}, E, k$)
    $p \leftarrow identifyPerimeter(\mu_l, \mu_u, \mathcal{I})$
    while p $!= null$ **do**
        $c \leftarrow determineCluster(p, \mathcal{I})$
        if $k == null$ **then**
            $k_{tmp}.c \leftarrow c$
            $E \leftarrow E + new\ PatternEvent(k_{tmp})$
        else
            $c.k \leftarrow k$
        end if
        $\mathcal{C} \leftarrow \mathcal{C} + c$
        $\mathcal{I} \leftarrow \mathcal{I} - c$ ▷ erase cluster from matrix
        $p \leftarrow identifyNextPerimeter(\mu_l, \mu_u, \mathcal{I})$
    end while
    $\mu_l \leftarrow \mu_l + \gamma$
    for all c in $\mathcal{C}$ **do**
        ANALYSE($\mu_l, \mu_u, \gamma, c.\mathcal{I}, E, c.k$)
    end for
    return E
end function

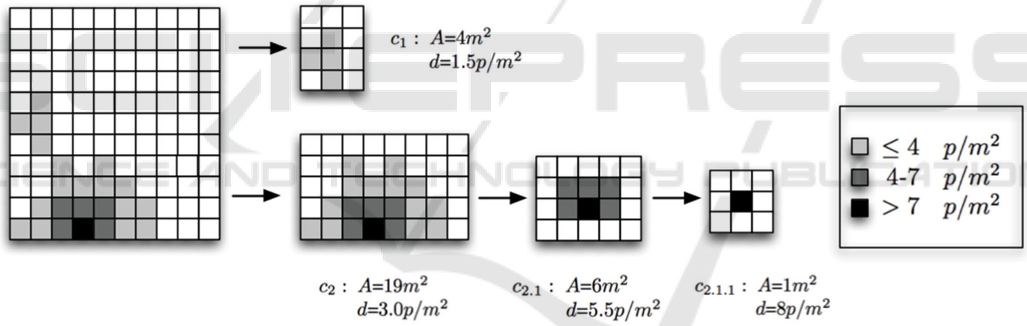

Figure 8: Recursive interval-based Marching-Squares.

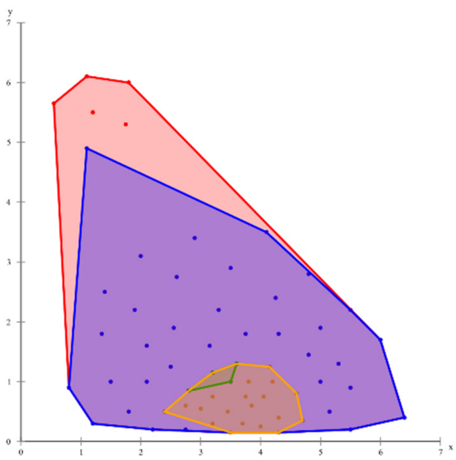

Figure 7: OPTICS.

3. Low-Density Clusters: The results for the third scenario, which are not illustrated here, KMeans, DBSCAN and Expectation-Maximization detected and differentiated the three clusters correctly. The algorithm OPTICS however did not identify the clusters sufficiently for the chosen parameters.

Once the data clusters have been formed, the hull of the cluster, the size and the average density are determined as this information is decisive for further event processing, decision making and alerting. To determine the hull an algorithm implementing DeLaunay-triangulation is applied, Afterwards the area size and the person density are calculated.

Limitations: As the results demonstrated, clustering algorithms are appropriate to detect crowds in a given set of pedestrian coordinates.

However the analysis of intrinsic density structures causes some difficulties and the clustering results were not fully suffcient for this particular criterion.

5.2 Image Contouring - Adapted Marching Squares

Alternatively to data clustering also image contouring methods were investigated, in particular the Marching Squares algorithm. Initially the pedestrian coordinates are transformed to a 2-dimensional density map, which is composed of cells representing the respective number of persons in it. On the basis of the original Marching Squares various modifications and extensions had to be made. This includes the capability to specify a specific person-density interval and a granularity parameter for the degree of accuracy of the density structure. Additionally the algorithm had to be changed to support recursion and to support its infinite application to detected crowds to identify dense areas inside of the crowds. The algorithm requires a different set of input parameters and returns a list of pattern-events which contain meta-information about the identified crowd, including sub clusters with information about average-density, area size, location and number of persons.

Opposed to the clustering algorithms this solution also permits inner structure analysis in a configurable and customisable way and to decompose crowds, revealing decisive information such as the location of dense areas. In addition the algorithm is robust and especially appropriate for application on low-power platforms with limited processing capabilities and resource constraints, as it is computationally inexpensive.

Figure 8 shows the application of the algorithm to scenario 2 involving an arc-shaped formation. The algorithm begins with a low density interval and identifies corresponding paths. The result of the first call are the clusters c_1 and c_2 including corresponding meta-information. After the first call the density interval will be increased by the specified granularity level and now applied to all previously detected clusters, in this case c_1 and c_2, which were extracted and transformed to a separate matrix. Within c_2 a sub-cluster $c_{2.1}$ is detected, which is again analysed. The call-sequence ends with the identification of cluster $c_{2.1.1}$.

6 COUNTER STREAMS AND FLOW DISTURBANCES

Pedestrian counter streams within moving crowds, which can be caused by single persons or groups of people, moving into an opposite direction of the crowd, can decrease the movement velocity substantially and can cause severe congestions. In past crowd disasters such as the Loveparade 2010 in Duisburg (Krausz et al., 2010) or in Mecca 2006 (Helbing et al., 2007) counter streams had occurred and had a negative impact on the situations.

In the following a monitoring and analysis component will be described, which is part of the above described system and which is capable of revealing disturbances in person flows and to localise counter streams. The component interacts with the crowd-analysis component and is notified upon detection of critical events, involving low movement velocities or dense areas. Upon reception of a critical event the crowd data will be analysed by application of the clustering algorithm DBSCAN.

The processed data contains three dimensions, which area the person coordinates x and y and the movement direction z. The information is pre-processed and normalised in a next step, so that data can be clustered in a robust way and data involving opposite movement directions are separated accordingly (Fig. 9).

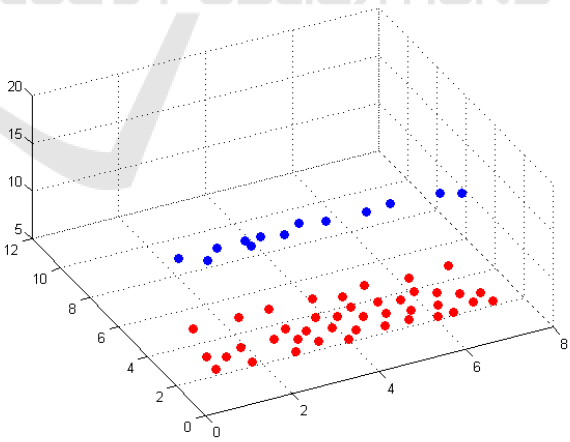

Figure 9: Counter stream detection: 3D-DBScan clustering.

After creation of clusters the hulls are computed using Delaunay hull detection and then area size and locations are analysed.

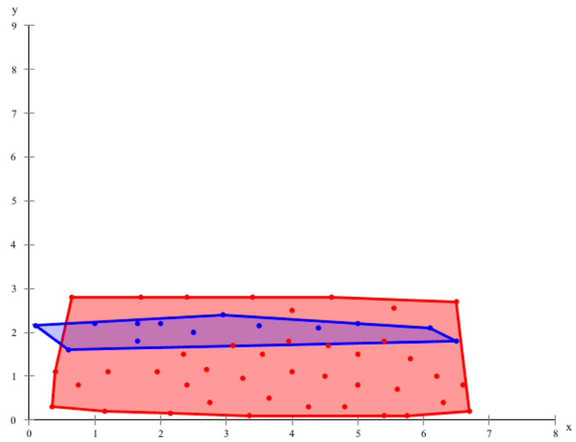

Figure 10: Counter stream detection: Delaunay hull identification.

In the next step rules with corresponding threshold values are applied, assessing severity by person quantity limits and velocity thresholds. Regarding the location it is differentiated between counter streams at the borders with only one disturbance side and streams with two disturbance sides, causing a stronger impact. In the final step the computed meta information is aggregated into an event and published on the respective message channel, to which other system components can listen.

7 CONCLUSIONS AND OUTLOOK

In this paper a comparison of different clustering algorithms was demonstrated for robust and performant detection of crowds and analysis of density structures. The clustering results were satisfying for the detection, but not for structure analysis. A recursive image-contouring algorithm was developed on the basis of the Marching Squares algorithm and 2D density grids, which has the capability to analyse intrinsic structures in a customisable way, making it possible to identify critical areas inside of crowds. Moreover a novel analysis component has been described for identification of flow disturbances, in particular counter streams, and emission of corresponding events, which can be received by listening components. It supports rapid deployability on smart-nodes and light-weight platforms and is capable of being integrated into distributed surveillance systems.

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