A Fuzzy Logic-based Approach to Detection of Abnormal Crowd Behaviour

Darijan Marčetić, Slobodan Ribarić
University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia
{darijan.marcetic, slobodan.ribaric}@fer.hr

***Abstract*— The paper presents an approach to detection of abnormal crowd behaviour at microscopic level. The characteristic individual and group motion patterns are specified with fuzzy predicates. The human interpretation of video sequences of abnormal crowd behaviour, based on common-sense knowledge, is mapped into fuzzy logic functions. Based on the evaluation of these functions, the abnormal crowd behaviour is detected. The usability of the proposed approach is tested on video sequences with ground truth annotations. The preliminary experimental results showed that the approach supports an efficient representation of expert knowledge and detection of anomaly crowd behaviour.**

***Keywords*—Crowd; Crowd behaviour; Fuzzy logic; Common-sense knowledge**

I. Introduction

Recently, crowd analysis is one of the most active research areas in computer vision [1-5]. Among four main processes of crowd analysis: crowd motion detection, crowd tracking, crowd density estimation, and crowd behaviour, the last is perhaps the most challenging. Crowd behaviour combines crowd detection, motion and tracking and it is based on different models [6] (social force model (SFM), Bayesian model, Hidden Markov model (HMM), model based on histograms of motion, flow-based model, …).

Crowd motion patterns include any recognizable spatio-temporal regularity of moving crowds. Depending on the level of a crowd representation and analysis (microscopic, macroscopic, or mesoscopic) motion patterns represent object/entity movement, global movement of the crowd and combination of object/entity and global movement (e.g. movement of an individual in the crowd).

Crowd motion patterns are important for understanding the behaviour of small or medium groups in pedestrian crowds or large-scale crowds of thousands and thousands of people. Crowd behaviour analysis usually classifies crowd scenes manly into normal and abnormal. There are approaches which refine crowd behaviour into classes such as bottlenecks, fountainheads, lanes, arches, and blocking, or escape and non-escape activity [7].

Solmaz et al. described five basic motion patterns for classification of crowd behaviours: blocking, lane, bottleneck, arches and fountainheads [7]. The authors used a fluid-dynamic-like model (Lagrangian particle model) where crowds are treated as collection of interacting particles. The proposed method combines low-level local motion features obtained by optical flow and high-level information obtained by analysing several regions of interest in the scene. By using the stability analysis of fluid-dynamic model, the determinant and corresponding eigenvalues of the Jacobian matrix are obtained and applied for recognition crowd motion patterns (Figure 1.).

a) Blocking ($\Delta < 0$) b) Lane ($\Delta = 0$) c) Bottleneck ($\Delta > 0; \tau < 0$) d) Arch ($\Delta > 0; \tau < 0$) e) Fountainhead ($\Delta > 0; \tau < 0$)

Figure 1. Crowd motion patterns [7]; $\Delta = \lambda_1 \lambda_2$ is determinant of the Jacobian matrix J_F, and $\tau = \lambda_1 + \lambda_2$, where λ_1 and λ_2 are eigenvalues of J_F.

In [8], a vision-based approach to analyse small groups in pedestrian crowds is described. The approach combines detection, multi-object tracking and sociological models of small groups of individuals. The groups are discovered by hierarchical clustering using the Hausdorff distance defined with respect to pairwise proximity and velocity of the pedestrians in a crowd. Trajectories of moving groups are obtained by solving a linear tracklets assignment problem and using Hungarian algorithm.

In [9], Heldens et al. used a three-stage pipeline for analysing crowd movements. In the first stage, the behaviour of each person at each moment in time is represented using low-dimensional data point. In the second stage, these data points are clustered based on spatial relations. In the third stage, concatenation of these clusters is performed based on temporal relations. The authors define four types of crowd motion patterns: curved lanes, parallel lanes, intersecting lanes and divergent lanes.

In this paper, the fuzzy logic predicates for specifying the crowd motion patterns are proposed. The fuzzy logic functions based on the subset of fuzzy logic predicates for describing motion patterns for a group of objects/individuals are used to represent common-sense knowledge for two anomaly crowd behaviour models: Alarm_runaway and Alarm_bottleneck. The assignment functions for fuzzy predicates and fuzzy functions for detection of anomaly behaviour are determined by using ground truth notations for the crowd video sequences.

II. Fuzzy Logic Predicates, Fuzzy Logic Functions and Crowd Behaviour

To represent and describe crowd motion patterns at the microscopic level which is suitable for low-density crowds where the movement of each individual (or small group) pedestrian is concerned, we propose two types of fuzzy predicates for describing crowd motion patterns of individual and group of individual.

A. *Fuzzy predicates for the individual motion patterns*

Let us suppose that the position of each tracked individual o_i, $i = 1, \ldots, n$, at discrete time point t_j, $j = 1, \ldots, k$, is represented with space points (x_i^j, y_i^j), where n is the number of tracked individuals and k is the total number of frames in a video sequence. The positions of all tracked individuals in the video sequence (x_i^j, y_i^j), $i = 1, \ldots, n$, and $j = 1, \ldots, k$, are obtained by multi-object detection, tracking and re-identification algorithms [10].

Let us define a fuzzy predicate as a mapping (called an assignment function or simply, assignment): O×T×R → [0,1], where O is a set of n tracked individuals, T is a set of k time points and R is a set of n trajectories of individuals. Each trajectory consists of corresponding position points, i.e. trajectory r_i contains k position points $\{ (x_i^1, y_i^1), (x_i^2, y_i^2), \ldots, (x_i^k, y_i^k) \}$ of an individual o_i [11]. The assignment function maps an element of **s** ∈ O×T×R to a degree of fulfilment which determines to what *degree* the predicate is valid. The assignment functions are determined based on human common-sense knowledge and interpretation of the ground truth anotations of a learning set of video sequences.

Definitions, as well as, illustrations of direction fuzzy predicates for motion patterns for individual objects (Inline, Turn_left, Turn_right, Circle) and velocity fuzzy predicates (Standstill_Individual, Slow_individual, Fast_individual) are given in our paper [11].

B. *Fuzzy predicates for the motion patterns for a group of individuals*

Fuzzy predicates for the motion patterns for a group of individuals on microscopic level are defined based on interactions of the individuals and their trajectories. In general, each fuzzy predicate for a group of individuals is defined as $\mathcal{P}$(O)×T× $\mathcal{P}$(R) → [0,1] which maps each element of **g** ∈ $\mathcal{P}$(O)×T× $\mathcal{P}$(R) to a degree of fulfilment, where $\mathcal{P}$(O) is a power set of tracked individuals O $= \{\mathrm{o}_1, \mathrm{o}_2, \ldots, \mathrm{o}_n\}$, T $= \{\mathrm{t}_1, \mathrm{t}_2, \ldots, \mathrm{t}_k\}$ is a set of time points, and $\mathcal{P}$(R) is a power set of trajectories of objects, i. e. R $= \{\mathrm{r}_1, \mathrm{r}_2, \ldots, \mathrm{r}_n\}$ [11]. A heuristic assignment function is used to compute the actual truth value to which a sample **g** fulfils the given predicate. The main reason for above definition of the fuzzy predicate for a group of individuals is our intention to define different groups of individuals in several regions of interest in a video scene. To demonstrate behaviour model for only one group, the mapping is restricted to samples **g** represented by triplets $(\mathrm{O}, t_j, \mathrm{R})$, where j =1, ..., k.

The fuzzy predicates for a group of individuals are classified as follows: distance predicates (Next_to, Near_to, Faraway); velocity predicates (Standstill_group, Slow_group, Fast_group) and dynamic predicates (Dispersing, Gathering).

1) *Distance predicates*

The truth value estimation procedure for the Next_to$(\mathrm{O}, t_j, \mathrm{R})$ predicate is as follows:

INPUT: n position points for the time point t_j, $\{ (x_1^j, y_1^j), \ldots, (x_n^j, y_n^j) \}$ from the set R, where n is the number of objects in a group.

STEP 1: At the time point t_j for a set of corresponding n position points $\{(x_i^j, y_i^j)\}_{i=1}^n$ average value of $n(n-1)/2$ distances between all possible point pairs is determined.

STEP 2: The estimated truth value of the Next_to$(\mathrm{O}, t_j, \mathrm{R})$ predicate is obtained by mapping the average value of distances to an interval $[0, 1]$ with an experimentally determined assignment function (Figure 2.).

The truth value estimation procedure described for Next_to predicate, is also used for other distance predicates (Near_to and Faraway), except that in **STEP 2** appropriate assignment functions are used.

2) *Velocity predicates*

The truth value estimation procedure for the Fast_group$(\mathrm{O}, t_j, \mathrm{R})$ predicate is:

INPUT: n position points for each one of m time points t_{j-m+1}, ..., t_j, $j \geq m$, the total of $n \times m$ position points are given, $\{(x_1^{j-m+1}, y_1^{j-m+1}), \ldots, (x_n^{j-m+1}, y_n^{j-m+1}), \ldots, (x_1^j, y_1^j), \ldots, (x_n^j, y_n^j)\}$ from the set R, where n is a number of objects in a group. The value of m is constant, and it is experimentally determined based on a learning dataset. It defines a time window (m frames in the past, starting from the current frame with index j).

STEP 1: Determine an average distance that all objects travel between two consecutive frames:

$$\frac{1}{n(m-1)} \sum_{i=1}^{n} \sum_{k=j-m+1}^{j-1} \left[(x_i^{k+1}, y_i^{k+1}) - (x_i^k, y_i^k) \right].$$

STEP 2: The estimated truth value of the Fast_group$(\mathrm{O}, t_j, \mathrm{R})$ predicate is obtained by mapping the average distance obtained in the **STEP 1** to an interval $[0, 1]$ with an experimentally determined assignment function (Figure 2.).

The truth value estimation procedure described for Fast_group predicate, is also used for other velocity predicates (Standstill_group and Slow_group), except that in **STEP 2** appropriate assignment functions are used.

3) *Dynamics predicates*

The truth value estimation procedure for the Dispersing$(\mathrm{O}, t_j, \mathrm{R})$ predicate is as follows:

INPUT: n position points for the time point t_{j-m} and n position points for the time point t_j from the set R: $\{ (x_1^{j-m}, y_1^{j-m}), \ldots, (x_n^{j-m}, y_n^{j-m}), (x_1^j, y_1^j), \ldots, (x_n^j, y_n^j) \}$, where n is the number of objects in a group.

STEP 1: At the time point t_{j-m} for the set of corresponding n position points $\{(x_i^{j-m}, y_i^{j-m})\}_{i=1}^n$ the average value of $n(n-1)/2$ distances between all possible point pairs is determined. The same procedure is performed at time point t_j and corresponding n position points $\{(x_i^j, y_i^j)\}_{i=1}^n$.

STEP 2: The difference of the average value of distances for the time point t_j and the average value of distances for the time point t_{j-m} is calculated.

STEP 3: The estimated truth value of the Dispersing$(0, t_j, \mathrm{R})$ predicate is obtained by mapping the difference of the average value of distances to an interval $[0, 1]$ with an experimentally determined assignment function (Figure 2.).

The truth value estimation procedure for the Gathering $(0, t_j, \mathrm{R})$ predicate is the same as that for the Dispersing $(0, t_j, \mathrm{R})$ predicate, except that in **STEP 3** an appropriate experimentally determined function is used. A high positive and negative difference of the average value of distances indicates a high degree of fulfilment for the Dispersing and Gathering predicates, respectively.

The assignment functions for the fuzzy predicates: Fast_group, Disspersing, Faraway and Near_to, which are used in runaway scenario are depicted in Figure 2.

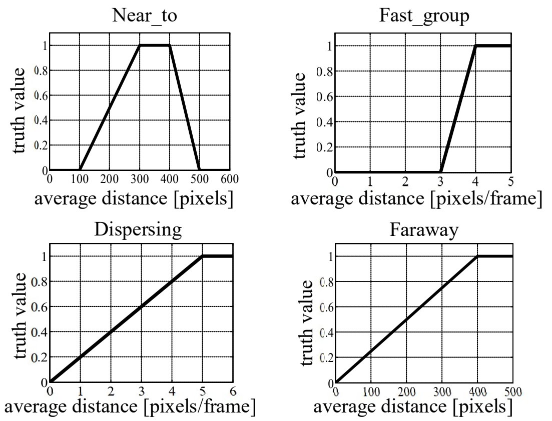

Figure 2. Assignment functions for fuzzy predicates used in runaway scenario.

The above mention fuzzy predicates for the motion patterns for a group of individuals and/or for the individual motion patterns can be used for building the fuzzy functions suitable for making inferences about complex crowd behaviour. The fuzzy functions are application specific and their truth values are, in general, obtained with a composition of fuzzy predicates and fuzzy logical operators [12, 13]: negators, conjunctors (t-norms), disjunctors (t-conorms) and implicators.

C. Common-sense knowledge for defining two models of anomaly crowd behaviour

In the context of common-sense knowledge by observing the specific video sequences [14], the scenarios of anomaly crowd behaviour (Alaram_runaway and Alarm_ bottleneck) at the microscopic level in the surveillance applications can be described as follows:

Alarm_runaway:

A runaway situation occurs when at the beginning, several individuals that are close to each other (i.e. they form a group of people). Suddenly, they start to run away, velocity of each individual increases, the group is dispersing, and the individuals are becoming more and more distant.

Alarm_bottleneck:

A bottleneck occurs when at beginning, several individuals are near to each other and moving fast in the same direction. With the passing of time, the individuals become closer and closer to each other, and they move slowly or stand still.

The Alarm_runaway fuzzy function at the time point t_j is defined as follows:

Alarm_runaway (t_j) = Near_to$(0, t_{j-l}, \mathrm{R}) \wedge$ Fast_group$(0, t_j, \mathrm{R}) \wedge$ Dispersing$(0, t_j, \mathrm{R}) \wedge$ Faraway$(0, t_j, \mathrm{R})$, where $j > l$, and $\wedge$ is a conjunctor and it corresponds to minimum value of fuzzy predicates.

The Alarm_bottleneck fuzzy function at the time point t_j is defined as follows:

Alarm_bottleneck (t_j) = Near_to$(0, t_j, \mathrm{R}) \wedge$ Gathering$(0, t_j, \mathrm{R}) \wedge$ [(Fast_group$(0, t_{j-l}, \mathrm{R}) \wedge$ Slow_group$(0, t_j, \mathrm{R})) \vee$ (Fast_group$(0, t_{j-l}, \mathrm{R}) \wedge$ Standstil_group$(0, t_j, \mathrm{R})$)], where $j > l$.

Note that due to limited space of the paper, we only defined the fuzzy predicates needed for fuzzy function which specifies the Alarm_runaway behaviour model (Figure 2.).

III. PRELIMINARY RESULTS

The feasibility of the proposed approach for detection of the abnormal crowd behaviour is verified on a crowd video dataset [14]. The ground truth annotations of the positions of individuals in the videos and crowd behaviour patterns are obtained by crowdsourcing. The videos used for testing contain normal and abnormal crowd scenarios. Figure 3. depicts the truth values of the selected predicates and the values of the fuzzy logic function Alarm_runaway. The alarm threshold for the runaway scenario is experimentally selected as 0.4. The tracklets of the individuals in the selected frames at the interesting time points are depicted in Figures 4 and 5. The obtained predicate truth values and the fuzzy logic function values are in accordance with the ground truth annotations. In the experiment, we illustrated that the proposed approach successfully predicted the exact time point at which abnormal crowd runaway behaviour scenario occurred.

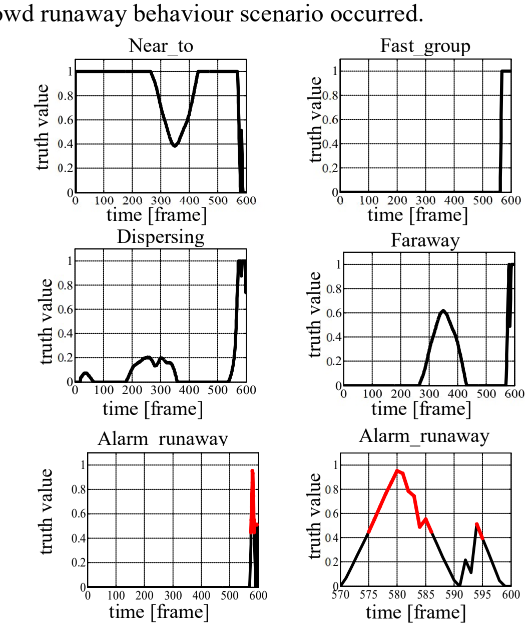

Figure 3. Fuzzy predicates and Alarm_ runaway fuzzy function.

Figure 4. Tracklets for selected frames.

Figure 5. Selected frames illustrate active occurrence of the Alarm_runaway (threshold 0.4).

IV. Conclusion

An approach to detection of the abnormal crowd behaviour in video surveillance scenes at the microscopic level is proposed. It is based on human interpretation of video sequences and mapping this common-sense knowledge interpretation into fuzzy logic functions for two types of anomaly behaviour: runaway and bottleneck. The building blocks of the fuzzy logical functions are the fuzzy predicates for which the assignment functions are determined based on an expert interpretation of training video sequences. The proposed approach is evaluated on the simulated crowd events [11] and ground truth annotations of the real video sequences. The obtained results of the preliminary experiments showed that the approach supports an efficient representation of the expert knowledge, and detection of the anomaly crowd behaviour. The research in the near feature will be oriented to anomaly behaviour detection based on the non-ideal, i.e. real trajectories and tracklets obtained by robust multi-object tracker, and exhaustive testing of the proposed approach on the video sequences of the real crowd scenes.

Acknowledgments

This work has been supported by the Croatian Science Foundation under projects IP-2018-01-7619 “A Knowledge-based Approach to Crowd Analysis in Video Surveillance” (KACAVIS).

References

[1] T. Li, H. Chang, M. Wang, B. Ni, R. Hong, and S. Yan, “Crowded Scene Analysis: A Survey”, IEEE Transactions on Circuits and Systems for Video Technology, Vol. 25, No. 3, March 2015, pp. 367-386.

[2] S. Ali, K. Nishino, D. Manocha, and M. Shah, “Modeling, Simulation and Visual Analysis of Crowds: A Multidisciplinary Perspective”, In: Ali S., Nishino K., Manocha D., Shah M. (eds.) Modeling, Simulation and Visual Analysis of Crowds, Vol. 11, 2013, Springer, New York.

[3] H. Y. Swathi, G. Shivakumar, and H. S. Mohana, “Crowd Behavior Analysis: A Survey”, In Proc. 2017 Int. Conf. on Recent Advances in Electronics and Communication Technology, 2017., pp. 169-178.

[4] J. C. S. Jacques, S. R. Musse, and C. R. Jung, “Crowd Analysis Using Computer Vision Techniques, A survey”, IEEE Signal Magazine, 2010, pp. 66-77.

[5] B. Zhan, D. N. Monekosso, P. Remagnino, S. A. Velastin, and L.-Q. Xu, “Crowd analysis: A survey”, Machine Vision and Applications, Vol. 19, 2008, pp. 345-357.

[6] M. T. Khan., A. Ali, M.Y. Durrani, and I. Siddiqui, “Survey of Holistic Crowd Analysis Models”, J. Comp. Sci. Comm., 1(1), 2015, pp. 1-9.

[7] B. Solmaz, B. E. Moore, and M. Shah, “Identifying Behaviors in Crowd Scenes Using Stability Analysis for Dynamical Systems”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, Issue: 10, Oct. 2012, pp. 2064- 070.

[8] W. Ge, R. T. Collins, and R. B. Ruback, “Vision-Based Analysis of Small Groups in Pedestrian Crowds”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, 2012, No. 5, pp. 1003-1016.

[9] S. Heldens, N. Litvak, and M. Van Steen, “Scalable Detection of Crowd Motion Patterns”, IEEE Transactions on Knowledge and Data Engineering, (Early Access), 2018, 13 pages.

[10] D. Marčetić, and S. Ribarić, “An Online Multi-Face Tracker for Unconstrained Videos”, 14th International Conf. on Signal-Image Technology & Internet-Based Systems. 2018, pp. 159-163.

[11] D. Marčetić, L. Maleš, S. Ribarić, “Crowd Motion Pattern Detection at the Microscopic Level”, Int. Conf. MIPRO, May 2019, 6 pages.

[12] M. Nachtegael and E.E. Kerre, “Fuzzy logical operators on finite chains”, Int. Journal of General System, 29(1),2000, pp. 29-52.

[13] I. Perfilieva, “Fuzzy function: theoretical and practical point of view”, In Proc. of the 7th Conf. of the European Society for Fuzzy Logic and Technology, 2011, pp. 480-486.

[14] UMN dataset. http://mha.cs.umn.edu/proj_events.shtml