Detecting Events in Crowded Scenes using Tracklet Plots

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Abstract: The main contribution of this paper is a compact representation of the 'short tracks' or *tracklets* present in a time window of a given video input, which allows to analyse and detect different crowd events. To proceed, first, tracklets are extracted from a time window using a particle filter multi-target tracker. After noise removal, the tracklets are plotted into a square image by normalising their lengths to the size of the image. Different histograms are then applied to this compact representation. Thus, different events in a crowd are detected via a Bag-of-words modelling. Novel video sequences, can then be analysed to detect whether an abnormal or chaotic situation is present. The whole algorithm is tested with our own dataset, also introduced in the paper.

1 INTRODUCTION

Automatic analysis of crowded scenes appears as a need to reduce costs and improve people's safety, while reducing the burden of manual video surveillance (Candamo et al., 2010; Davies et al., 1995). Crowd analysis has received attention in the last decade, and is of interest for a very wide range of fields, as described in (Zhan et al., 2008; Jacques Junior et al., 2010).

There are different ways to approach crowd dynamics modelling. Many different scenes, ranging from sparse scenes, with few individuals, to crowds, all forming a continuum. This calls for a topology of scenes, such as the one proposed by (Zhan et al., 2008), with three levels: micro-, meso- and macroscopic which would be roughly equivalent to individual, group or crowd levels. Topologies show the human need for categorisation of situations, but this does not mean that interaction among methods from different levels cannot be possible.

In fact, in Thida et al. (Thida et al., 2013), the authors state that approaches considered to be part of the microscopic modelling (as it is the tracking of individuals in a scene) can be used in a bottom-up approach, which allows us to look at crowded situations from the individual tracking perspective.

In this paper, we will present an idea based on that concept. To do this, we obtain short tracks from the people in the scene, and then use this information and merge it into the 'tracklet plot', a feature that will be described in Subsection 2.2. After that, a bag of words modelling will extract the most common *words*, and their appearance frequencies in different situations (Section 2.3). We will also introduce a novel dataset for crowded scene analysis from multiple views. Finally, the results for our method, as well as the conclusions drawn will be presented in Section 4.

1.1 Event Recognition and Tracklet Exploitation

The work by Ballan et al. (Ballan et al., 2011) surveys the field of event recognition, from interest point detectors and descriptors, to event modelling techniques and knowledge management technologies. The authors imply that the recognition of crowd events, and the recognition of actions, performed by a single actor using a single camera, have much in common, since the event modelling techniques can be quite similar, if not the same, regardless of the feature being used, which will depend on the case.

Hu et al. (Hu et al., 2008) are able to extract the dominant motion patterns of a video, by using sparse optical flow vectors as their tracklets, these are then associated into motion patterns by a sink-

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seeking process, followed by the construction of super tracks which represent the dominant/collective motion patterns discovered. The authors obtain the dominant motion patterns or trajectories, and these can be used to detect deviations from the pattern. Nevertheless, other types of events cannot be detected. Lasdas et al. (Lasdas et al., 2012) use tracklets obtained from a Kanade-Lucas-Tomasi (KLT) tracker, instead of sparse flow vectors. Furthermore, they enumerate the desirable features of a motion summarisation system to which the reader is referred.

Similarly, in Gárate et al. (Garate et al., 2009), the authors track FAST points (Features from Accelerated Segment Test) extracted from the bounding boxes of objects detected via background subtraction. Density is estimated in the image by superimposing a grid and counting the number of FAST feature points in each cell in the grid. Furthermore, the tracklets extracted from the tracking of the FAST features are used to detect dominant directions of motion.

On the other hand, Dee and Caplier (Dee and Caplier, 2010) present an analysis of crowd events based on histograms of motion direction (HMDs), which, to some extent are similar to the tracklet plot, except for the fact that the HMDs are obtained for the whole video sequence, instead of smaller intervals, as is done in this paper. Using small intervals allows the analysis of particular situations happening at a given moment in a long video, rather than analysing the video as a whole.

2 METHODOLOGY

There are two main contributions in this paper. On the one hand, a feature based on the compact representation of tracklets is presented (see Fig. 2 for examples). On the other, a dataset for crowded scene analysis is introduced. In this section, the first contribution will be explained.

The proposed feature enables the detection of anomalous events in crowded scenarios. The tracklet plot representation is, to some extent, similar to the Motion History Images (MHI) introduced by Bobick and Davis (Bobick and Davis, 2001), but instead, the tracklet superimposition represents the density and orderliness of a particular interval: for instance, if all the tracklets are parallel they will generate an area in the image that is particularly bright (high intensity in a narrow band), while a chaotic situation will be represented by an image which has no particular bright areas. Figure 1 shows an overview of the whole feature extraction process, including also the training stage.

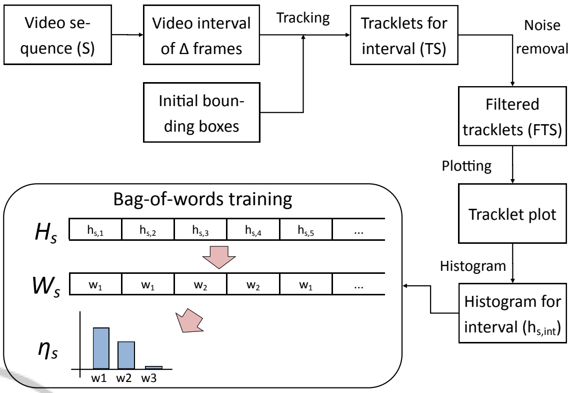


Figure 1: Overview of the whole process up to Bag-of-words training.

2.1 Tracking Multiple Targets

The first step of the algorithm entails the extraction of short tracks or *tracklets*. To do this, a tracking algorithm needs to be employed. Most trackers need an initialisation step, in which the moving objects or people are detected. Once the algorithm has its initialisation *seeds*, the tracking then proceeds automatically.

Furthermore, in our case, multiple targets need to be tracked at the same time, in order to obtain the motion patterns of the whole scene. Thus, a multi-target tracker, or a tracker running in parallel for each detected individual must be used. In this step, a Particle Filter based algorithm is used (Pérez et al., 2002), and run in parallel for each of the individuals present in the scene.

2.1.1 Tracklet Extraction

Since most trackers deal badly with tracking over long periods of time, intervals of Δ frames are used. Tracklet sets $TS_{n\Delta}$ are obtained for each interval, where n is the interval number and so $n \cdot \Delta$ is the initial frame for that tracklet set. These sets will contain the tracklets for each individual being tracked during the interval. At this point, the tracklet sets consist of a series of $2D$ points for each individual; so $TS = \{P_{t=0}, \cdots, P_{\Delta-1}\}$, that is, for each frame t, P is a set of $2D$ points, containing the centres of mass of the bounding boxes of the people being tracked. It has the form: $P_t = \{c_0, \cdots, c_M\}$, where each c_i represents the center of mass of a tracked box with id i, and M is the total amount of individuals in the scene for the tracklet set TS.

Since the Particle Filter tracker yields a noisy output due to the change in scale of the bounding boxes that happens during tracking, a Kalman filter is applied to the sequences of centres of mass, so that smoother tracklets are retrieved. By doing so, a series of filtered tracklet sets FTS are obtained.

2.2 Feature Extraction

Feature extraction is performed in two steps. The first step consists of tracklet plotting. This step plots the tracklets into a fixed-size image, centered and normalised (Sec. 2.2.1). Then, in the second step, a histogram is obtained from the image, which allows further analysis of the individuals' speed and direction of motion (Sec. 2.2.2).

2.2.1 Tracklet Plotting

Once the tracklets have been filtered, the compact representation is obtained, namely the *tracklet plot*. To do so, the tracklets in each set FTS are first fit into a square image by normalising their lengths to the size of the image. Each filtered tracklet ft in the set is assigned an equal weight:

$$\text{weight} = \frac{I(\max)}{||FTS||} \qquad (1)$$

which is represented as an intensity value in the image. Here, $I(\max)$ is the maximum intensity (255 for 8-bit images) and $||\cdot||$ denotes the number of elements in the filtered tracklet set FTS. Each tracklet is then centered and superimposed in the tracklet plot, as it is depicted in Fig. 2. It is worth noting that this representation tracks global behaviour, and not situated actions.

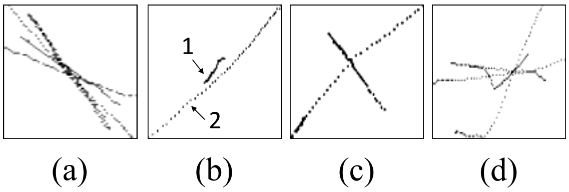


Figure 2: Example of different tracklet plots. a) Ordered group of people walking at the same speed and direction; b) a fast biker (b.2) and a slower pedestrian (b.1); c) Two people walking in perpendicular directions; d) A chaotic situation, where people run away. Pictures are shown in inverted colour and enhanced contrast.

2.2.2 Histogram Extraction

After the above process, a histogram can be extracted from the tracklet plot. To do this, two methods are proposed:

- **Circular Histogram.** This histogram takes concentric disc-shaped regions R into account, being $R = r_{0,\rho-1}, r_{\rho,2\rho-1}, \cdots, r_{n\rho,\max}$ a set of ranges, where $r_{0,\rho}$ is a circular region around the centre of the image with a radius of ρ, and *max* is the radius of the image. The histogram for a given window (of a sequence s) $h_{(s,\text{win})}$ is then calculated as:

$$h_{(s,\text{win})}(r, I(x)) = \sum_{p_i \in r} I(p_i) \text{ if } I(p_i) = I(x), \forall r \in R, \qquad (2)$$

  where each p_i is a pixel in the region r. The main advantage of this kind of histogram is that it can control differences in velocity for the different tracked individuals.

- **Angle-distance Histogram.** On the other hand, a histogram based on sectors can be better to detect the *orderliness* of a crowd, since it can detect whether all the tracklets follow a particular direction of motion, or an small amount of them, or the movement in the scene is chaotic, with individuals running in many different directions. For this, sectors A are introduced, such that $A = \alpha_{0,\gamma-1}, \cdots, \alpha_{(n-1)\gamma,n\gamma}$ being γ the angle span for each sector and with $n\gamma = 2\pi$. Thus, the equation for the histogram can be modified from (2), to look like:

$$h_{(s,\text{win})}(\alpha, r, I(x)) = \sum_{p_i \in (r,\alpha)} I(p_i) \mid I(p_i) = I(x), \qquad (3)$$

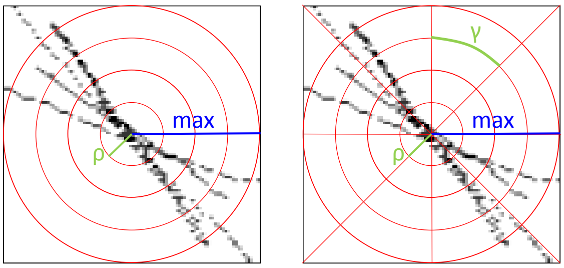
  for all $r \in R$ and all $\alpha \in A$.

Furthermore, two more histogram extraction methods have been envisaged, each one based on the two already presented, but with the particularity that they have one fewer dimension (totalling 1 dimension for the circular counterpart, and 2 dimensions for the angle-distance). In these two modalities, the binning in the intensity dimension is not performed; instead, only the count of pixels in the plot that are not equal to zero is kept. Different experiments have been carried out, in order to establish which is the best histogram modality to use (see Sec. 3).

Regardless of the method employed, all the histograms $h_{(s,\text{win})}$ are normalised to sum 1. Since the method is applied to each window of a video sequence, sets of histograms H_s can be obtained for each sequence s in the set of video sequences for training. Figure 3 shows the two main histogram modalities for clarity; a) shows the circular histogram, with the different regions with their radius being multiples of ρ. `max` depicts the maximum plot radius. In the same figure, in b) the γ angle span is also shown, along with the lines delimiting the sectors.

2.3 Bag of Words Modelling

To perform a modelling of the different crowd situations in the video input, a series of training video sequences S_{train} are employed. Each sequence s has an



(a) (b)

Figure 3: Example of the two main histogram extraction modalities presented: a) circular histogram; b) polar histogram.

associated set of histograms H_s. And $h_{(s,\text{win})}$ denotes the histogram for an interval (win) of sequence s.

A bag-of-words (BoW) modelling is applied to the sequences (Sivic and Zisserman, 2003). This approach was first used for the categorisation of documents in a corpus, and introduced the concept of a histogram of *key word* frequencies (Ballan et al., 2011).

In our case, a video is the analogue of a document; the words in our documents will be tracklet plot histograms; and the "key words" frequency histograms for each document will be extracted by the BoW algorithm as follows:

- Step 1. First, all the sequences of tracklet plot histograms (H_s) are taken, and the tracklet plot histograms ($h_{(s,\text{win})}$) are fed into a k-Means clustering, regardless of the sequence they are originally part of. This will return a fixed number of cluster representatives or *key words* (w).
- Step 2. These key words are used to generate keyword sequences (W_s), in which each of the original words is replaced by the nearest key word from Step 1.
  - The distance to the a key word w is calculated by the Jeffrey distance, as:

$$J(h_{(s,\text{win})}, w) = \frac{KL(h_{(s,\text{win})}, w) + KL(w, h_{(s,\text{win})})}{2}, \quad (4)$$

    where $KL(\cdot,\cdot)$ is the Kullback-Leibler distance between the key word, or more generally for two discrete probability distributions p, q:

$$KL(p,q) = \sum_{i=1}^{||p||} p_i \ln \frac{p_i}{q_i}, \quad (5)$$

    for all $p_i, q_i \mid p_i \neq 0$ and $q_i \neq 0$.
- Step 3. A histogram of key-word frequencies (η) is obtained for each key-word sequence W_s. Each bin of this histogram is:

$$\eta_s(w) = \sum_{x=1}^{||W_s||} \delta(w, W_s(x)), \quad (6)$$

  being

$$\delta(w, W_s(x)) = \begin{cases} 1 & \text{if } W_s(x) = w, \\ 0 & \text{otherwise.} \end{cases} \quad (7)$$

- Step 4. All η_s histograms are then normalised to sum 1, this will make them invariant to sequence length.

Once this process is finished, the model is trained, and any future video input can be recognised by means of the k-nearest neighbour (k-NN) algorithm.

3 EXPERIMENTATION

The algorithm described in the previous subsection (Sec. 2.3), has been used to evaluate the performance of the feature described in subsection 2.2. To do so, first a dataset was acquired. Then, a validation was performed, using a leave-one-sequence-out cross-validation (LOOCV). In the next subsections, the set-up is explained in more detail.

3.1 The Penrhyn Road Campus Dataset

A set of four cameras were placed in a building adjoining the courtyard in the Penrhyn Road campus. Two cameras were installed on the second floor, and two were placed on the fourth floor, all overlooking the courtyard. A group of 20 actors performed various stage group behaviours in the courtyard, such as walking normally as one group, walking normally as two crossing groups, walking in one direction with some people abnormally deviating from the trajectory followed by the rest, or simulating a chaotic event where everybody runs away from a danger. These videos have been labelled into three categories, namely `normal`, `abnormal` and `chaotic`, respectively. For the purpose of this work, 18 sequences from one of the views are used. Table 1 summarises the details of the dataset.

Table 1: Characteristics of the dataset.

Category	Sequences
Normal	10
Abnormal	5
Chaotic	3

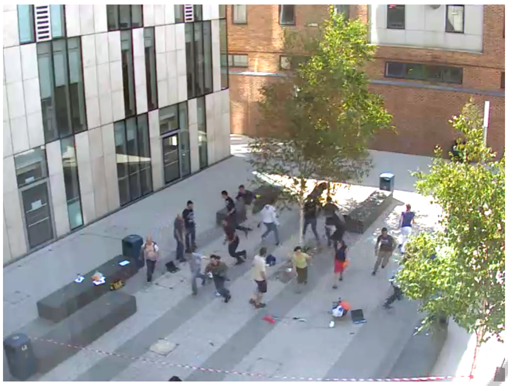


Figure 4: Example of a frame from a chaotic (panic event) situation from the Penrhyn Road Courtyard dataset.

3.2 Testing Set-up and Validation

To test our method, a set of features (H) needs to be obtained. It is a superset formed by all the sets of features $H_s \mid s \in S$, which in turn contain all the features for all the intervals of sequence s: $h_{(s,\text{win})}$. The bag of words modelling algorithm takes H as input and yields a set of key-words w and the set of key-word frequency histograms η (one per sequence: η_s).

In order to validate our method, a leave-one-sequence-out cross-validation (LOOCV) is employed. This process will take all the sequences except for one, and create the training sequences set $S_{\text{train}} = S - s_{\text{test}}$. Then H_{train} is obtained as per the process already described; subsequently, the BoW model is trained. Then, the test sequence, s_{test} is used to check. This is done for all the folds, that is, by leaving one sequence out for test at each fold.

All the steps through the process involve a number of parameter decisions, set as shown in Table 2. The parameter `iter` is in reference to the number of *iterations* that the k-Means algorithm is run during the Bag-of-words model acquisition. The parameter named `reps` is the number of times that the BoW is run per test. Also, Table 3 is given, which shows the bins used for the different histogram extraction methods employed.

Table 2: Parameters used for the validation of the method.

Parameter	Value or range
Δ	50
plot radius	50
$h_{(s,\text{win})}$ bins	See Table 3
k-Means K	2–64
k-Means `iter`	1; 3
BoW `reps`	5; 15

Table 3: Size (as number of bins) for the histograms used.

Histogram	Bins
Circular	6×255
Polar	$8 \times 6 \times 255$
Circular w/o int.	10
Polar w/o int.	8×6

4 RESULTS AND CONCLUSIONS

As said, different configurations have been tested. Table 2 shows the values which have been used for each of the parameters. These have been obtained experimentally.

The k-Means clustering algorithm is prone to give different results due to the random process related to the cluster centre selection. As said, the variable `iter` is related to the number of times the k-Means is run. The clustering error is calculated each time, and the clustering with the lower error is picked at the end of the process. On the other hand, the Bag-of-Words modelling can also be run multiple times (repetitions or `reps`) with different k-Means centres, so that the random initialisation problem is overcome.

Two different configurations have been tried, once with `iter` = 3 and `reps` = 5; as well as `iter` = 1, and `reps` = 15. Table 3 shows the size of the histograms that have been used for the different modalities.

Figure 5 shows the results in a graphical form, each of the series representing a different configuration. Four series are shown in the figure. `CI` stands for circular histogam, and `LP` stands for polar. Both include intensity bins. The numbers next to the two letters (`CI` or `LP`) correspond to the iterations of k-Means (`iter`) and the repetitions of BoW (`reps`), respectively.

Figures 6 and 7 show the behaviour of the algorithm for the polar histogram that has been presented, both without and with intensity bins respectively. It is worth noting that the best result is achieved when no intensity bins are used and reaches a maximum success rate of 83% ($K = 2$). In the case of using intensity bins, the maximum success rate is of 67% ($K = 2$). Table 4 shows the maximum, mean and minimum success rates for the both modalities of polar histogram.

Figures 8 and 9 show the behaviour of the algorithm for the circular histogram that has been presented, both without and with intensity bins respectively. In this case, the maximum success rates are 72.7% ($K = 21$), for the circular histogram without intensity bins; and 61.6% ($K = 7$) for the histogram with intensity bins. Table 5 shows the maximum,

Table 4: Results for polar histograms.

Histogram	Success %	K
Polar		
Lowest Min.	5.6%	$K = 51$
Highest Max.	66.7%	$K = 6$
Highest Mean.	51.5%	$K = 5$
Polar w/o intensities		
Lowest Min.	16.7%	$K = 18$
Highest Max.	**83.3%**	$K = 2$
Highest Mean.	70.0%	$K = 2$

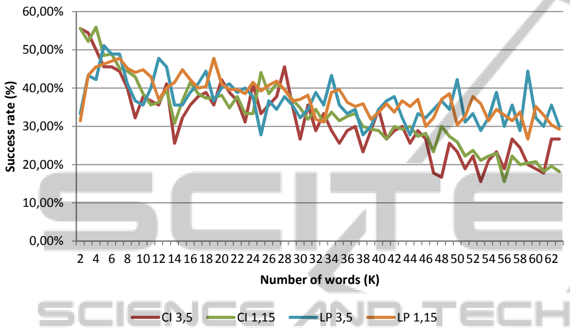


Figure 5: Graphical view of the success rate for increasing values of K, using polar and circular histograms (with intensity bins).

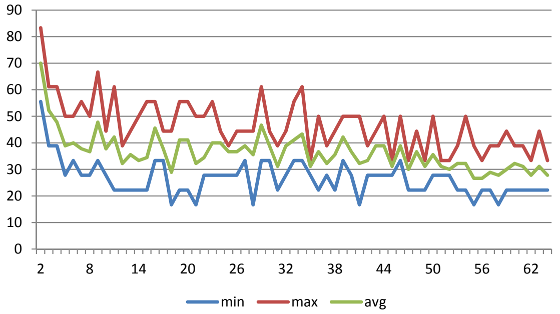


Figure 6: Maximum, mean and minimum success rates for increasing values of K using the polar histogram (without intensity values).

mean and minimum success rates for the both modalities of circular histogram.

4.1 Discussion and Conclusions

A compact representation of the *tracklets* present in a time window of a given video input has been presented. Tracklets are extracted from a time window using a particle filter multi-target tracker. Noise is then filtered out, to obtain smooth tracklet trajectories. The tracklets are then plotted into a square image, and a circular histogram is then applied to this compact representation. Furthermore, a Bag-of-words modelling has been employed over these fea-

Table 5: Results for circular histograms.

Histogram	Success %	K
Circular		
Lowest Min.	5.6%	$K = 53$
Highest Max.	61.6%	$K = 7$
Highest Mean.	55.6%	$K = 2$
Circular w/o intensities		
Lowest Min.	11.1%	$K = 8$
Highest Max.	**72.2%**	$K = 21$
Highest Mean.	57.8%	$K = 2$

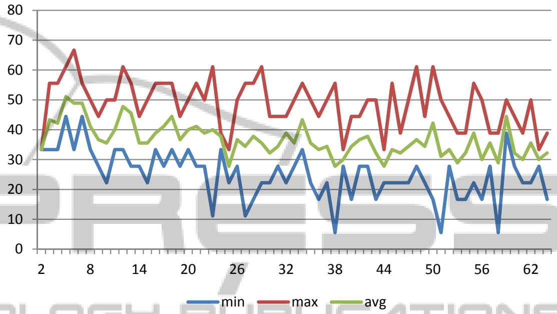


Figure 7: Maximum, mean and minimum success rates for increasing values of K using the polar histogram (with intensity values).

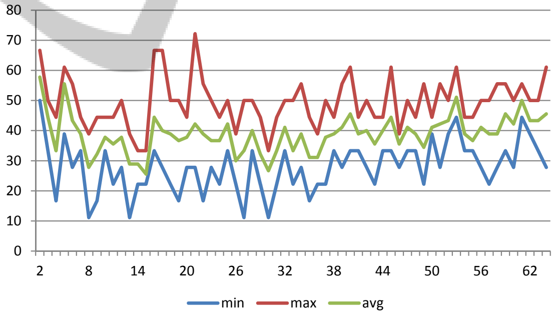


Figure 8: Maximum, mean and minimum success rates for increasing values of K using the circular histogram (without intensity values).

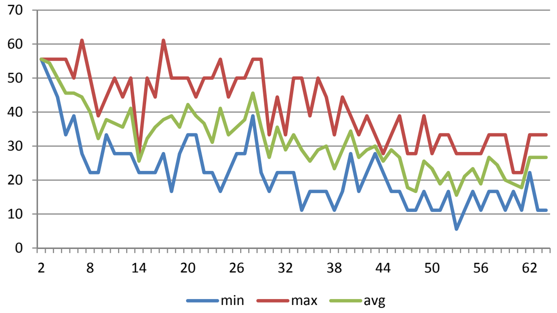


Figure 9: Maximum, mean and minimum success rates for increasing values of K using the circular histogram (with intensity values).

tures for crowd event recognition. Our method has been validated by using a LOOCV cross-validation on a novel dataset.

From the results, some conclusions can be drawn. First, it can be seen that results are generally better for lower values of K. This seems to be logical, since there should be, at most, three or four different situations at a given moment in time; that is: normal, deviations from normal and chaotic. Also, it can be seen that results with histograms that do not take intensity into account are better than their intensity-aware counterparts. Finally, polar histogram seems to perform better than circular; which again, seems logical due to the fact that the circular histogram does not take *orderliness* into account.

It has to be noted that the dataset in use in this case is a very challenging one, due to the presence of heavy clutter due to objects in the scene (trees, benches...) which complicates the tracking, which is the bottleneck of the process. A poor tracking result will always yield to worse results in general. Further work needs to be carried out in this regard.

4.2 Future Work

In this section a series of immediate and future improvements are shown, which are considered to ameliorate the results.

As just said, the bottleneck of the whole process is in the tracking. If the tracking fails, the tracklet plots will not be representative of the situation in the scene. For this reason, a good tracker is essential. Tracking perfectly and flawlessly is still an open challenge in the computer vision research community. Thus, and since the aim of this work is not achieving better tracking, ground truth data of the people could be used to evaluate the tracklet plot histograms and the bag-of-words modelling being applied. Another option would be using promising trackers such as the recent work by Kwon et al. (Kwon and Lee, 2013).

Furthermore, testing our method on other datasets is a pending task. Nevertheless, most existing datasets are near-field, and thus, ours seems more appropriate for group and crowd analysis. Also, most of them provide video footage from a single view. Furthermore, the types of situations present in our dataset, are not always present in other publicly available datasets. For instance, the UMN dataset[1], would be the best candidate to try our algorithm next. However, it has two main drawbacks: first, it includes scenes were people wander, which is not considered 'normal' behaviour as defined and used in this paper; second, it is single view, so planned extensions of our work for multiple views could not be tested on it.

Finally, as just mentioned, future work also includes the use of video footage from multiple views. To this end, information from all the available cameras (four in our dataset) is to be combined and tested either by a fusion method at the "feature level", or by merging by means of a "model-level" algorithm. For the former, synchronised video is to be used, so obtaining the features from the various video sources simultaneously. The features are then fused by merging them into a longer feature. Dimensionality reduction techniques might be needed, since the features are now much longer (i.e. four-fold) than the original. In the latter, on the other hand, different models for the different cameras are learnt, and then fusion is performed afterwards, using a voting mechanism, that in turn could assign weights to the different views (e.g. by using an additional neural network layer).

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