The S-HOCK Dataset: Analyzing Crowds at the Stadium

Davide Conigliaro[1], Paolo Rota[2], Francesco Setti[3], Chiara Bassetti[3], Nicola Conci[4], Nicu Sebe[4], and Marco Cristani[1]

[1]University of Verona , [2]Vienna University of Technology , [3]ISTC–CNR (Trento) , [4]University of Trento

Abstract

The topic of crowd modeling in computer vision usually assumes a single generic typology of crowd, which is very simplistic. In this paper we adopt a taxonomy that is widely accepted in sociology, focusing on a particular category, the spectator crowd*, which is formed by people "interested in watching something specific that they came to see" [6]. This can be found at the stadiums, amphitheaters, cinema, etc. In particular, we propose a novel dataset, the Spectators Hockey (*S-HOCK*), which deals with 4 hockey matches during an international tournament. In the dataset, a massive annotation has been carried out, focusing on the spectators at different levels of details: at a higher level, people have been labeled depending on the team they are supporting and the fact that they know the people close to them; going to the lower levels, standard pose information has been considered (regarding the head, the body) but also fine grained actions such as hands on hips, clapping hands etc. The labeling focused on the game field also, permitting to relate what is going on in the match with the crowd behavior. This brought to more than 100 millions of annotations, useful for standard applications as people counting and head pose estimation but also for novel tasks as* spectator categorization*. For all of these we provide protocols and baseline results, encouraging further research.*

1. Introduction

Capturing and understanding crowd dynamics is an important problem under diverse perspectives. From sociology to public safety management, modeling and predicting the crowd presence and its dynamics, possibly preventing dangerous activities, is absolutely crucial.

In computer vision, crowd analysis focuses on modeling large masses, where a single person cannot be finely characterized, due to the low resolution, frequent occlusions and the particular dynamics of the scene. Therefore,

Figure 1. Example of images collected for both the spectators and the rink, plus the annotations.

many state-of-the-art algorithms for person detection and re-identification, multi-target tracking, and action recognition cannot be directly applied in this context. As a consequence, crowd modeling has developed its own techniques such as multi-resolution histograms [45], spatio-temporal cuboids [24], appearance or motion descriptors [3], spatio-temporal volumes [28], dynamic textures [30], computed on top of the flow information. The extracted information is then employed to learn different dynamics like Lagrangian particle dynamics [36], and in general fluid-dynamic models. The most important applications of crowd analysis are abnormal behavior detection [30], detecting/tracking individuals in crowds [25], counting people in crowds [8], identifying different regions of motion and segmentation [40].

All these approaches focus on a generic definition of crowd, while a thorough analysis of the sociological liter-

ature offers a taxonomy which could be very interesting for computer vision. In particular, crowds – better defined as large gatherings [17, 18, 31] – can be divided into four broad categories:

1. *prosaic* [31] or *casual* [7, 19] crowd, where members have little in common except their spatio-temporal location (e.g., a queue at the airport check-in counter);
2. *demonstration/protest* [31] or *acting* [7, 19] crowd, a collection of people who gather for specific protest events (e.g. mob/riot/sit-in/march participants);
3. *spectator* [31] or *conventional* [7, 19] crowd, a collection of people who gather for specific social events (e.g. cinema/theater/sport spectators);
4. *expressive* crowd [7, 19], a collection of people who gather for specific social events and want to participate in the "crowd action" (e.g. flash-mob dancers, mass participants, sport supporters).

Considering this taxonomy, we can say that most of the approaches in the computer vision literature focus primarily on casual [8, 25, 36], and protest crowd [26], with hundreds of approaches and various datasets, while very few (if any) deal with the spectator crowd and its expressive segment. This is a critical point: from a recent statistics of 2014 conducted by UK Home Office[1], disorders at stadiums caused 2,273 arrests only considering the FA (Football Association) competitions in the last year. Moreover, in the last 60 years 1447 people died and at least 4600 were injured at the stadiums during major events around the world[2]. These statistics motivated in several countries the implementation of emergency plans to ensure a better safety and order management, and it is here where computer vision may consistently help.

This paper is an initial attempt to address this topic, focusing on the analysis of the spectator crowd, and offering the first dataset on the subject, S-HOCK. S-HOCK focuses on an international hockey competition (12 countries from all around the world have been invited) held in Trento (Italy) during the 26th Winter Universiade, focusing on the final 4 matches of the tournament.

The dataset is unique in the crowd literature, and in general in the surveillance realm. The dataset analyzes the crowd using 4 cameras, at different resolutions and different levels of detail. At the highest level, it models the network of social connections among the public (who knows whom in the neighborhood), what is the supported team and what has been the best action in the match; all of this has been obtained by interviews at the stadium. At a medium level, spectators are localized, and information regarding the pose of their heads and body is given. Finally, at a lowest level, a fine grained specification of all the actions performed by each single person is available. This information is summarized by a large number of annotations, collected over a year of work: more than 100 millions of double checked annotations. This permits potentially to deal with hundreds of tasks, some of which are documented in the next paragraphs.

Other than this, the dataset is multidimensional, in the sense that it offers not only the view of the crowd, but also on the matches. This enlarges the number of possible applications that could be assessed, investigating the reactions of the crowd to the actions of the game, opening up to applications of summarization and content analysis. Besides these figures, S-HOCK is significantly different from all the other crowd datasets, since the crowd as a whole is mostly static and the motion of each spectator is constrained within a limited space in the surrounding of his position.

In this paper we discuss issues related to low and high level detail of the crowd analysis, namely, people detection and head pose estimation for the low level analysis, and the spectator categorization for the high level analysis. Spectator categorization is a kind of crowd segmentation, where the goal is to find the group of supporters for each team. For all of these applications, we define the experimental protocols, promoting future comparisons.

From the experiments we conducted, we show how standard methods for crowd analysis, which work well on state-of-the-art datasets, are not fully suited to the data we are dealing with, thus requiring us to face the problem from a different perspective. For this reason, together with baselines, we also propose customized approaches specifically targeted at the spectator crowd.

Summarizing, the contributions are:

- A novel dataset for spectator crowd[3], which describes at different levels of detail the crowd behavior with millions of ground truth annotations, synchronized with the game being played in the field. Crowd and game are captured with different cameras, ensuring multiple points of view;
- A set of tasks for analyzing the spectator crowd, some of them are brand new;
- A set of baselines for some of these tasks, with novel approaches which definitely overcome the standard crowd analysis algorithms.

The rest of the paper is organized as follows: The details of the data collection and labeling are reported in Sec. 2; the tasks of people detection, head pose estimation, and spectator categorization are introduced in Sec. 3, focusing on contextualizing the problem, discussing the related state of the art (if any), presenting the considered baselines and our

[1] Football-related arrests and football banning order statistics, Season 2013–14, available online at http://goo.gl/j9yYYQ.

[2] See at http://goo.gl/xMU2Zf.

[3] The database is available at http://vips.sci.univr.it/dataset/shock

Annotation	Typical Values
People detection	full body bounding box $[x, y, \text{width}, \text{height}]$
Head detection	head bounding box $[x, y, \text{width}, \text{height}]$
Head pose*	left, frontal, right, away, down
Body position	sitting, standing, (locomotion)
Posture	crossed arms, arms alongside body, elbows on legs, hands on hips, hands in pocket, hands on legs, joined hands, hands not visible, crossed legs, parallel legs, legs not visible
Locomotion	walking, jumping (each jump), rising body slightly up
Action / Interaction	waving arms, pointing toward game, pointing outside game, rising arms, waving flag, hands a cone, whistling, positive gesture, negative gesture, applauding, clapping (each clap), using device, using binoculars, using megaphone, patting somebody, call for attention, hugging somebody, kissing somebody, passing object, hit for fun, hit for real, opening arms, hands to forehead, hitting hands (once), none
Supported team	the team supported in this game (according to the survey)
Best action	the most exciting action of the game (according to the survey)
Social relation	If he/she did know the person seated at his/her right (according to the survey)

Table 1. The annotations provided for each person and each frame of the videos. These are only typical values that each annotation can have, a detailed description of the annotations is provided with the dataset. The meaning of the head pose attributes will be explained later in the paper. [*] For the experiments in Sec. 3.2, *away* class has been further divided in *far-left* and *far-right* to discriminate the head pose even when a spectator is not looking toward the rink.

approaches, and discussing the results obtained. Finally, in Sec. 4, other applications worth investigating are briefly discussed, promoting further research on this new topic.

2. Data Collection & Annotation

The 26th Winter Universiade was held in Trento (Italy) from 11 to 21 of December 2013, attracting about 100,000 people from all over the world among athletes and spectators. The data collection campaign focused on the last 4 matches (those with more spectators) held in the same ice-stadium: here we used 5 cameras, a full HD camera (1920×1080, 30 fps, focal length 4mm) for the ice rink, another one for a panoramic view of all the bleachers, and 3 high resolution cameras (1280×1024, 30 fps, focal length 12mm) focusing on different parts of the spectator crowd. In total, 20 hours of recordings have been collected, with inter-camera synchronization: this brought the interesting feature of having the crowd synchronized with the game on the rink.

After the match, we asked to a percentage of uniformly distributed spectators (30%) to fill a simple questionnaire with three questions (i.e. whose significance will be clear later in the paper):

- Which team did you support in this match?
- Did you know at the beginning of the match who was sitting next to you?
- Which has been the most exciting action in this game?

In S-HOCK we focus on game segments from different hockey matches in order to stress the generalization capability of the considered algorithms, since in different matches we have different people and illumination conditions. In particular, from each match we selected a pool of sequences in order to represent a wide, uniform and representative spectrum of situations, e.g. tens of instances of goals, shots on goal, saves, faults, timeouts (each sequence has more than one event). Each video is 31 seconds long (930 frames), for a total of 75 sequences, namely 15 for each camera. The annotations reported in Tab.1 have been performed on one of the three close-field cameras, whereas the videos recorded with the other two cameras were annotated only with the survey information. The fourth view is a wide-field view of the previous three views and the fifth is oriented toward the ice rink in order to record the game events.

Each sequence has been annotated frame by frame, spectator by spectator, by a first annotator, using the ViPER format [11][4]. The annotator had to perform three different macro tasks: detection (localizing the body and the head), posture and action annotation, respectively. This amounted to deal with a set of 50 labels, listed in Tab. 1.

From the whole set of possible features that can characterize the human dynamics, we selected the annotated *elementary forms of action* [31] as they are strictly connected with the analysis of social interaction, and are related to our specific setting, i.e. sport spectator crowd. In particular, we considered the available literature on social interactions [17, 18, 31], with particular attention to non-verbal conduct (proxemics, bodily posture, gesture, etc.), especially in public places; we focus also on the so-called crowd behavior literature, i.e., social interaction in large gatherings, in particular sport spectator gatherings [5].

Each annotator had two weeks to annotate 930 frames, and was asked to do it in a specific lab, in order to monitor him/her and ensure a good annotation quality. After that all the sequences have been processed, producing a total amount of more than 100 millions of annotations, a second round of annotations started, with the "second annotators" that were in charge of correcting the errors from the first-round annotation phase. The whole work involved 15 annotators and lasted almost 1 year, with all annotators paid for their duties.

[4]The toolkit is available at http://viper-toolkit.sourceforge.net/

3. Evaluation

In this section we present a set of possible applications on S-HOCK. In particular we focus on two classical tasks, such as people detection and head pose estimation, and one more interesting application from the social point of view, such as spectator categorization. For each one of the tasks we briefly present the state of the art, taking into account only the methods potentially applicable in our particular scenario and some preliminary experiments conducted on our dataset. We also propose some ways to improve their performance by exploiting the specific structure of the crowd and the relation between the crowd behavior and the ongoing game.

3.1. People Detection

People detection is a standard and still open research topic in computer vision, with the HOG features [10] and the Deformable Part Model (DPM) [15] as workhorses, and plenty of alternative algorithms [13]. Unfortunately, most of the methods in the literature are not directly usable in our scenario, mostly for two reasons: low resolution – a person has an average dimension of 70×110 pixels – and occlusions – usually only the upper body is visible, rarely the entire body and sometimes only the face.

Recently, some works studied how to improve the performance of detectors by means of an explicit model of the visual scene. Specifically, focusing on people detection in crowded scenes, Barina et al. [4] used the Hough transform to overcome the non-maxima suppression stage for detecting multiple instances of the same object, while San Biagio et al. [39] proposed a new descriptor able to treat complex structural information in a compact way. To overcome occlusion issues, Wu and Nevatia [44] used a number of weak part detectors based on edgelet features and Eichner et al. [14] fused DMP [15] and Viola-Jones [34] detectors to identify upper bodies. Finally, Rodriguez et al. [37] proposed to optimize a joint energy function combining crowd density estimation and the localization of individual people.

Here we provide 5 different baselines for people detection: the first method is a simple detector based on HOG [10] (cell size of 8×8 pixels) and a linear SVM classifier dubbed in the following *HOG+SVM*. The second method only differs in the descriptor, which is the Heterogeneous Auto-Similarities of Characteristics (HASC) descriptor [39]. We use the same sliding window as HOG+SVM to generate the map and the detections. We will refer to this method as *HASC+SVM*.

We also test 3 state-of-the-art methods for people detection: (1) the Aggregate Channel Features (*ACF*) detector [12], which uses the Viola-Jones framework to compute integral images (and Haar wavelets) over the color channels, fusing them together; (2) the Deformable Part Model (*DPM*) [15] combines part's templates arranged in a deformable configuration fed into a latent SVM classifier; and (3) the Calvin Upper Body Detector (*CUBD*) [14], a combination of the DPM framework trained on near-frontal upper-bodies – i.e. head and upper half of the torso of the person – and the Viola-Jones face detector.

On top of all these methods, we propose an extension based on the strong prior we have in our kind of crowd, i.e. the people are "constrained" by the environment to arrange in a grid – the seats on the bleachers. Assuming a regular grid (considering the camera perpendicular at the plane of the bleachers and ignoring distortion effects) and acounting for the fact that people are more likely to be located on the same rows and columns, we can just add to the detection confidence map the average of the map over the rows and the columns. Consider $D(x, y)$ the output of the detector for the patch (x, y), the modified output for a target location $(\hat{x}, \hat{y})$ is:

$$\tilde{D}(\hat{x}, \hat{y}) = D(\hat{x}, \hat{y}) + \sum_i D(x_i, \hat{y}) + \sum_j D(\hat{x}, y_j)$$

In the case there is a distortion due to the camera point of view, this could be easily recovered by using Hough transform for detecting the "principal directions" and summing over these direction (which has not been done here).

As experimental protocol, we use two videos from a single game for training and two from different games for validation, leaving the 11 sequences of the final for testing. A set of 1,000 individuals randomly selected from the training videos are used as positive samples, while a background image is used to generate the negative samples for training. Then, 20 random frames from the validation videos are used to tune the best values for the minimum detection score threshold and the non-maxima suppression parameters. A subsampling of 1 frame every 10 for each video is used for testing, resulting in 1,000 images and 150,000 individuals. While ACF, DPM and CUBD have their own searching algorithms to generate candidate bounding boxes, for HOG+SVM and HASC+SVM we consider a sliding window of 72×112px with a step of 8px, generating a detection confidence map of 160×118 patches. A threshold on the minimum detection score and a non-maxima suppression stage have been applied to generate the predicted detections.

We consider an individual as correctly identified if the intersection area between the predicted and the annotated bounding boxes is more than 50% of the union of the two rectangles by the formula

$$B_p \cap B_{gt} > \frac{(B_p \cup B_{gt})}{2} \tag{1}$$

where $B_p \cap B_{gt}$ denotes the intersection of the predicted and ground truth bounding boxes and $B_p \cup B_{gt}$ their union.

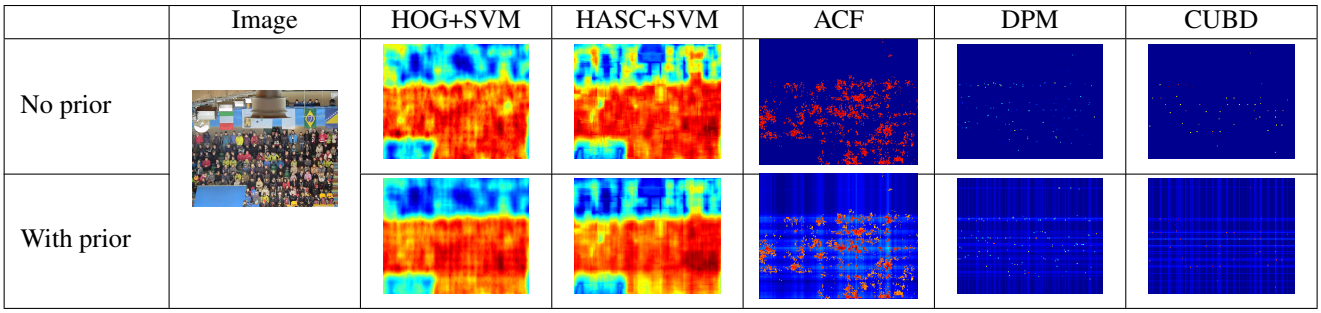


Figure 2. Qualitative results for people detection algorithms. Detection confidence map for each method with and without imposing the grid-arrangement prior (best viewed in color).

As performance measures we use precision, recall and F_1 scores.

A qualitative evaluation of the baselines and the grid arrangement prior contribution is in Fig. 2, while quantitative results are in Tab. 2. We can notice how the best performing method is the HOG+SVM, while part based frameworks (i.e. DPM and CUBD) perform poorly in their standard version; this is probably due to the small size of the person bounding boxes which makes it very difficult to detect single parts like arms and legs. By introducing our proposed prior, we can see how all the methods increase their performances in terms of F_1 score, and in particular CUBD increases of about 10%, becoming one of the best detectors for this kind of scenario.

3.2. Head Pose Estimation

Once the body has been detected, and the head has been localized, a consequent operation to be carried out is the head pose estimation.

The literature on head pose estimation is large and heterogeneous as for the scenarios taken into account; most of the approaches assume that the face is prominent in the image, as in a multimodal interaction scenario, and rely on the detection of landmark points [48, 23, 9]. Here these solutions are inapplicable since the faces are too small (50x40 pixels on average). In a low resolution domain the work proposed by Orozco et al. [33] seems to fit better, relying on the computation of the mean image for each orientation class. Distances w.r.t. the mean images are used as descriptors and fed into SVMs. In [43], the authors exploit an array of covariance matrices in a boosting framework. The image of the head is divided into different patches, that are weighted depending on their description capability. On S-HOCK these methods perform roughly the same in terms of classification accuracy, with a huge time consumption (see Tab. 3).

Method	no prior			with prior		
	Prec.	Rec.	F_1	Prec.	Rec.	F_1
HOG + SVM	0.743	0.561	**0.639**	**0.662**	**0.709**	**0.684**
HASC+SVM [39]	0.365	**0.642**	0.465	0.357	0.685	0.469
ACF [12]	0.491	0.622	0.548	0.524	0.649	0.580
DPM [15]	0.502	0.429	0.463	0.423	0.618	0.502
CUBD [14]	**0.840**	0.303	0.444	0.613	0.553	0.581

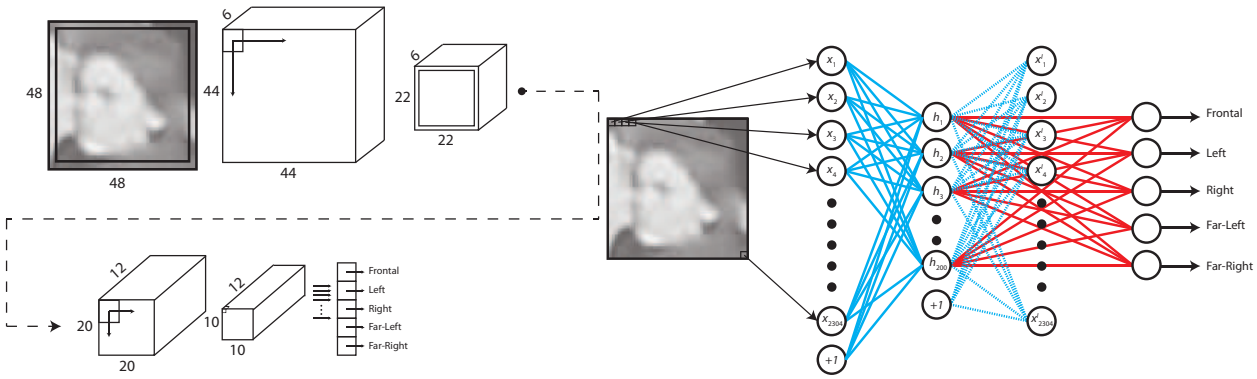
Table 2. Quantitative results of people detection methods, with and without the grid-arrangement prior.

In order to overcome this issue, we propose two novel approaches based on Deep Learning, with comparable results which are obtainable at a much higher speed. The choice of Deep Learning is motivated by the large number of effective approaches in the object recognition literature, witnessing its versatility in many scenarios [29, 22, 27, 42, 41].

In particular, we evaluate the performance of the Convolutional Neural Network (*CNN*) and the Stacked Autoencoder Neural Network (*SAE*) architecture. In both methods we feed the Neural Network with the original image, resized to a standard size of 50x50 pixels, so as to have uniform descriptors. The CNN is composed by 5 layers: an input layer followed by 2 sets of convolution-pooling layers (see Fig. 3 (a)). Both kernels in the convolutional layers are 5×5 pixels, the scaling factor of the pooling layer is 2 and the training has been performed over 50 iterations.

The SAE architecture is depicted in Fig. 3 (b), the input images are fed into an auto-encoder with hidden layers of size $h = 200$, trained separately. A second training phase is performed on the Neural Network initialized with the weights learned in the previous stage. Both training procedures are refined in 100 epochs.

The experimental protocol is the same as in the previous case, except for the fact that there is no validation set; all the training sequences are employed to extract a total of 107299 head instances while the test set is composed by 34949 head instances from the testing sequences. In this experiment, we take as input the head locations coming from the ground truth, in order to derive a sort of upper bound on the estimation performances. In this respect, faces are annotated as *frontal*, *left*, *right*, *far left* and *far right*. In a more quantitative fashion, frontal faces are considered roughly in the range between $-10°$ and $10°$, left and right spans from



(a) (b)

Figure 3. (a) Architecture of CNN. (b) SAE architecture: in cyan are pictured the interconnections between the auto-encoder that must be trained separately, in red instead there are the interconnections of the final NN.

(a) (b) (c) (d) (e)

Figure 4. Examples of the five head poses considered for the experiments in Sec. 3.2; in order (a) to (e): *far left*, *left*, *frontal*, *right*, *far right*.

Method	AVG Accuracy	Training time [sec]	Testing time [sec]
Orozco et al. [33]	0.368	105303	6263
WArCo [43]	0.376	186888	87557
CNN	0.346	16106	68
SAE	0.348	9384	3
CNN + EACH	0.354	16106	68
SAE + EACH	0.363	9384	3

Table 3. Classification accuracy for state-of-the-art methods averaged on the five classes and the computation time. The time used to refine the prediction through EACH is negligible comparing to the one used to train and test the neural network.

$-10°$ to $-80°$ and $10°$ to $80°$ respectively. The heads exceeding those angles in both directions are considered as *far left* and *far right*. This has been detailed to the annotators during the data labeling (see Fig. 4).

Tab. 3 shows the results of the current state of art methods compared with the two proposed approaches. The overall accuracy spans within a range of 3% for Orozco et al. [33], WArCo [43], CNN and SAE but in neural networks approaches the computation workload is much smaller. This speed up in classification time for both training and testing phases makes our method more suitable for real life applications where a quick response and an imminent decision is required. As a further remark, we trained WArCo by randomly sampling 5000 samples among all those available for training; this has been necessary for the huge computation time required to learn the model in case of using the whole set of data.

In the case of large sport events, the spectator crowd attention tends to be attracted by the location of the action. This observation can be exploited to benefit the final classification. For this reason we propose an additional experiment named EACH (Event Attention CatcH). In order to accomplish this task we consider the ice rink as our universe of locations where the puck can be. We are not interested in the pitch information of the head so we reduce the rink to a monodimensional space. We model the position of the puck as a Gaussian distribution over all the possible locations and we consider it as a prior probability in order to refine the final head pose estimation. This probability $P_A^{(c)}$ is formalized in Eq. (2)

$$P_A^{(c)} = \sum_{i=L^{(c)}}^{U^{(c)}} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - m^{(c)})}{2\sigma}} \tag{2}$$

where $L^{(c)}$ and $U^{(c)}$ are the lower and the upper boundaries of the rink for the specific class c respectively, $m^{(c)}$ is the position of the puck.

$$c = \arg\max_c \left(\alpha P_A^{(c)} + (1-\alpha) P_N^{(c)}\right) \tag{3}$$

The final decision is taken according to Eq. (3), where α is a weighting parameter, $P_N^{(c)}$ is the probability of the head pose being assigned to class c computed by the Neural Network.

We observe that this model is much more beneficial when players are playing with respect to when the game is paused by a foul. This particular aspect suggests us to tune the α parameter according to the game phase. The results reported in Tab. 3 are computed using $\sigma = 15$ and $\alpha = 0.3$. The ice rink information increases the accuracy by approximately 2% on both CNN and SAE frameworks.

3.3. Spectator Categorization

The *spectator categorization* task consists in finding the supporters of each team, accounting for the fact that fan of the same team will have a similar behavior at some events (a goal etc.) which is strongly different from that of the other supporters.

Spectator categorization can be considered a subtask of the crowd behavioral analysis, which is generally associated with human activity analysis [20, 35, 1]. As stated by Jaques et al. [21], in computer vision there are two main philosophies for crowd behavior analysis: the *object-based* one where the crowd is considered as a collection of individuals, and the *holistic* approach, which treats the crowd as a single entity. This second approach is the one that best suits the spectator crowd analysis because it directly tackles the problem of dense occluded crowds. The holistic approaches usually start from optical flow to extract global information from the crowd. In [2], the authors use Lagrangian particle dynamics to segment the flow; here the notion of a flow segment is equivalent to a group of people that perform a coherent motion. More recently, Mehran et al. [32] propose a streakline representation of flow to address various computer vision problems, including crowd flow. They use a simple watershed segmentation of streaklines to cluster regions of coherent motion.

Both these works and several datasets proposed in the literature focus on pedestrian crowds [38, 2], instead with S-HOCK we propose a crowd with different dynamics and behavior, where the people are assumed to stay near a fixed location for most of the time and their movements are limited to their position. For this reason, the works listed above require some adjustments in order to be applied to the spectator categorization task.

In this paper we also present a new method for spectator categorization: as most of the holistic approaches, our method starts from dense optical flow computation too. Then we decompose the flow map into a set of overlapping patches and we describe each patch with five features: x and y coordinates of the patch's centroid, the average flow intensity I (over all the pixels belonging to the patch), the entropy of flow intensity E_I and directions E_D (both directions and intensities are quantized to compute the entropy).

These feature vectors are then passed to a Gaussian clustering approach with automatic model selection [16], obtaining an instantaneous spatial clustering of the patches for each frame. After that, we perform a temporal segmentation based on the similarity between patches: we will call it Patch Similarity History (*PSH*).

Consider the matrix H_τ^f where each entry $H_\tau^f(i,j)$ measures the similarity between patches p_i and p_j considering the evolution of patches' labels until frame f of the video. $H_\tau^f(i,j)$ can be computed as:

$$H_\tau^f(i,j) = \begin{cases} H_\tau^{f-1}(i,j) + \tau, & \text{if } \Psi^f(i,j) = 1 \\ \max(0, H_\tau^{f-1}(i,j) - \delta), & \text{otherwise} \end{cases}$$

where τ decides the temporal extent of the similarity in term of frames duration, δ is the decay parameter and $\Psi^f(i,j)$ is an update function defined as:

$$\Psi^f(i,j) = \begin{cases} 1, & \text{if } Lab_i^f = Lab_j^f \\ 0 & \text{otherwise} \end{cases}$$

Lab_i^f and Lab_j^f indicate the labels associated to patches p_i and p_j at the same frame f, during the previous spatial clustering. In this way PSH represents a similarity matrix since it describes how much two patches are similar over time, depending on the spatial cluster to which they belong. By computing the reciprocal of PSH we can obtain a distance matrix and use it to perform a complete linkage hierarchical clustering. The result is a dendrogram where clusters are defined by cutting branches off the tree. Depending on the height of the cut we can obtain diverse spectator categorizations where the clustered patches could represent the whole crowd or a subset of it.

In order to set up a common test protocol for all the methods we divided the scene into overlapping patches. We created a grid of Np=585 patches with size 64×128px and half a patch size of overlap. Each patch is associated with a ground truth label of the person's bounding box with the highest overlapping area (if any). The main difference between our method and those in the literature lies in the fact that the output of the latter methods are based on a pixels-wise segmentation. So in order to fit such per-pixel protocol, with our per-patch assignment, we let the pixels of a patch inherit the majority label of all those patches that insist on it.

Method	Accuracy
AS2007 [2]	0.592
MMS2010 [32]	0.559
Our	**0.621**

Table 4. Spectator categorization accuracy obtained from the normalized confusion matrix.

Each method was tested using the standard setting given by their authors. The parameters of the PSH τ and δ have been set respectively to 30 and 1. For the methods that use optical flow this was computed every 10 frames. Tab. 4 shows the accuracies resulting from the spectator categorization tasks.

The results show that the proposed method is able to categorize the spectator better than the other methods with an accuracy of 62.1%. Since the temporal segmentation was the same for all methods, the best result obtained by our

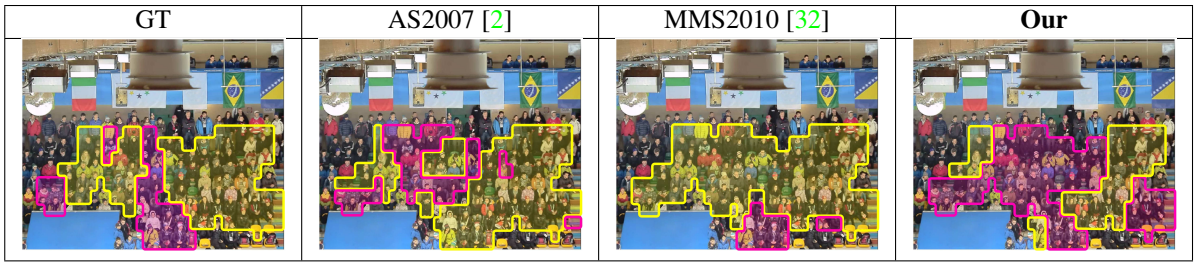


Figure 5. Qualitative results for spectator categorization. The colored areas represent the two groups of spectators supporting different teams.

method is probably due to the features extracted from each patch. In fact we are able to describe the behavior of the people from the patches, considering how much they move (with the intensity I) and describing the kind of movement (with the flow entropy E_D and E_I). Figure 5 shows a qualitative evaluation.

4. Conclusions

This paper introduced S-HOCK, a novel dataset focusing on a brand-new issue, the modeling of the spectator crowd. The goal of the paper was to highlight that S-HOCK is very useful for testing many, diverse and in some cases brand-new applications: actually, we have focused on some low-level, traditional tasks (people detection and head pose estimation) and a novel, high-level challenge, the spectator categorization. This choice has been motivated by the fact that on one side we wanted to show the impact a similar scenario has on the realm of already existent crowd analysis algorithms; on the other side, we wanted to disclose one of the many new challenges that a spectator crowd scenario does offer, the spectator categorization. Many other are the open challenges for example: capturing actions such as hugging, clapping hands etc. is difficult due to the dimension and the dense distribution of the spectators; for the same reason, understanding groups of people that know themselves will be certainly hard for the classical approaches of group estimation; in facts, they are usually based on proxemics principles, not usable here due to the fixed positions of the people.

Different brand-new applications could be very interesting, such as excitement detection (detecting the peak of excitement of the crowd), crowd/people action forecasting, which is also intriguing since in this case we may consider the behavior of a person as being influenced by the neighbors and by the game, etc.

Such applications make S-HOCK richer compared to all other crowd datasets, where usually only the position of the people is annotated (or in some cases estimated, as in [47]), without ground truth obtained also from the people in the crowd itself, and where only tasks of counting, tracking and event detection can be assessed, as in [46]. Therefore, we are confident that S-HOCK may trigger the design of novel and effective approaches for the analysis of the human behavior in crowded settings.

Acknowledgments

This research has been supported by the UNITN Universiade project Oz (Osservare l'attenZione). D. Conigliaro, F. Setti and C. Bassetti have been supported by the VISCOSO project grant, financed by the Autonomous Province of Trento through the "Team 2011" funding program. P. Rota and N. Sebe have been supported by the MIUR cluster project Active Ageing at Home.

References

[1] J. Aggarwal and M. Ryoo. Human activity analysis: A review. *ACM Comput. Surv.*, 43(3):16:1–16:43, 2011. 7

[2] S. Ali and M. Shah. A lagrangian particle dynamics approach for crowd flow segmentation and stability analysis. In *CVPR*, 2007. 7, 8

[3] E. L. Andrade, S. Blunsden, and R. B. Fisher. Modelling crowd scenes for event detection. In *ICPR*, 2006. 1

[4] O. Barinova, V. Lempitsky, and P. Kholi. On detection of multiple object instances using hough transforms. *PAMI*, 34(9):1773–1784, 2012. 4

[5] C. Bassetti. A novel interdisciplinary approach to socio-technical complexity sociologically-driven, computable methods for sport spectator crowds semi-supervised analysis. In *CARVING SOCIETY: New frontiers in the study of social phenomena*, 2015. 3

[6] A. Berlonghi. Undestanding and planning for different spectator crowds. *Safety Science*, 18:239–247, 1995. 1

[7] H. Blumer. Collective behavior. In *A. McClung Lee and R. Park (Eds.) New Outline of the Principle of Sociology, Barnes & Noble*. 1951. 2

[8] A. B. Chan and N. Vasconcelos. Bayesian poisson regression for crowd counting. In *ICCV*, 2009. 1, 2

[9] S.-C. Chen, C.-H. Wu, S.-Y. Lin, and Y.-P. Hung. 2d face alignment and pose estimation based on 3d facial models. In *ICME*, 2012. 5

[10] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *CVPR*, 2005. 4

[11] D. Doermann and D. Mihalcik. Tools and techniques for video performance evaluation. In *ICPR*, 2000. 3

[12] P. Dollar, R. Appel, S. Belongie, and P. Perona. Fast feature pyramids for object detection. *PAMI*, 36(8):1532–1545, 2014. 4, 5

[13] P. Dollár, C. Wojek, B. Schiele, and P. Perona. Pedestrian detection: A benchmark. In *CVPR*, 2009. 4

[14] M. Eichner, M. Marin-Jimenez, A. Zisserman, and V. Ferrari. Articulated human pose estimation and search in (almost) unconstrained still images. Technical report, ETH Zurich, 2010. 4, 5

[15] P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. *PAMI*, 32(9):1627–1645, 2010. 4, 5

[16] M. A. T. Figueiredo and A. Jain. Unsupervised learning of finite mixture models. *PAMI*, 24(3):381–396, 2002. 7

[17] E. Goffman. *Encounters: Two studies in the sociology of interaction.* 1961. 2, 3

[18] E. Goffman. *Behaviour in Public Places*. 1963. 2, 3

[19] E. Goode. *Collective behavior*. 1992. 2

[20] D. Gowsikhaa, S. Abirami, and R. Baskaran. Automated human behavior analysis from surveillance videos: a survey. *Artificial Intelligence Review*, 42(4):747–765, 2014. 7

[21] J. Jacques, Junior, S. Raupp Musse, and C. Jung. Crowd analysis using computer vision techniques. *IEEE Signal Processing Magazine*, 27(5):66–77, 2010. 7

[22] S. Ji, W. Xu, M. Yang, and K. Yu. 3d convolutional neural networks for human action recognition. *PAMI*, 35(1):221–231, 2013. 5

[23] I. Kemelmacher-Shlizerman and R. Basri. 3d face reconstruction from a single image using a single reference face shape. *PAMI*, 33(2):394–405, 2011. 5

[24] L. Kratz and K. Nishino. Anomaly detection in extremely crowded scenes using spatio-temporal motion pattern models. In *CVPR*, 2009. 1

[25] L. Kratz and K. Nishino. Tracking with local spatio-temporal motion patterns in extremely crowded scenes. In *CVPR*, 2010. 1, 2

[26] B. Krausz and C. Bauckhage. Loveparade 2010: Automatic video analysis of a crowd disaster. *CVIU*, 116(3):307–319, 2012. 2

[27] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012. 5

[28] I. Laptev. On space-time interest points. *IJCV*, 64(2-3):107–123, 2005. 1

[29] H. Lee, R. Grosse, R. Ranganath, and A. Y. Ng. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *ICML*, 2009. 5

[30] V. Mahadevan, W. Li, V. Bhalodia, and N. Vasconcelos. Anomaly detection in crowded scenes. In *CVPR*, 2010. 1

[31] C. McPhail. *The myth of the madding crowd*. 1991. 2, 3

[32] R. Mehran, B. Moore, and M. Shah. A streakline representation of flow in crowded scenes. In *ECCV*. 2010. 7, 8

[33] J. Orozco, S. Gong, and T. Xiang. Head pose classification in crowded scenes. In *BMVC*, 2009. 5, 6

[34] M. J. P. Viola. Rapid object detection using a boosted cascade of simple features. In *CVPR*, 2001. 4

[35] R. Poppe. A survey on vision-based human action recognition. *Image and Vision Computing*, 28(6):976–990, 2010. 7

[36] R. Raghavendra, A. Del Bue, M. Cristani, and V. Murino. Abnormal crowd behavior detection by social force optimization. In *Human Behavior Understanding*, pages 383–411, 2011. 1, 2

[37] M. Rodriguez, I. Laptev, J. Sivic, and J.-Y. Audibert. Density-aware person detection and tracking in crowds. In *ICCV*, 2011. 4

[38] M. Rodriguez, J. Sivic, I. Laptev, and J.-Y. Audibert. Data-driven crowd analysis in videos. In *ICCV*, 2011. 7

[39] M. San Biagio, M. Crocco, M. Cristani, and V. Martelli, S. andMurino. Heterogeneous auto-similarities of characteristics (HASC): Exploiting relational information for classification. In *ICCV*, 2013. 4, 5

[40] P. Sand and S. Teller. Particle video: Long-range motion estimation using point trajectories. *IJCV*, 80(1):72–91, 2008. 1

[41] J. M. Susskind, G. E. Hinton, J. R. Movellan, and A. K. Anderson. Generating facial expressions with deep belief nets. *Affective Computing*, pages 421–440, 2008. 5

[42] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf. Deepface: Closing the gap to human-level performance in face verification. In *CVPR*, 2014. 5

[43] D. Tosato, M. Spera, M. Cristani, and V. Murino. Characterizing humans on riemannian manifolds. *PAMI*, 35(8):1972–1984, 2013. 5, 6

[44] B. Wu and R. Nevatia. Detection and tracking of multiple, partially occluded humans by bayesian combination of edgelet based part detectors. *IJCV*, 75(2):247–266, 2007. 4

[45] H. Zhong, J. Shi, and M. Visontai. Detecting unusual activity in video. In *CVPR*, 2004. 1

[46] B. Zhou, X. Tang, H. Zhang, and X. Wang. Measuring crowd collectiveness. *PAMI*, 36(8):1586–1599, 2014. 8

[47] B. Zhou, X. Wang, and X. Tang. Understanding collective crowd behaviors: Learning a mixture model of dynamic pedestrian-agents. In *CVPR*, 2012. 8

[48] X. Zhu and D. Ramanan. Face detection, pose estimation, and landmark localization in the wild. In *CVPR*, 2012. 5