Salient Parts based Multi-people Tracking

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Abstract: The saliency of an object or area is the quality to stand out from its neighborhood, it is an important component when we observe objects in the real world. The detection of saliency has been studied for years and has already been applied in many areas. In this paper, salient parts based framework is proposed for multi-people tracking. The framework follows tracking-by-detection approach and performs multi-people tracking from frame to frame. Salient parts are detected inside the human body area by finding high contrasts to their local neighborhood. Short-term tracking of salient parts are applied to help locating targets when the association with detections fails. And supporting models are on-line learnt to indicate the locations of targets based on the tracking results of salient parts. Experiments are carried out on PETS09 and Town Center datasets to validate the proposed method. The experimental result shows the promising performance of the proposed method and comparison with state-of-the-art works is provided.

1 INTRODUCTION

Multi-people tracking has been studied for a long time. It is an important research topic which can be applied to many areas such as people tracking in public places, abnormal action/event detection. It faces many serious problems including occlusion by background object, mutual occlusion between targets, ID switch and so on. Traditional methods (Checka et al., 2003; Storms and Spieksma, 2003; Oh et al., 2004) depend on short-term tracking from frame to frame. Kalman filtering or data association were common methods used. Andriluka (Andriluka et al., 2008) introduced a way to solve people tracking problem by combining detection and tracking. Since then, the task of multi-people tracking has benefited a lot from the powerful human detectors (Dalal and Triggs, 2005; Felzenszwalb et al., 2010), which provide possible locations of human existence in images. Methods in recent years consider multi-people tracking as an optimization problem of data association over a period of time. With the assistance of human detection in each frame, Dynamic Programming (Fleuret et al., 2008) or Linear Programming (Jiang et al., 2007) methods are used to associate detections in different frames. The aim is to reach the global optimum and form consecutive trajectories.

In this paper, we propose a multi-people tracking method by tracking salient parts concurrently. Methods pursuing global optimization are always applied on a batch of frames. Usually the number of frame is from tens to hundreds, thus it causes time delay which is not preferred in real application. The proposed method performs frame to frame tracking and estimates locations of targets in current frame only based on the previous frame. Saliency detection is introduced into multi-people tracking in this paper. For human visual perception, saliency is a very important component when we observe objects in real world. It was first introduced to computer vision area by (Itti et al., 1998). Now many techniques have been developed to detect salient regions/objects (Cheng et al., 2011; Perazzi et al., 2012; Yeh et al., 2014). And Saliency has been used in many areas in computer vision, such as object segmentation (Li et al., 2014; Tian et al., 2014) and people re-identification (Zhao et al., 2013; Iodice and Petrosino, 2013). As far as we know, saliency has not been applied to multi-people tracking yet, so this is the first work to introduce saliency to the multi-people tracking task. For each target, we construct a salient parts based model by extracting salient regions inside the human body area. Salient regions are detected by using color and orientation information, respectively. These salient parts will be tracked concurrently along with the tracking of target people. They will provide relative spatial information with the

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whole body to help locating the target. Experimental results show the satisfying performance of the proposed method in multi-people tracking.

The rest of the paper is constructed as follows. Section 2 gives a brief review on existing methods on multi-people tracking. Section 3 presents the overview of the proposed method, followed by detailed description in Section 4. Experimental results are addressed in Section 5. Finally, conclusion and future work are given in Section 6.

2 RELATED WORKS

Multi-people tracking problem is mainly the combination of two tasks: inference of people locations and data association. Some of existing works follow frame to frame tracking by detection approach. Andriluka (Andriluka et al., 2008) combined people detector and tracker for frame to frame multi-people tracking. A hierarchical Gaussian Process Latent Variable Model (hGPLVM) is used to model the human walking cycle with prior knowledge, which helps to improve the accuracy of articulation based people detection. Breitenstein (Breitenstein et al., 2011) applied tracking by detection on a single camera. Particle filter is used for tracking. Person-specific classifiers are on-line learnt and used to detect people. Zhang (Zhang et al., 2012) proposed a multi-people tracking framework by tracking with an ensemble of on-line updated templates. Both mean-shift tracking and Kalman filtering are included to perform tracking. The birth and death of Trackers are controlled to eliminate unwanted false detections. Wu (Wu et al., 2012) combined a sparsity-driven people detection and network-flow data association method for multi-people tracking. It is performed in a 3D grid formed by three simultaneously-recorded cameras.

Recently, data association approaches focusing on pursing the global optimization become popular. Some methods perform adding, merging and splitting of tracklets recursively to obtain a minimal global cost function. These methods are processed over a large batch of frames. Cost functions are defined individually. In Ge's work (Ge and Collins, 2008), Markov Chain Monte Carlo Data Association (MCMCDA) is used to estimate a varying number of trajectories, based on tracklets extracted from the video. Benfold (Benfold and Reid, 2011) also used MCMCDA for data association. HOG detections along with KLT tracking are used. Estimations on head locations are provided for maintaining target IDs when occlusion or false detection is encountered. In Segal's work (Segal and Reid, 2013), Latent Data Association parametrization and inference algorithm are introduced to multi-people tracking. Associations between observations are implicit, rather than being explicitly sought as in most traditional formulations, thus the number of tracks can be determined automatically during inference. In (Fleuret et al., 2008), a Probabilistic Occupancy Map (POM) is estimated based on images from multiple cameras with different viewing angles. Locations of people are determined based on POM, then a Dynamic Programming method is applied to form trajectories over sequences of frames. Andriyenko (Andriyenko and Schindler, 2011) proposed a multi-people tracking method based on global optimization method. An energy function is constructed with consideration of detection of people, target dynamic, collision avoidance, persistence of tracklet and regularization. The objective is to find the set of trajectories which achieves minimum global energy function. Milan (Milan et al., 2014) extended Andriyenko's work by including additional appearance component into the energy function, in order to improve the performance against mutual occlusion.

Those methods pursuing global optimization with large batch of frames usually require complicated model and heavy calculation. Therefore, some researchers find reliable tracklets in a smaller batch of frames first. Concatenation is later performed to form longer trajectories. Kuo (Kuo et al., 2010) proposed an on-line learning appearance model for multi-people tracking. Reliable tracklets linking detection responses are first formed, followed by the linking of tracklets based on the appearance models. Yang (Yang and Nevatia, 2012a) extended Kuo's work by introducing on-line learned Conditional Random Field (CRF) model. Multi-people tracking is transformed into an energy minimization problem, and CRF model is used to differentiate pairs of tracklets. Pirsiavash (Pirsiavash et al., 2011) proposed a greedy algorithm based tracking method to track a variable number of people from a single camera. Multi-people tracking is considered as an Integer Linear Programming problem and follows the min-cost flow method. Birth and death of trackers are estimated by evaluating the cost function. Pursuing a global optimization, Berclaz (Berclaz et al., 2011) applied K-shortest Paths algorithm on Direct Acyclic Graphs (DAGs), which is formed based on the POM from (Fleuret et al., 2008). Shitrit (Shitrit et al., 2013) extended the work in (Berclaz et al., 2011) by introducing sparse appearance information of people. This is used to prevent ID switches when the trajectories of two targets have intersects.

Besides data association, some approaches focus on occlusion reasoning. Tang (Tang et al., 2012) tried to solve the occlusion by targets during multi-people tracking. Based on Deformable Part Model (DPM), he built a double-person detector. Several components are included to solve different level of occlusion problem. A joint detector is further formed by combining DPM and double-person detector. Ouyang (Ouyang and Wang, 2013) proposed a probabilistic approach which incorporated single pedestrian detector and multi-pedestrian detector. A mixture model of multi-pedestrian detectors is trained by using DPM.

Tracking parts of human body can always help improving the accuracy of the tracker. Wu (Wu and Nevatia, 2006) used the human body part detection in static images to help the tracking of human. Part detectors are only used when data association is failed. Izadinia (Izadinia et al., 2012) proposed a multi-people tracking method with the assistance of fixed human parts tracking concurrently. In Yangs work (Yang and Nevatia, 2012b), discriminative part-based appearance model (DPAM) is proposed to deal with occlusion problem and help tracking multiple humans in real scenes. DPAM explicitly finds unoccluded parts by occlusion reasoning and can be on-line updated.

3 OVERVIEW

An overview of the proposed methods is presented in Figure 1. Deformable Part Model (DPM) (Felzenszwalb et al., 2010) is used for human detection in each frame. Locations detected are further used for data association. Before a tracker is confirmed, a tracker initialization step is performed to remove transitory false positive detections from DPM. For each following frame, the tracker is first associated with detections from DPM. If matching fails, short-term tracking of salient parts and head part are applied. The tracking results of salient parts and head are used to confirm the location of target person. Trackers are updated after the determination of targets locations. Those trackers have not been updated for a certain period of time are removed to keep computing efficiently. More details are presented in next section.

4 MULTI-PEOPLE TRACKING

4.1 Tracking Model Representation

The objective of the proposed multi-people tracking method is to maximize the joint posterior probability of all people trajectories χ_t based on the observations I_t in current frame

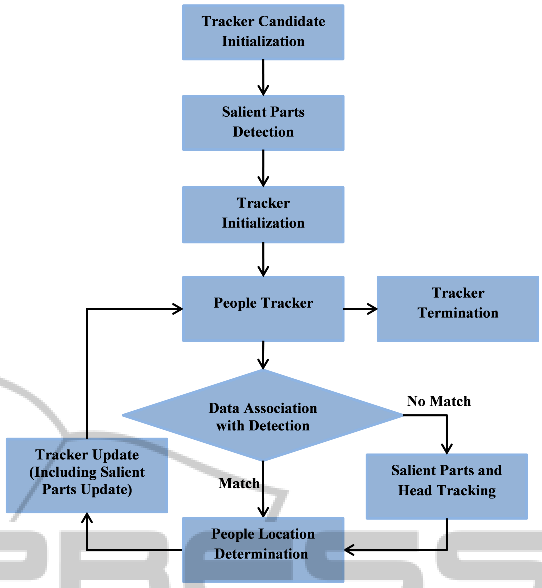


Figure 1: Overview of the proposed method.

$$\chi_t = \underset{\chi_t}{\operatorname{argmax}} P(\chi_t|I_t) \quad (1)$$

During the tracking process, a model is constructed for each target person. Use $\chi = \{\theta_i\}$ to represent a set of people trajectories in a video, where $\theta_i = \{x_{i,t}\}$ is one trajectory containing locations across frames. $x_{i,t} = (l_{i,t}, p_{i,t}, s_{i,t}, c_{i,t}, h_{i,t}, SP_{i,t})$ is the model of trajectory i at frame t, containing label $l_{i,t}$, position of human $p_{i,t}$, scale of human $s_{i,t}$, human appearance (represented in color histogram) $c_{i,t}$, head part $h_{i,t}$ and salient parts $SP_{i,t} = \{sp_{i,t,k}\}$. For head part $h_{i,t} = (p^h_{i,t}, s^h_{i,t}, c^h_{i,t}, r^h_{i,t}, rp^h_{i,t})$ and salient parts $sp_{i,t,k} = (p^{SP}_{i,t,k}, s^{SP}_{i,t,k}, c^{SP}_{i,t,k}, r^{SP}_{i,t,k}, rp^{SP}_{i,t,k})$, they all contain position $p_{i,t,k}$, scale $s_{i,t,k}$, color histogram (represents the appearance of the part) $c_{i,t,k}$, ratio of the part to the human patch $r_{i,t,k}$ and the relative position inside the human body $rp_{i,t,k}$, respectively.

4.2 People Detection

As an important part in tracking by detection, the accuracy of human detection has a great impact on the performance of multi-people tracking. Fortunately, recent works on human detection (Dalal and Triggs, 2005; Felzenszwalb et al., 2010) show promising results. In this paper, the human detection method Deformable Part Model (DPM) (Felzenszwalb et al., 2010) is employed in each frame. DPM is an object detection method based on mixtures of multi-scale star-structured deformable part models. The model usually is constructed with a root filter which captures the global shape information, plus a set of part filters

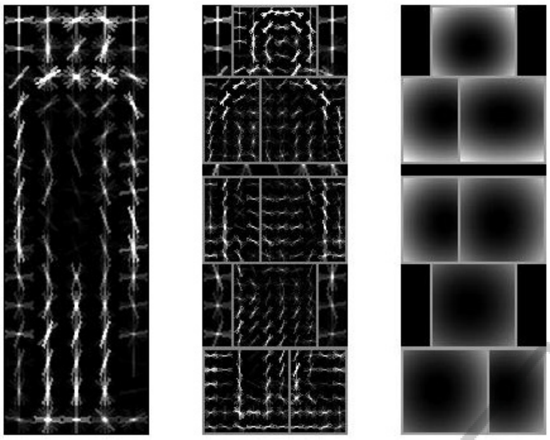


Figure 2: Deformal part model.

with relatively constrained locations capturing local shape information. The model of DPM used in this paper is shown in Figure 2, which is trained by INRIA Person dataset (Dalal and Triggs, 2005). Locations of full body and head obtained from DPM detection are kept for further processing.

4.3 Salient Parts Detection

In this section, the method used in this paper to obtain salient parts is described. These salient parts are further used to assist people tracking.

Salient regions of human body can be considered as important properties if an appearance model is constructed. They are highly contrast to the local or global neighborhood. Therefore, it could stand out from the background, or be representative for the human body.

From Itti (Itti et al., 1998), we learn that using the differences with local neighborhood is a good way to detect saliency. It is computational efficient as well. To detect the salient parts, the most common used features–color and orientation are selected in the proposed method.

A bottom up method is first used to form the saliency map, as shown in Figure 3. The human patch is first smoothed by using Gaussian pyramids with 8 different scales. Then 4 contrast maps are obtained by subtracting patches smoothed with larger scales from patches smoothed with smaller scales. These contrast maps denote the difference between pixels and their neighborhood in different scales. They are combined to form the saliency map. A sliding window with fixed size will be applied to find areas with top saliency scores. Saliency score in a window is calculated as the average saliency value of pixels inside the window. Those windows with saliency score Sal_i exceed the threshold $\tau_{sal} = 0.9Sal_{max}$ are kept. Among them, spatially close windows are combined together by weight to decide the location of this salient part. Weight of window is calculated as

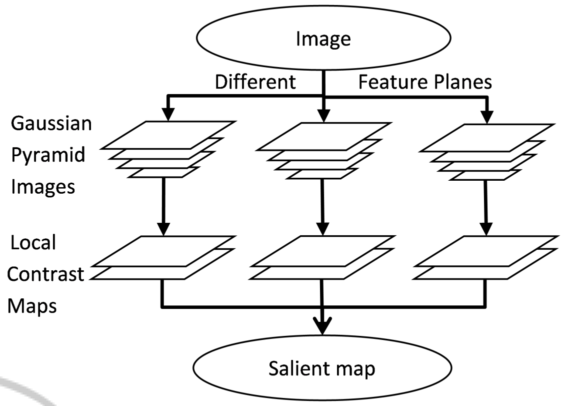


Figure 3: Flow chart of salient map formation.

$$Weight_i = \frac{Sal_i - \tau_{sal}}{\sum_j (Sal_j - \tau_{sal})} \tag{2}$$

Windows with higher salient score receives higher weight. Then the location of salient part is decided as

$$p^{SP} = \sum Weight_i \times p_i \tag{3}$$

where p_i is the location of a window.

In this paper, color and orientation salient maps are not combined together. Instead, we detect the color salient parts and orientation salient parts separately. For color salient map, it is a combination of local contrast maps from different color planes, while orientation salient map is a combination of different local contrast maps from different orientations. Examples of salient parts detection are shown in Figure 4. Color and orientation are used separately to detect salient regions. In Figure 4 (d), yellow boxes are parts extracted from color saliency detection, while green boxes are parts extracted from orientation saliency detection.

4.4 People Tracking along with Salient Parts Tracking

4.4.1 Data Association

The proposed method follows the tracking by detection approach. Therefore, after locations of human are detected by DPM, data association is used to link detection results with existing trajectories. Hungarian Algorithm (Kuhn, 1955) is applied in this paper to associate detections in current frame with locations of trackers in previous frame. For one obser-

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

Figure 4: Examples of salient parts detection. (a) is the original image. (b) and (c) are saliency maps formed by color and orientation respectively. (d) is the result of detected salient parts.

vant $y_{j,t} = (p_{j,t}, s_{j,t}, c_{j,t})$, the cost of linking this observant to a tracker location in previous frame $x_{i,t-1} = (p_{i,t-1}, s_{i,t-1}, c_{i,t-1})$ considers the difference on spatial location, scale size and appearance. It is calculated as

$$\begin{aligned} cost(y_{j,t}, x_{i,t-1}) = & \; cost_p(p^y_{j,t}, p^x_{i,t-1}) \\ & + cost_s(s^y_{j,t}, s^x_{i,t-1}) \\ & + cost_c(c^y_{j,t}, c^x_{i,t-1}) \end{aligned} \tag{4}$$

$$cost_p(p^y_{j,t}, p^x_{i,t-1}) = 1 - \frac{Area(p^y_{j,t} \bigcap p^x_{i,t-1})}{Area(p^y_{j,t} \bigcup p^x_{i,t-1})} \tag{5}$$

$$cost_s(s^y_{j,t}, s^x_{i,t-1}) = 1 - \frac{min(s^y_{j,t}, s^x_{i,t-1})}{max(s^y_{j,t}, s^x_{i,t-1})} \tag{6}$$

$$cost_c(c^y_{j,t}, c^x_{i,t-1}) = 1 - \sum_b min(c^y_{j,t,b}, c^x_{i,t-1,b}) \tag{7}$$

Observant receives higher cost are those with smaller overlap area, larger size change and lower appearance similarity. For those costs larger than thresholds of $cost_p$, $cost_s$ or $cost_c$ are set to be infinite.

4.4.2 Tracker Initialization

In a video, the number of people in frames is usually varying, people entering or leaving the scene is quite common. Therefore, a flexible way to handle the number of people tracker should be applied. The initialization and termination of trackers are included in the proposed method, they can also help to exclude false positive detections from DPM.

With DPM, locations with high probability of people existence are detected. New detections are recorded as tracker candidates, and they are updated in following frames by matched detections with small spatial distance and high appearance similarity. Here the appearance similarity is simply calculated by color histograms, no specific appearance model is involved. After the existence of a tracker candidate in frames reaches the threshold, the tracker candidate is transited to a tracker.

4.4.3 Tracking of Salient Parts and Head Part

Salient parts tracking along with head part tracking are used when the tracker fails to associate with detections. As representative parts of the human body, locations of salient parts and head part can provide reliable information indicating the whole body location. Only those salient parts or head part updated in previous frame are used for tracking, otherwise it will deteriorate the performance of tracking. Median Flow (Kalal et al., 2010) is used for parts tracking from previous frame to current frame. Then the location of the tracker in current frame can be obtained by using a supporting model $P_t(p_i|SP_i)$ similar in (Grabner et al., 2010). The supporting model indicates the location of human $p_{i,t}$ based on information from head and salient parts observed

$$P(p_{i,t}|I) \propto P_t(p_i|SP_i)P(SP_{i,t}|I) \tag{8}$$

Some examples of the salient parts tracking are shown in Figure 5. The first two pairs come from Town Center dataset and the last pair comes from PETS09 dataset. Blue boxes are head parts, yellow boxes are color salient parts and green boxes are orientation salient parts.

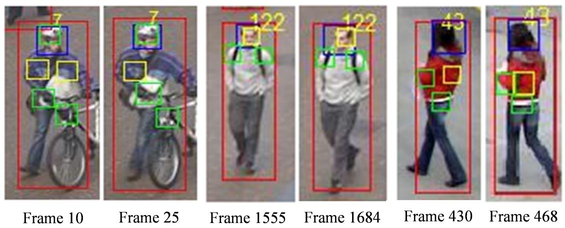


Figure 5: Examples of salient parts tracking.

4.4.4 Tracker Update

Either by detection association or by salient parts tracking, the tracker is updated after the current location of tracker is determined. Contents to be updated include the location of the human, human appearance represented as color histogram. Information about head and salient parts are updated as well if these parts are detected or tracked validly, satisfying appearance similarity and spatial overlap conditions

$$\sum_b min(c^{SP}_{i,t,k,b}, c^x_{i,t-1,k,b}) > \tau_c \tag{9}$$

$$\frac{Area(p^{SP}_{i,t,k} \bigcap p^{SP}_{i,t-1,k})}{Area(p^{SP}_{i,t,k} \bigcup p^{SP}_{i,t-1,k})} > \tau_p \quad (10)$$

where τ_c and τ_p are thresholds.

Besides, the supporting model is updated for those updated salient parts. The exponential forgetting principle is used to achieve on-line updating:

$$P_t(p_i|SP_i) \propto \alpha P_{t-1}(p_i|SP_i) + (1-\alpha)p(p_{i,t}|SP_{i,t}) \quad (11)$$

where $p(p_{i,t}|SP_{i,t})$ indicates the spatial relation between salient parts and human location.

4.4.5 Tracker Termination

As the number of frames increase, the number of tracker could increase as well. The computation keeps increasing if no deletion of unused tracker is made. Therefore, those trackers have not been updated for a period of time are terminated and no longer considered in the tracking process.

5 EXPERIMENTS AND RESULTS

There are four parts in this section. First, brief introduction of datasets and evaluation criterion used is given. Then, performances of the proposed method are compared with method of data association and method of head tracking. Thirdly, performances of the proposed method by using different features are compared. Finally, the proposed method is compared with state-of-the-art works.

5.1 Introduction of Datasets and Evaluation Criterion

5.1.1 Datasets

The proposed method has been carried out on PETS09 (Ferryman and Shahrokni, 2009) and Town Center (Benfold and Reid, 2011) to evaluate its performance.

Sequence S2L1 from PETS09 is one of the most used sequences in multi-people tracking. It was captured outdoor with an elevated viewpoint. People in the video perform usual walking as well as some irregular non-linear motions. The sequence also includes occlusions by object and mutual occlusions between people.

Town Center dataset contains a video capturing a street in a town center. It includes mid-level people density with some severe mutual occlusion conditions. In addition, the scale of people changes as they walk through the image.

5.1.2 Evaluation Criterion

As other methods in multi-people tracking, this paper follows the CLEAR MOT (Kasturi et al., 2009) to evaluate the performance of the proposed method. By comparing the tracking result with Ground Truth provided by datasets, two important metrics are obtained. The Multiple Object Tracking Accuracy (MOTA) evaluates three types of errors: False Positive (denoted as fp_t), False Negative (called miss detected target and denoted as m_t) and ID switch (called mismatches and denoted as mme_t).

$$MOTA = 1 - \frac{\sum_t (m_t + fp_t + mme_t)}{\sum_t g_t} \quad (12)$$

where g_t is the number of ground truth at frame t.

The Multiple Object Tracking Precision (MOTP) evaluates the ability of the tracker to estimate precise object positions to the Ground Truth. The higher score is, the smaller distance has between tracking result and ground truth.

$$MOTP = \frac{\sum_{i,t} d^i_t}{\sum_t c_t} \quad (13)$$

where c_t is the number of matches between tracking result and ground truth at frame t. And d^i_t is the distance between matches, which can be calculated as overlap of bounding boxes.

5.2 Performance Evaluation of Salient Parts Tracking

Since in the proposed method, salient parts tracking are used along with data association and head part tracking. In this section, to prove the impact of salient parts tracking, comparison is given between the performance of the proposed method and performances using only data association or using data association with head part tracking.

Some quantitative comparisons are provided in Table 1. As can be observed, with salient parts tracking, the performance of multi-people tracking improves.

Some qualitative analysis is provided in Figure 6. First rows in Figure 6 (a) and Figure 6 (b) are results from DPM detection, while second rows are the results from the proposed method. In Figure 6 (a), the woman in blue is not tracked due to miss detection. Also, in frame 157 and frame 192, a person at the right top corner fails to be tracked by data association

Table 1: Comparison of the proposed Salient Parts based Tracking (DA+HP+SP) with Data Association (DA) and Data Association with Head Part Tracking (DA+HP). The best is shown in bold.

Method	PETS09	Town Center
DA	MOTP=75.69 MOTA=74.37	MOTP=73.71 MOTA=70.80
DA+HP	MOTP=75.68 MOTA=87.18	MOTP=72.05 MOTA=72.80
DA+HP+SP	MOTP=75.45 **MOTA=90.84**	MOTP=71.75 **MOTA=74.07**

method. The proposed method tracked the woman in blue in most of frames, it also keeps tracking of the man at the right top corner. In Figure 6 (b), the woman with pram is not detected by DPM, therefore she can not be tracked by data association method. In frame 933 and frame 957, some people on the edge of frame are not tracked by data association method as well. While the proposed method accurately tracked the woman with pram and those people on the edge of frame. Overall, when human detection fails, salient parts could be a good complementary to the tracking of targets.

5.3 Evaluation of the Performances of Different Features

Salient detection result may vary with different feature used. In this section, the performances of the proposed method are evaluated with different saliency detection settings.

From the Table 2, it can be observed that using combination of several color channels performs slightly better than using single color channels in saliency detection. In addition, we compared HSV color space, RGB color space, as well as combination of 4 color channels RGBY, which is similar in Ittis work (Itti et al., 1998). The result shows that detecting salient parts in HSV color space outperforms the other two color spaces for multi-people tracking. Besides, we compared two different sets of scales when performing Gaussian pyramids. Smaller scale used, the salient region detected is more contrast to local neighborhood, while salient region detected by using larger scale is more contrast to the neighborhood with a wider range. Table 2 shows smaller scale is more helpful to salient parts based multi-people tracking.

5.4 Comparison with State-of-the-Art Methods

In this section, the proposed method is compared with some state-of-the-art works on PETS09 (Ferryman and Shahrokni, 2009) and Town Center (Benfold and Reid, 2011) datasets.

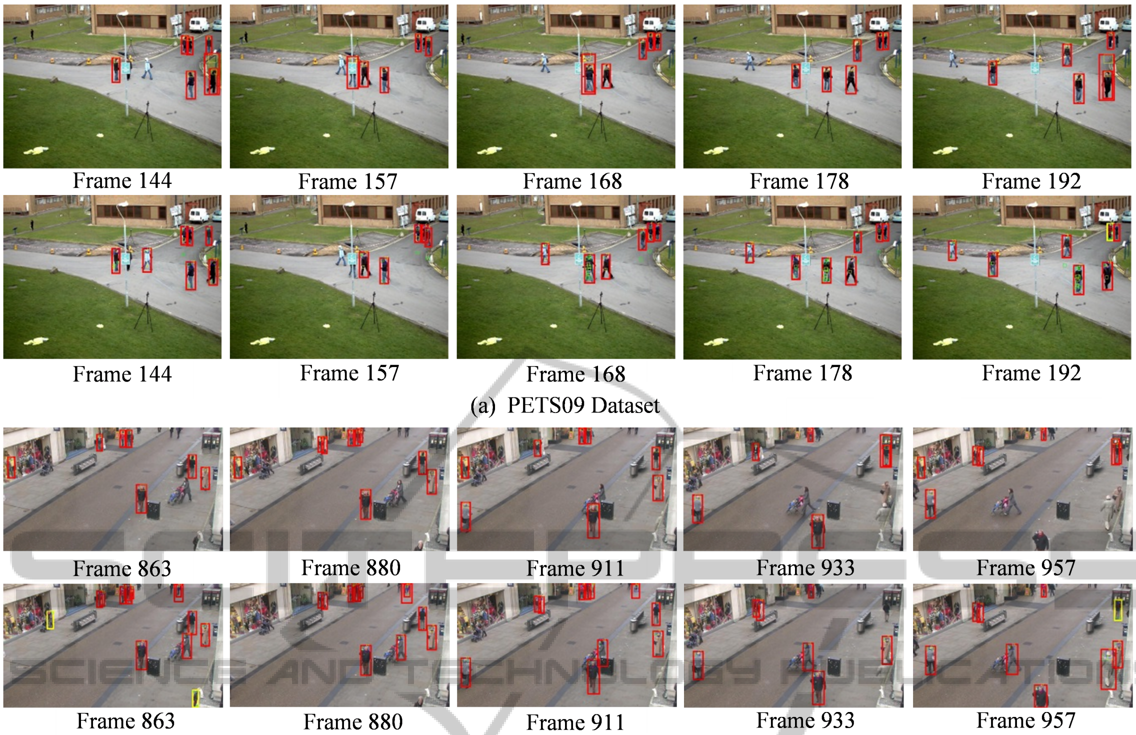
Table 2: Comparison of tracking performance with different salient detection settings. The best is shown in bold.

Feature	Large Scale	Small Scale
H	MOTP=75.7 MOTA=88.2	MOTP=75.5 MOTA=90.3
S	MOTP=75.6 MOTA=88.4	MOTP=75.6 MOTA=90.5
V	MOTP=75.7 MOTA=88.2	MOTP=75.4 MOTA=89.8
HSV	MOTP=75.7 MOTA=88.3	MOTP=75.4 **MOTA=90.8**
RGB	MOTP=75.7 MOTA=88.1	MOTP=75.5 MOTA=89.8
RGBY	MOTP=75.6 MOTA=89.6	MOTP=75.4 MOTA=88.2

Table 3: Comparison on PETS09 dataset. The best is shown in bold.

Method	MOTP	MOTA	Precision	Recall
(Berclaz et al., 2011)	62	78	78	62
(Breitenstein et al., 2011)	59	74	89	60
(Pirsiavash et al., 2011)	73.7	84.6	96.8	93.2
(Izadinia et al., 2012)	76	90.7	96.8	95.2
(Yang and Nevatia, 2012b)	-	-	94.8	**97.8**
(Zhang et al., 2012)	68.17	**93.27**	97.14	96.52
(Milan et al., 2013)	74.3	90.3	-	-
(Segal and Reid, 2013)	75	92	-	-
(Shitrit et al., 2013)	-	81	-	-
(Milan et al., 2014)	**80.2**	90.6	**98.4**	92.4
Proposed	75.45	90.8	96.89	95.68

Table 3 shows the comparison of the proposed method with other methods on PETS09 dataset, while Table 4 shows the comparison with other methods on Town Center dataset. As can be observed, there is no one method shows overwholming performance on all evaluation parameters. In PETS09 dataset, the proposed method achieves comparable performance on all evaluation parameters with most of the state-of-the-art works. And in Town Center dataset, the pro-



(a) PETS09 Dataset

(b) Town Center Dataset

Figure 6: Comparison of results from the proposed method and DPM detections.

Table 4: Comparison on Town Center dataset. The best is shown in bold.

Method	MOTP	MOTA	Precision	Recall
(Benfold and Reid, 2011)	**80.3**	61.3	82	79
(Leal-Taixé et al., 2011)	71.5	67.3	71.6	67.6
(Pirsiavash et al., 2011)	68.8	63.5	84.9	78.9
(Yamaguchi et al., 2011)	70.9	63.3	71.1	64
(Izadinia et al., 2012)	71.6	**75.7**	**93.6**	81.8
(Zhang et al., 2012)	68.75	73.61	91.06	82.19
Proposed	71.75	74.07	87.23	**88.36**

posed has comparable score on MOTA with the best performance, and outperforms other methods on Recall score.

It should be noted that the proposed method do not use any information in following frames to avoid time delay. Those methods with data association over a period of time have the advantage that they can locate the missing targets by linking tracklets over a period of time, therefore improving the tracking performance. However, such methods would cause some delay on the tracking performance which sometimes may not be desired in real application.

6 CONCLUSION AND FUTURE WORK

In this paper, we introduced salient parts into multi-people tracking. Following the tracking-by-detection approach, salient parts tracking can be a good complementary to data association and head tracking. Supporting models are constructed and on-line updated to indicate the spatial relations between salient parts and target locations. Experimental results validate the improvement of performance by adding salient parts tracking. Furthermore, it shows the comparable performance of the proposed method with state-of-the-art methods.

In the future work, there are a lot of works can be done to improve the performance. In this paper, only RGB and HSV color space and orientation of edges are tested for salienty detection, more features or combination of features could be tested in future to exploit better performance. Besides, salient regions used in this paper are square boxes with fixed size. However, salient areas usually are in irregular shapes. A method to detect regions in their own shapes might improve the short term tracking performance. In addition, salient parts outside the human body area could also be considered to help the tracking of people.

REFERENCES

Andriluka, M., Roth, S., and Schiele, B. (2008). People-tracking-by-detection and people-detection-by-tracking. In *Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on*, pages 1–8. IEEE.

Andriyenko, A. and Schindler, K. (2011). Multi-target tracking by continuous energy minimization. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 1265–1272. IEEE.

Benfold, B. and Reid, I. (2011). Stable multi-target tracking in real-time surveillance video. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 3457–3464. IEEE.

Berclaz, J., Fleuret, F., Turetken, E., and Fua, P. (2011). Multiple object tracking using k-shortest paths optimization. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 33(9):1806–1819.

Breitenstein, M. D., Reichlin, F., Leibe, B., Koller-Meier, E., and Van Gool, L. (2011). Online multiperson tracking-by-detection from a single, uncalibrated camera. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 33(9):1820–1833.

Checka, N., Wilson, K., Rangarajan, V., and Darrell, T. (2003). A probabilistic framework for multi-modal multi-person tracking. In *Computer Vision and Pattern Recognition Workshop, 2003. CVPRW'03. Conference on*, volume 9, pages 100–100. IEEE.

Cheng, M.-M., Zhang, G.-X., Mitra, N. J., Huang, X., and Hu, S.-M. (2011). Global contrast based salient region detection. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 409–416. IEEE.

Dalal, N. and Triggs, B. (2005). Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 886–893. IEEE.

Felzenszwalb, P. F., Girshick, R. B., McAllester, D., and Ramanan, D. (2010). Object detection with discriminatively trained part-based models. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(9):1627–1645.

Ferryman, J. and Shahrokni, A. (2009). Pets2009: Dataset and challenge. In *Winter-PETS*.

Fleuret, F., Berclaz, J., Lengagne, R., and Fua, P. (2008). Multicamera people tracking with a probabilistic occupancy map. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 30(2):267–282.

Ge, W. and Collins, R. T. (2008). Multi-target data association by tracklets with unsupervised parameter estimation. In *BMVC*, volume 2, page 5.

Grabner, H., Matas, J., Van Gool, L., and Cattin, P. (2010). Tracking the invisible: Learning where the object might be. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 1285–1292. IEEE.

Iodice, S. and Petrosino, A. (2013). Person re-identification based on enriched symmetry salient features and graph matching. In *Pattern Recognition*, pages 155–164. Springer.

Itti, L., Koch, C., and Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on pattern analysis and machine intelligence*, 20(11):1254–1259.

Izadinia, H., Saleemi, I., Li, W., and Shah, M. (2012). 2t: Multiple people multiple parts tracker. In *Computer Vision–ECCV 2012*, pages 100–114. Springer.

Jiang, H., Fels, S., and Little, J. J. (2007). A linear programming approach for multiple object tracking. In *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on*, pages 1–8. IEEE.

Kalal, Z., Mikolajczyk, K., and Matas, J. (2010). Forward-backward error: Automatic detection of tracking failures. In *Pattern Recognition (ICPR), 2010 20th International Conference on*, pages 2756–2759. IEEE.

Kasturi, R., Goldgof, D., Soundararajan, P., Manohar, V., Garofolo, J., Bowers, R., Boonstra, M., Korzhova, V., and Zhang, J. (2009). Framework for performance evaluation of face, text, and vehicle detection and tracking in video: Data, metrics, and protocol. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 31(2):319–336.

Kuhn, H. W. (1955). The hungarian method for the assignment problem. *Naval research logistics quarterly*, 2(1-2):83–97.

Kuo, C.-H., Huang, C., and Nevatia, R. (2010). Multi-target tracking by on-line learned discriminative appearance models. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 685–692. IEEE.

Leal-Taixé, L., Pons-Moll, G., and Rosenhahn, B. (2011). Everybody needs somebody: Modeling social and grouping behavior on a linear programming multiple people tracker. In *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*, pages 120–127. IEEE.

Li, Y., Hou, X., Koch, C., Rehg, J., and Yuille, A. (2014). The secrets of salient object segmentation. CVPR.

Milan, A., Roth, S., and Schindler, K. (2014). Continuous energy minimization for multi-target tracking.

Milan, A., Schindler, K., and Roth, S. (2013). Detection- and trajectory-level exclusion in multiple object tracking. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 3682–3689. IEEE.

Oh, S., Russell, S., and Sastry, S. (2004). Markov chain monte carlo data association for general multiple-target tracking problems. In *Decision and Control,* *2004. CDC. 43rd IEEE Conference on*, volume 1, pages 735–742. IEEE.

Ouyang, W. and Wang, X. (2013). Single-pedestrian detection aided by multi-pedestrian detection. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 3198–3205. IEEE.

Perazzi, F., Krahenbuhl, P., Pritch, Y., and Hornung, A. (2012). Saliency filters: Contrast based filtering for salient region detection. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 733–740. IEEE.

Pirsiavash, H., Ramanan, D., and Fowlkes, C. C. (2011). Globally-optimal greedy algorithms for tracking a variable number of objects. In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 1201–1208. IEEE.

Segal, A. V. and Reid, I. (2013). Latent data association: Bayesian model selection for multi-target tracking. In *Computer Vision (ICCV), 2013 IEEE International Conference on*, pages 2904–2911. IEEE.

Shitrit, B. H., Berclaz, J., Fleuret, F., and Fua, P. (2013). Multi-commodity network flow for tracking multiple people.

Storms, P. P. and Spieksma, F. C. (2003). An lp-based algorithm for the data association problem in multi-target tracking. *Computers & Operations Research*, 30(7):1067–1085.

Tang, S., Andriluka, M., and Schiele, B. (2012). Detection and tracking of occluded people. *International Journal of Computer Vision*, pages 1–12.

Tian, Y., Li, J., Yu, S., and Huang, T. (2014). Learning complementary saliency priors for foreground object segmentation in complex scenes. *International Journal of Computer Vision*, pages 1–18.

Wu, B. and Nevatia, R. (2006). Tracking of multiple, partially occluded humans based on static body part detection. In *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*, volume 1, pages 951–958. IEEE.

Wu, Z., Thangali, A., Sclaroff, S., and Betke, M. (2012). Coupling detection and data association for multiple object tracking. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 1948–1955. IEEE.

Yamaguchi, K., Berg, A. C., Ortiz, L. E., and Berg, T. L. (2011). Who are you with and where are you going? In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 1345–1352. IEEE.

Yang, B. and Nevatia, R. (2012a). An online learned crf model for multi-target tracking. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 2034–2041. IEEE.

Yang, B. and Nevatia, R. (2012b). Online learned discriminative part-based appearance models for multi-human tracking. In *Computer Vision–ECCV 2012*, pages 484–498. Springer.

Yeh, H.-H., Liu, K.-H., and Chen, C.-S. (2014). Salient object detection via local saliency estimation and global homogeneity refinement. *Pattern Recognition*, 47(4):1740–1750.

Zhang, J., Presti, L. L., and Sclaroff, S. (2012). Online multi-person tracking by tracker hierarchy. In *Advanced Video and Signal-Based Surveillance (AVSS), 2012 IEEE Ninth International Conference on*, pages 379–385. IEEE.

Zhao, R., Ouyang, W., and Wang, X. (2013). Unsupervised salience learning for person re-identification. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 3586–3593. IEEE.