

# AUTOMATIC DESCRIPTION OF OBJECT APPEARANCES IN A WIDE-AREA SURVEILLANCE SCENARIO

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## ABSTRACT

In this paper we present a complete system for object tracking over multiple uncalibrated cameras with or without overlapping fields of view. We employ an approach based on the bag-of-visual-words technique to represent and match tracked objects. The tracks are compared with a global object model based on an ensemble of individual object models. The system can globally recognise objects and minimise common tracking problems such as track drift or split. The output is a timeline representing the objects present in a given multi-camera scene. The methods employed in the system are online and can be optimized to operate in real-time.

**Index Terms**— System-wide tracking, visual tracking, wide-area surveillance, automatic event timeline generation.

## 1. INTRODUCTION

In fact, the problem of tracking multiple objects is a difficult one, presenting many challenges, especially if it occurs in non-controlled environments as is the case of most everyday scenarios. Real environments are too intricate to be covered by a single camera, requiring multiple cameras for monitoring. While a single-camera tracker searches for correspondences only between consecutive frames, a multi-camera tracker must also establish correspondences between observations of objects across cameras. The ultimate goal is to correctly tag all instances of the same visual object at different locations and time instants. One of the main problems in multi-camera scenarios is how to establish correspondences between multiple instances of the same object, that can be detected simultaneously by different cameras or in different time instances. A common strategy used for detecting objects across multiple cameras is to use *camera calibration* [1]. Alternatively, *alignment*-based approaches rely on recovering the geometric transformation between cameras automatically [2] using overlapping fields of view (FOV). However, using alignment requires overlapping fields of view which is not always feasible. To avoid using overlapping field of views, cameras are located in non-overlapping locations that nonetheless allow establishing path dependencies between them using probabilistic models[3].

In many scenarios, methods that rely on additional information about the surveillance system may not be applied. In these cases, the object detection across all cameras can be based on *feature matching*; the main challenge is the feature variability caused by different capture conditions, namely lighting, pose and scale variations. An approach similar to ours was formulated by Madden et al.[4]. They

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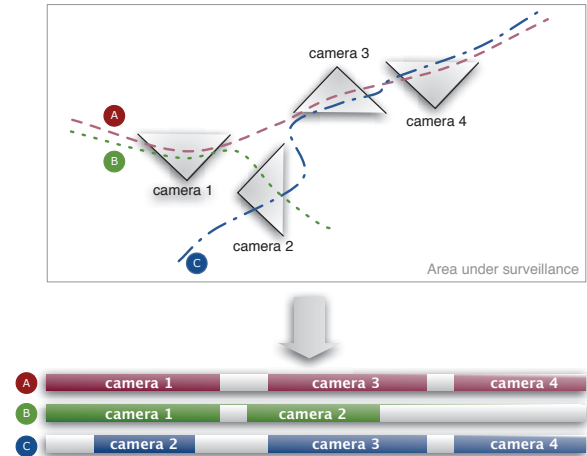


Fig. 1. Problem characterisation and system output.

propose an approach a feature-based matching to find track correspondences across multiple cameras. Unlike our work, they consider that the single-camera tracking outputs are known and use a different object representation based on colour histograms. The appearance representation is obtained with an online k-means colour clustering algorithm and a data-adaptive intensity transformation. Other similar approaches were proposed by Liu et al. [5], Satta et al. [6]. An overview of methods based on appearance is available in [7].

We propose a system to perform multi-camera tracking without information about the displacement of the cameras. Fig. 1 illustrates the application scenario. This scenario consists of a set of disjoint areas covered by a single camera. Objects move around, crossing one or more areas. Since tracking is to be performed for the full monitored area, it is necessary to establish a global identity for each tracked object. We adopted a representative description of each object based on local descriptors to enable a correct object matching. As a result, it is possible to link together different views of the same object, while discriminating robustly views of different objects. We achieve four important results: (1) multiple appearances of objects are detected across multiple independent cameras using an object identity verification method, (2) the multi-camera tracking can be agnostic of the single camera algorithm, (3) single-view tracking results can be improved with the feedback provided by the object identity verification method, and (4) a timeline-based output enables more efficient browsing of the captured sequences.

## 2. PROPOSED SYSTEM

The goal of the system is to automatically obtain a description of where and when each person is detected by the system. An object that crosses multiple camera FOV is tracked independently for each camera and the resulting information collected from each track (sequence of object images) compared with a global visual object model. For the same visual object, the system establishes links between that object's tracks. In Fig. 2 the block diagram of the proposed system is shown. The main steps involved in the process are: (1) obtain the location of potential objects using an object segmentation algorithm, (2) filter the objects of interest and track each object using a single-view tracking algorithm, (3) match the track with a global visual object model, which comprises (a) obtaining an appearance description and (b) comparing it with the model to verify its identity, (4) update the model with the new track information, and (5) optionally, use the identity information to give feedback to the tracking algorithm.

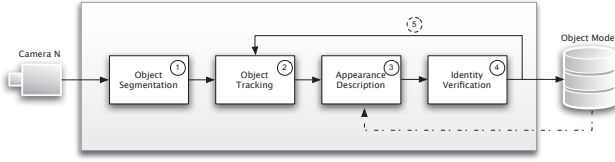


Fig. 2. Block diagram of the system architecture.

### 2.1. Object segmentation, tracking and matching

We used the algorithm proposed by Zhao and Nevatia [8] to achieve single camera tracking. It was developed to track humans using an ellipsoid shape model and texture information. It uses segmentation masks and head detection to identify possible humans and initialize tracks. To obtain the segmentation masks we used the method proposed in [9].

The method for object matching is an improvement of the system described in [10]. The description and matching scheme relies on SIFT local descriptors and a text-like bag-of-words representation. Object images are identified by a histogram of visual words that are identified in the image. We now propose a model  $\mathcal{M}$  that consists of  $C$  classifiers. Each individual model  $\mathcal{M}_k$ ,  $k = 1, \dots, C$  is associated with an object known by the system and outputs one of two results:  $+1, -1$ . The results correspond to acknowledging or not, respectively, that the frame being tested contains the object  $k$ . As new object classes are detected by the system, more of these individual models can be added. The main advantage compared to the approaches proposed in [10], is that we only need to train a binary model when a new object class is added. Each model is trained using AdaBoost, with linear kernel Support Vector Machines (SVMs) as its base classifier.

Given the global model  $\mathcal{M}$ , and the input frame described by  $x$ , the global hypothesis  $\mathcal{H}(x)$  consists of the combination of the individual hypothesis  $\mathcal{H}_k(x)$ ,  $k = 1, \dots, C$  where  $C$  is the total number of objects. For each model  $\mathcal{M}_k$ , an hypothesis  $\mathcal{H}_k(x)$  is defined as

$$\mathcal{H}_k(x) = \begin{cases} \{\mathcal{O}_k\}, & \text{if } H(x) = 1 \\ \emptyset, & \text{otherwise} \end{cases} \quad (1)$$

where  $\mathcal{O}_k$  is the label defined for object  $k$  (for example, Person01) and  $\emptyset$  is the empty set.

The aggregate set of hypothesis  $\tilde{\mathcal{H}}$  is thus given by:

$$\tilde{\mathcal{H}}(x) = \bigcup_{k=1}^C \mathcal{H}_k(x) \quad (2)$$

Finally, the global hypothesis is based on the cardinality of the aggregate set of hypothesis, such that:

$$\mathcal{H}(x) = \begin{cases} \mathcal{U}, & \text{if } \#\tilde{\mathcal{H}}(x) = 0 \\ \tilde{\mathcal{H}}(x), & \text{if } \#\tilde{\mathcal{H}}(x) = 1 \\ \text{rand}(\tilde{\mathcal{H}}(x)), & \text{otherwise} \end{cases} \quad (3)$$

where  $\#$  is the set cardinality, rand is a random operator with uniform distribution, and  $\mathcal{U}$  represents the label Unknown.

### 2.2. Identity verification

The identification of each visual object's is done in multiple steps, as depicted in Fig. 3. Each track outputted by the tracking algorithm is first divided into segments comprising  $N$  frames. The segments are analysed separately by associating a label  $\mathcal{L}_i$  to the respective segment  $i$  and comparing each of the  $N$  frames with the global object model; a single label is obtained by majority voting. The process is repeated for all the segments in a track and the final estimation for the object label  $\hat{\mathcal{L}}$  is again done by majority voting. In this case the votes correspond to the segment labels  $\mathcal{L}_i$ . A common tracking error is identity drifting, where a track outputted by the algorithm contains more than one object. To help correct this, we apply the following test: for each segment  $i$ , if  $\mathcal{L}_{i-P} = \dots = \mathcal{L}_{i-1} = \mathcal{L}_i \neq \hat{\mathcal{L}}$  the track is split, otherwise the analysis proceeds with the current track. The splitting consists of two substeps: 1) close the current track and attribute a final label  $\hat{\mathcal{L}}$ ; 2) start a new track containing the last  $P+1$  frames and continue analysing the remaining segments associated with this new track. We chose to set  $P$  to 2, as shown in Fig 3.

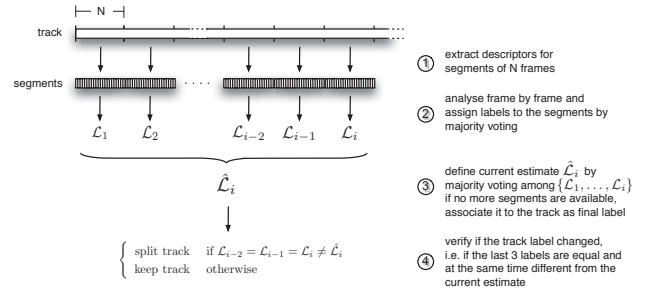


Fig. 3. Algorithm to verify objects' identities in a given track.

By dividing the track in segments we are in fact smoothing errors caused by incorrect object description, often due to a deficient segmentation. For all experiments we considered segments of  $N = 25$  frames.

The identity verification can be performed online, since all tracks are analysed independently and we only need to keep the last 3 segment labels for each track. However, this process introduces a delay of  $3N$  frames, which for a frame rate of  $25\text{fps}$  and  $N = 25$  corresponds to a  $3\text{s}$  delay.

### 3. EXPERIMENTAL SETUP AND RESULTS

#### 3.1. Dataset

The training set consists of images containing 30 visual objects, or persons in this case, from the Shopping Center dataset of the CAVIAR project<sup>1</sup>. We extracted each object from the 26 scenarios that comprise the original set, using the provided CVML-based ground-truth information. This dataset was used to train the model  $\mathcal{M}$  defined previously.

The evaluation dataset consists of 11 sequences also from the CAVIAR shopping set. Each sequence contains more than one person and some persons appear multiple times. To complement the results with the CAVIAR dataset we captured 3 additionally sequences at two independent locations. These sequences present challenging situations with cluttered scenes, high rates of occlusion, different illumination conditions as well as different scales of the persons being captured.

#### 3.2. Model evaluation

The model used consists of an ensemble of binary individual models, each associated with a given object class. We compared this model with the straightforward approach of having a multi-class SVM. To train the individual AdaBoost-based models we used a random sample of 1000 images from other objects to represent the “unknown” object. The evaluation consisted of randomly dividing the training dataset into train and validation subsets and perform a 5-fold cross-validation.

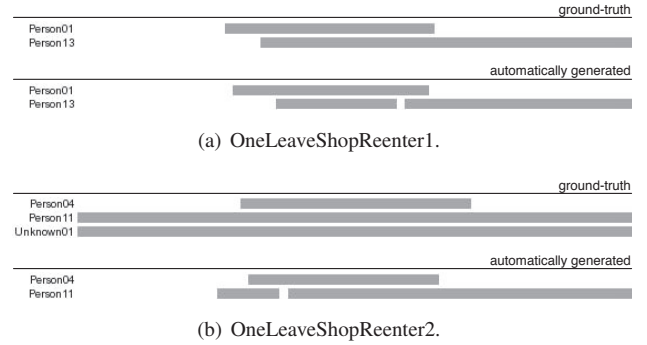
Using the ensemble of models, the performance drops significantly from an average successful classification rate of 94.6% to 73.3%. By considering the object class “unknown”, we are contributing to the performance degradation since the sample used to represent it may be insufficient to obtain the best discriminative model between classes. However, in the trade-off between complexity and performance we opted for simpler and more feasible models in detriment of performance. For the task of track classification it is possible to afford this penalisation, as we show in the next subsections.

#### 3.3. Timeline generation

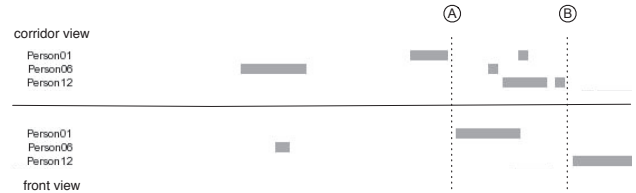
Timelines are generated from the combination of the results produced by the tracking algorithm and the identity verification process. Fig. 4 shows an example of automatically generated timelines and the respective ground-truth. This can be considered a successful case, since all known objects are correctly identified. The main difference to the ground-truth is the length of the detected tracks. The result tracks usually are shorter essentially due to two reasons: when the objects are distant, the tracking results are usually unstable; and, when the objects leave the field of view, the rules defined specifically for person tracking filter out those object images.

Timelines from different views can be combined to analyse the appearance of objects throughout the area covered by the camera system. Fig. 5 shows an example of that for the WalkByShop1 and WalkByShop1front sequences. In the scene captured by both cameras, Person01 and Person12 at some point in time enter a shop, leaving the first field of view and entering the second. These instants are marked with the rounded labels A and B.

To evaluate the timeline generation quality we rely on the commonly used and well known precision and recall measures. More-



**Fig. 4.** Examples of automatically generated timelines compared with the respective ground-truth.



**Fig. 5.** Generated timelines for two different cameras capturing the same scene from different views.

over, a measure that combines both precision and recall is called F-measure. A more generic  $F_\beta$  measure weighs either the precision if  $\beta < 1$  or the recall if  $\beta > 1$ . In our case, lower values for the recall should mean that the resulting timeline has many gaps, while lower values of the precision represent incorrect labelling. If the tracking algorithm wrongly ignores objects in the scene, the recall will essentially reflect this. Since we are not evaluating the tracking algorithm itself, we will be using as the main measure  $F_\beta$  with  $\beta = 0.5$ , i.e.  $F_{0.5}$ . The results for the 14 sequences comprising the evaluation set are presented in Table 1.

As expected, precision is generally higher than the recall. The best results have a precision of 1.0 and  $F_{0.5}$  higher than 0.8, i.e. most of the objects were correctly identified. We observe that in more crowded sequences (e.g. OneStopMoveEnter1) the performance measures are considerably lower, with a classification rate  $F_{0.5}$  lower than 0.5. This is largely due to the high number of unknown objects. To better evaluate the performance of the identity verification algorithm we also present in Table 1 the precision, recall and  $F_{0.5}$  of the generated timelines considering only the known objects.

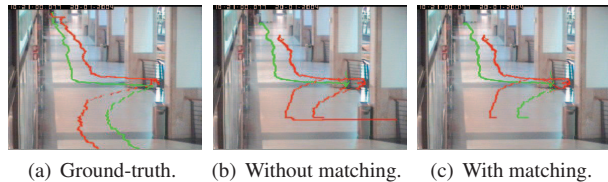
#### 3.4. Interaction with tracking

In this article we are not evaluating the tracking results, but it is nevertheless important to observe how the tracking results are improved by the matching step. In Fig. 6 two different tracking results are shown, as well as the respective ground-truth. In Fig. 6(b) the track is obtained without matching. At some point in time there is an identity drift between the two persons, resulting in incorrect labelling afterwards. If we apply both the object matching method and the identity verification algorithm, the drift is detected and the track is split correctly (Fig. 6(c)). These results can be further explored in the future. A tighter integration between tracking and matching is expected to enable a higher performance.

<sup>1</sup><http://homepages.inf.ed.ac.uk/rbf/CAVIAR/>

**Table 1.** Results for the scenarios under evaluation. For each sequence, the number of frames, the number of known (gk) and total (gt) objects in the ground-truth, and number of known (rk) and total (rt) objects in the result timeline are presented.

sequence	# of objects				all objects			only known objects		
	gk	rk	gt	rt	precision	recall	$F_{0.5}$	precision	recall	$F_{0.5}$
EnterExitCrossingPaths1	2	2	4	6	0.69	0.69	0.69	0.39	0.83	0.44
OneLeaveShopReenter1	2	3	2	2	1.00	0.94	0.98	1.00	0.94	0.98
OneLeaveShopReenter2	2	2	3	2	1.00	0.45	0.80	1.00	0.86	0.97
OneShopOneWait1	4	4	4	4	0.89	0.67	0.83	0.89	0.67	0.83
OneStopEnter2	3	3	6	6	0.75	0.51	0.68	0.77	0.57	0.71
OneStopMoveEnter1	7	7	18	29	0.13	0.12	0.13	0.27	0.44	0.30
OneStopMoveNoEnter1	1	1	2	3	1.00	0.68	0.91	0.89	0.68	0.84
OneStopNoEnter1	2	3	3	4	0.70	0.39	0.61	0.82	0.77	0.81
ShopAssistant2	8	8	17	18	0.59	0.40	0.54	0.68	0.62	0.67
WalkByShop1	4	4	10	14	0.14	0.11	0.13	0.53	0.84	0.57
WalkByShop1front	3	3	5	4	0.80	0.67	0.77	0.83	0.86	0.84
Hall1	5	5	11	14	0.43	0.26	0.39	0.57	0.46	0.54
Lobby1	5	5	14	23	0.37	0.61	0.40	0.64	0.84	0.73
Lobby2	5	5	12	16	0.53	0.79	0.63	0.76	0.68	0.72
Overall (all 14 scenarios)	—	—	—	—	0.64 (0.30)	0.52 (0.25)	0.61 (0.26)	0.72 (0.22)	0.72 (0.16)	0.71 (0.19)



**Fig. 6.** Improved results of tracking.

#### 4. CONCLUSIONS

In this paper, we focused on the problem of multi-camera tracking in a system of non-overlapping uncalibrated cameras. A complete surveillance system was designed, featuring a state-of-the-art tracking algorithm, whose output was given to a multi-tracker object matching algorithm. The system outputs timelines representing the presence of persons in the different cameras along time. If a person is matched with the stored model of persons, the associated track is labelled accordingly. Results have demonstrated that tracking is possible even when observations of objects are not available for relatively large time periods. We evaluated the system using a dataset of sequences with diverse scenes. The more crowded scenes presented more difficulties and worse results were obtained. Overall, a correct classification rate measured by  $F_{0.5}$  of 0.71 was achieved.

Finally, it is also important to emphasize that the results were obtained through the use of a real system composed of several modules performing a specific task. Each of these modules is a challenge per se and as such are themselves subject of specific attention. Introduced errors in one part of the system are propagated and sometimes increased throughout the processing chain.

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