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Multiple-object Tracking in Cluttered and Crowded Public Spaces

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Abstract. This paper addresses the problem of tracking moving objects of variable appearance in challenging scenes rich with features and texture. Reliable tracking is of pivotal importance in surveillance applications. It is made particularly difficult by the nature of objects encountered in such scenes: these too change in appearance and scale, and are often articulated (e.g. humans). We propose a method which uses fast motion detection and segmentation as a constraint for both building appearance models and their robust propagation (matching) in time. The appearance model is based on sets of local appearances automatically clustered using spatio-kinetic similarity, and is updated with each new appearance seen. This integration of all seen appearances of a tracked object makes it extremely resilient to errors caused by occlusion and the lack of permanence of due to low data quality, appearance change or background clutter. These theoretical strengths of our algorithm are empirically demonstrated on two hour long video footage of a busy city marketplace.

1 Introduction

In recent years the question of security in public spaces has been attracting an increasing amount of attention. While the number of surveillance cameras has steadily increased so have the problems associated with the way vast amounts of collected data are used. The inspection of recordings by humans is laborious and slow, and as a result most surveillance footage is used not preventatively but rather *post hoc*. Work on automating this process by means of computer vision algorithms has the potential to be of great public benefit and could radically change how surveillance is conducted.

Most objects of interest in surveillance footage move at some point in time. Tracking them reliably is a difficult but necessary step that needs to be performed before any inference at a higher level of abstraction is done. This is the problem we address in this paper.

1.1 Problem Difficulties

Public spaces are uncontrolled and extremely challenging environments for computer vision-based inference. Not only is their appearance rich in features, texture and motion – as exemplified in Figures 1 (a) and 1 (b) – but it is also continuously exhibiting variation of both high and low frequency in time: shopping windows change as stores

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(a) Original (b) Magnification

(c) Difference (d) Motion regions

Fig. 1. (a) A typical frame extracted from the video footage used in the evaluation of this paper, showing a busy city marketplace, (b) a magnified image region containing examples of occlusion of objects of interests, as well as a cluttered and feature rich background, (c) the difference between two successive frames and (d) the inferred motion regions

open and close, shadows cast by buildings and other landmarks move, delivery lorries get parked intermittently etc. This is a major obstacle to methods based on learning the appearance of the background, e.g. [1–4].

Indeed, little related previous research addressed the exact problem we consider in this paper, instead concentrating on simpler recognition and tracking environments. A popular group of methods is based on grouping low-level features, for example by detecting common motion patterns [5, 6] or using cascaded appearance classifiers [7, 8]. While these tend to perform well in uncrowded scenes, they have difficulties coping with occlusions. This is particularly the case with mutual occlusions, involving multiple tracked objects. Both methods of Rabaud and Belongie [5], and Brostow and Cipolla[6], share some similarity with the method proposed in this paper, in that they consider the coherence of feature motion. However, unlike our method, their approaches rely on having long, reliable tracks of interest points. Our experiments suggests that this is not a realistic assumption for uncontrolled crowded scenes – local features are difficult to detect reliably in videos of the kind of quality which is found in practice. These usually have poor resolution and are often compressed, making most local features very short lived. This is complicated further by frequent occlusion and object articulation.

In contrast, template-based methods which employ holistic appearance struggle with the issue of variability in appearance of tracked objects and their scale [9–12], and generally have high computational demands. Zhao and Nevatia [3], for example, employ more restrictive object and scene models, in the form of human shape and ground plane calibration and assume a bird's eye view of the scene. This approach is thus fundamentally more restrictive than ours in several important aspects. Additionally, unlike ours, models of this kind struggle with the problem of initialization which is usually manual. This is a major limitation in a practical application which involves a great number of moving entities which uncontrollably enter and leave the scene.

In summary, an algorithm successful at tracking moving entities in a crowded public space, has to, on the one hand, learn a model sufficiently persistent and discriminative to correctly track in the presence of occlusion and distinguish between potentially similar entities, yet flexible enough to allow for appearance changes due to articulation, pose and scale change. In the next section we describe the details of our approach at achieving this, followed by a section in which its performance is illustrated on real-world footage of a public square.

2 Algorithm Details

Our algorithm employs multiple (and in a sense complementary) representations as a means of capturing a suitably strong model that allows for reliable tracking and track continuity following partial or full occlusion, while at the same time exhibiting sufficient flexibility in changing appearance and computational efficiency. We first give an overview of the approach, followed by a detailed description of each of the steps.

2.1 Overview

The proposed method consists of an interlaced application of the following key algorithmic elements:

- Detection of motion regions (in all frames, across the entire frame area)
- Spatial grouping of motion regions
- Interest point detection (within motion regions only)
- Appearance model building by spatio-kinetic clustering of interest points (newly detected ones only)
- Correspondence matching of feature clusters between successive frames

We build appearance models from bottom up, grouping local features within motion regions into clusters, each cluster representing a moving object, according to the coherence of their motion and taking into account perspective effects of the scene. Permanence of appearance models is achieved by retaining all features added to a cluster even after their disappearance (which often happens, due to occlusion, articulation, or image noise, for example). Robustness in searching for feature and object correspondence between frames is gained by using constraints derived from detected motion regions, allowing us to account for occlusion or transiently common motion of two objects.

2.2 Detecting and Grouping Motion Regions

An important part of the proposed method lies in the use of motion regions. These are used to dramatically improve computational efficiency, reducing the image area which is processed further by focusing only on its "interesting" parts, as well as to constrain the feature correspondence search – described in Section 2.4 – which is crucial for reliable matching of appearance models of moving entities between subsequent frames.

Let $I_t \in \mathbb{R}^{H \times W}$ be the frame (as a $H \times W$ pixel image) at the t-th time step in the input video. At each time step, our algorithm performs simple motion detection by pixel-wise subtraction of two frames k steps apart:

$$\Delta I_t(x, y) = I_t(x, y) - I_{t-k}(x, y). \tag{1}$$

Typical output is illustrated in Figure 1 (c) which shows rather noisy regions of appearance change. Note that many locations which correspond to moving entities by coincidence do not necessarily significantly change in appearance. To account for this, we employ the observation that the objects of interest have some expected spatial extent. Thus, we apply a linear smoothing operator on the frame difference $\Delta I_t(x, y)$:

$$C_t(x, y) = \int_{u,v} \Delta I_t(x + u, y + v)\ G(u, v, y) \tag{2}$$

where $G(u, v, y)$ is an *adaptive* Gaussian filter. Specifically, the variances of the axis-aligned kernel are made dependent on the location of its application:

$$G\left(u, v, y \mid \sigma_u, \sigma_v\right) = \frac{1}{2\pi\ \sigma_u\ \sigma_v} \exp\Big\{ -0.5\ u^2/\sigma_u(y) - 0.5\ v^2/\sigma_v(y)\Big\}. \tag{3}$$

The variation of $\sigma_u(y)$ and $\sigma_v(y)$ is dependent on the scene perspective and the loose shape of the objects of interest. We learn them in the form $\sigma_u(y) = c_1\ y + c_2$ and $\sigma_v(y) = c_3\ y + c_2$. As our appearance model (described next) is top-down, that is, initial hypotheses for coherently moving entities are broken down, rather than connected up, we purposefully choose relatively large c_1 and c_3 (0.045 and 0.25, respectively). The remaining constant is inferred through minimal user input: the user is asked to select two pairs of points such that the points in each pair are at the same distance from the camera and at the same distance from each other, and that each pair is at a different distance from the camera.

Finally, we threshold the result and find all connected components consisting of positively classified pixels (those exceeding the threshold) which we shall for brevity refer to as motion regions. On our data set, on average they occupy approximately 8% of the total frame area. Examples are shown in Figure 1 (d).

2.3 Building Appearance Models using Spatio-Kinetic Clustering of Interest Points

Having identified regions of interest in the scene, we extract interest points in them as scale-space maxima [13]. While motion regions are used to constrain their matching and clustering, descriptors of local appearance at interest points are collectively used to represent the appearance of tracked objects.

Each interest point's circular neighbourhood is represented by the corresponding 128-dimensional SIFT descriptor [13]. These are then grouped according to the likelihood that they belong to the same object. Exploiting the observation that objects have limited spatial extent, as well as that their constituent parts tend to move coherently, we cluster features using both spatial and motion cues, while accounting for the scene geometry.

The spatial constraint is applied by virtue of hierarchial clustering – only the K nearest neighbours of each interest point are considered in trying to associate it with an existing cluster. Using a limited velocity model, an interest point and its neighbour are tracked N frames forwards and backwards in time to extract the corresponding motion trajectories. Let the motion of a tracked interest point be described by a track of its location through time $\{(x_t, y_t)\} = \{(x_{t_1}, y_{t_1}), (x_{t_1+1}, y_{t_1+1}), \ldots, (x_{t_2}, y_{t_2})$ and that of its i-th of K nearest neighbours $\{(x_t^i, y_t^i)\} = \{(x_{t_1}^i, y_{t_1}^i), (x_{t_1+1}^i, y_{t_1+1}^i), \ldots, (x_{t_2}^i, y_{t_2}^i)$, where the interval $[t_1, t_2]$ is determined by the features' maximal past and future co-occurrence. The two interest points are associated with the same appearance cluster – a cluster being the current best hypothesis of a single moving entity – if they have not been already associated with separate clusters and the motion incoherence of the corresponding trajectories does not exceed a threshold $t_{\text{coherence}}$:

$$\sum_{t=t_1}^{t_2} \left\| \frac{(x_t, y_t) - (x_t^i, y_t^i)}{(y_t + y_t^i)\ /\ 2 + c_2} \right\|^2 - \left(\sum_{t=t_1}^{t_2} \left\| \frac{(x_t, y_t) - (x_t^i, y_t^i)}{(y_t + y_t^i)\ /\ 2 + c_2} \right\| \right)^2 < t_{\text{coherence}}. \tag{4}$$

as conceptually illustrated in Figures 2 (a) and 2 (b). The coherence measure in Equation 4 accounts for the previously learnt perspective of the scene by inversely weighting the distance between two features by their distance from the horizon. Note that we make the implicit assumption that the vertical position of the camera is significantly greater than the height of tracked objects (if this assumption is invalidated, the denominators in Equation 4 can reach a small value without the objects being near the horizon).

The result of the described spatio-kinetic clustering is a set of clusters per each motion region. These are associated with the region only temporarily and it is not assumed that they correspond to the same object (indeed, in most cases they do not due to different motion characteristics).

2.4 Model Propagation through Time

Having learnt quasi-permanent appearance models of objects (as their constituent features are being detected using the approach described in Section 2.3), we turn our attention to the question of tracking these through time.

Consider a cluster of features in a particular motion region and the problem of localizing this cluster in the subsequent frame. We know that the features which belong in it move coherently and we know that this motion is limited in velocity. However, the corresponding motion region may no longer exist: the features may have temporarily ceased moving, or the objects which comprised a single motion region may have parted (e.g. two people separating, or after temporary occlusion), or it may have joined

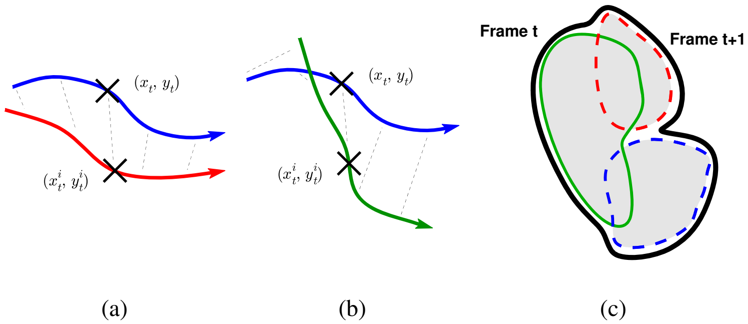


Fig. 2. Kinetic (a) coherence and (b) discrepancy result in two features with spatial proximity getting assigned to respectively the same and different clusters. (c) A feature located in a specific motion region in frame I_t is searched for in the subsequent frame I_{t+1} in the area occupied by the initial motion region (green, solid) and all motion regions that intersect it in I_{t+1} (blue and red, dashed).

another (e.g. two people meeting or occluding each other). To account for all of these possibilities, each feature in searched for in the area occupied by the original region it was detected in and all the regions in the subsequent frame which intersect it, as shown in Figure 2 (c).

Consider an interest point with the appearance at the time step t captured by the corresponding SIFT descriptor $\mathbf{d}_t \in \mathbb{R}^{128}$. It is matched to that in the next frame $t + 1$ and within the search area, which has the most similar appearance, $\mathbf{d}^k_{t+1}$, provided that their similarity exceeds a set threshold according to the following criterion:

$$\mathbf{d}_t \xrightarrow{match} \mathbf{d}^k_{t+1} \tag{5}$$

where

$$k = \begin{cases} \arg\min_i \ \rho(i) & \rho(k) \leq t_{\text{feature}} \\ \text{new feature} & \rho(k) > t_{\text{feature}} \end{cases} \qquad \text{and} \qquad \rho(i) = \frac{{\mathbf{d}_t}^T \ \mathbf{d}^i_{t+1}}{\|\mathbf{d}_t\| \ \|\mathbf{d}^i_{t+1}\|} \tag{6}$$

Features from the same cluster which are localized within the same motion region in the new frame are associated with it, much like when the model is first built, as described in Section 2.3. However, the cluster can also split when its constituent features are localized in different motion regions (e.g. when two people who walked together separate). Cluster splitting is effected by splitting the appearance model and associating each new cluster with the corresponding motion region. On the other hand, notice that clusters are never joined even if their motion regions merge, as illustrated in Figure 3. This is because it is the clusters themselves which represent the best current estimate of individual moving objects in the scene, whereas motion regions merely represent the image plane uncertainty in temporal correspondence, caused by motion of independent entities.

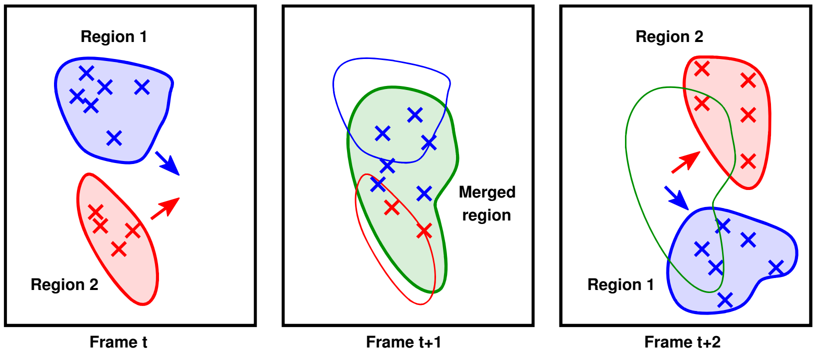


Fig. 3. A conceptual illustration showing the robustness of our appearance model in coping with partial or full occlusion regardless of its duration

2.5 Review of Handling of the Key Tracking Problems

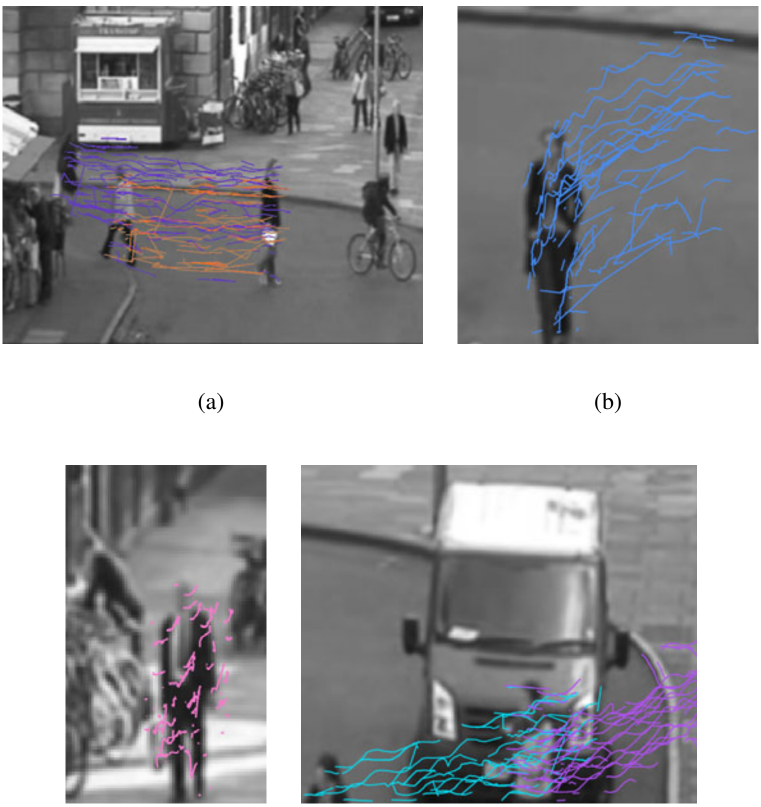
As a conclusion to the theoretical section of the paper, let us consider how our algorithm copes with some of the most important tracking scenarios.

– **Case 1, Independently moving entity:** An appearance model is built from the appearances of clustered local features. As the cluster is tracked by matching those features which are at the time reliably matched, the model in the form of a set of appearance features (many of which are *not* visible at any point in time) is constantly enriched as new appearances are observed.
– **Case 2, Coherently moving entities, which separate:** Motion incoherence after separation is used to infer separate entities, which are back-tracked to the time of common motion when the corresponding clusters (as their feature sets) are associated with the same moving region. Novel appearance, in the form of new local features is added to the correct appearance cluster using spatial constraints.
– **Case 3, Separately moving entities, which join in their motion:** This situation is handled in the same manner as that described previously as Case 2, but with tracking proceeding forwards, not backwards in time.
– **Case 4, Partial occlusion of a tracked entity:** The proposed appearance model in the form of a set of appearances of local features, is inherently robust to partial occlusion – correct correspondence between clusters is achieved by matching reliably tracked, visible features.
– **Case 5, Full occlusion of a tracked entity:** When a tracked entity is occluded by another, both of their clusters are associated with the same motion region. This association continues until sufficient evidence for the occluded entity re-emerges and a new motion region is detected. At that point the overlap of regions of interest is used to correctly match appearance models, separating them and re-assigning feature clusters with the correct moving regions.

An empirical demonstration of these theoretical arguments is presented next.

3 Empirical Analysis

To evaluate the effectiveness of the proposed method we acquired a data set fitting the problem addressed in this paper and containing all of the challenging aspects described in Section 1.1. Using a stationary camera placed on top of a small building overlooking a busy city marketplace we recorded a continuous video stream of duration 1h:59m:40s and having the spatial resolution of 720×576 pixels. A typical frame is shown in Figure 1 (a) while Figure 1 (b) exemplifies some of the aforementioned difficulties on a magnified subregion.



(a) (b)

(c) (d)

Fig. 4. Experimental results on a nearly two hour long video footage of a busy marketplace confirm the advantages of our method predicted from theory. Feature tracks corresponding to each person's model are shown in different colours. Illustrated is our method's robustness to (a) mutual occlusion of tracked objects, (b,c) successful tracking of an object in the presence of scale change, and unstable and changing set of detected local features associated with the object's appearance model, and (d) a combination of mutual occlusion, cluttered and texture-rich background, scale change and gradual disappearance of a tracked object from the scene.

Experimental results we obtained corroborate previously stated strengths of our method expected from theory. The permanence of the proposed model which captures all seen appearances of a tracked object, coupled with a robust frame-to-frame feature matching, makes it particularly resilient to errors caused by occlusion. An example of this can be seen in Figure 4 (a). It shows feature tracks associated with automatically learnt appearance models corresponding to two people (shown in different colours – green and purple), which are then successfully tracked even following their mutual occlusion, that is, after one passes in front of the other.

A magnification of a isolated person being tracked in Figure 4 (b) and another at an approximate 50% smaller scale in Figure 4 (c), serve to illustrate the role of several building elements of our algorithm. Specifically, it can be observed that few features last for more than 0.5s in the former example and more than 0.1s in the latter. This is a consequence of appearance change due to motion and articulation, as well as image and spatial discretization noise. It is the incremental nature of our algorithm, whereby novel features are added to the existing model, and the use of spatio-kinetic clusters, which allows all of the shown tracks to be associated with the same moving object. These examples should not be correctly tracked by such previously proposed method as those of Rabaud and Belongie [5], and Brostow and Cipolla[6].

Finally, Figure 4 (d) shows successful tracking in the presence of several simultaneous difficulties: the two tracked people cross paths, mutually occluding, in front of a feature-rich object, one of them progressively disappearing from the scene and both of them changing in scale due to the movement direction. As before, many of the associated features are short lived, disappearing and re-appearing erratically.

4 Summary and Conclusions

In this paper we described a novel method capable of automatically detecting moving objects in complex cluttered scenes, building their appearance models and tracking them in the presence of partial and full occlusions, change in appearance (e.g. due to articulation or pose changes) and scale. The proposed algorithm was empirically evaluated on a two hour long video footage of a busy city marketplace and the claimed theoretical properties of the approach substantiated by through successful performance on several difficult examples involving the aforementioned challenges.

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