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Tracking Algorithm for Videos with High Resolution and Frame Rate

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Abstract

In this paper we present an algorithm which allows us to have an object tracking close to real time in Full HD videos. The frame rate (FR) of a video stream is considered to be between 5 and 30 frames per second. The real time track building will be achieved if the algorithm can follow 5 or more frames per second. The principle idea is to use fast algorithms when doing preprocessing to obtain the key points and track them after. The procedure of matching points during assignment is hardly dependent on the number of points. Because of this we have to limit pointed number of points using the most informative of them.

1. Introduction

Tracking objects on video is one of the important attributes of the complex problem of object/human behaviour analysis and interpretation. There exist a lot of algorithms of object/human action analysis which have been build mostly as hierarchical algorithms of analysis of actions starting from very simple ones to more complicated [**?**]. The most advanced of them use probabilistic approaches such as Graphical models (Bayesian Networks (BN), Dynamical Bayesian Networks (DBN) and Random Fields(RF) that have an important subclass of Markov Random Fields (MRF)). All such approaches do not use the information about object tracking and often utilise full information about object which is available on video frames. As known using Graphical models could be very expensive in sense of computing when a number of random(hidden) variables is large [**?**, **?**]. On the other hand often to compute a value containing in every random variable needs to use all information from object and in case of Full HD video with high FR it is critical.

Another approach that refers to behaviour analysis is based on analysis of tracks. In track building there exist several principle approaches. The most important are based on Kalman filter and particle filter as generalization and extension to Kalman filter [**?**]. Both of them are of probabilistic character and can predict the dynamic of an object. T The difference between them consists in limitations of Kalman filter that needs model be linear and noise needs be of Gauss character. Particle filter uses sampling of posterior distribution having observations and to track objects with its application in case of Full HD video and high FR is problematic.

One more group of tracking algorithms do not use any probabilistic on doing tracking. The algorithms from these group generate a number of keypoints every of them to be assigned to separate path if the assignment is valid. By the path we understand a sequence of points matched on two consecutive frames and all these points define a trajectory of an object. Among algorithms producing local feature points we can mention SURF (Speeded up Robust Feature), SIFT (Scale-Invariant Feature Transform) [**?**] and IPAN algorithms [**?**]. Because IPAN algorithm generally finds much less points and each point could be much more informative (in average) than point generated by SIFT and SURF we use it as feature generation algorithm for tracking.

IPAN algorithm finds keypoints on the contour of an object and belongs to geometrical approach to feature generating. First of all we separate background from image using Gaussian Mixture Model (GMM) [**?**] . This allows us to findzones of motion, i.e. objects that move and which will be used for further processing. To obtain contours of objects we do their segmentation before. This guaranties that we are going to have only external contours of objects and not internal ones that could be in case of Canny detector application [**?**, **?**]. Canny filter uses gradients and finds all contours of an object. Keypoints are found in place where curvature of the contour segment is more than some given value. After finding critical points we use Hungarian algorithm for corresponding points assignment. This algorithm refers to the dynamic programming problem.

In the next sections we show how to use the algorithm which consists of different stages and some optimization tricks also. For any computing we use C++ for Windows (MS VS 2010) as well as for for Linux Ubuntu with libraries Open CV, Open GL, TBB, QT, BOOST, Open Threads and others.

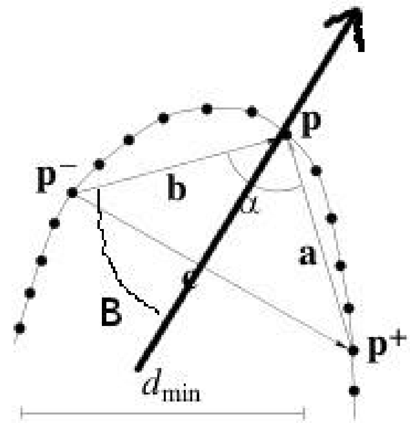
2. Video Preprocessing

By video preprocessing we mean the following operations on video: background subtraction, object segmentation, contour detection, contour filtering and dominant points detection. For background subtraction we use three operations). First operation computes the foreground mask after we compute background image. Then we subtract this background from the grayscale image to obtain an image with moving objects on the black background.

After that we do operations on obtained image using functions from Open CV library to make segmentation of objects and then we find contours for segmented objects. For initially found contours we apply circular averaging filter to smooth contours. This is needed because of possible local sharpness of contours where the IPAN algorithm could find a lot of local dominants what are not informative at all. Such a filter realise the averaging operation both on two coordinates in a window of a given size. Then for filtered contours we apply IPAN algorithm. The function that realises such algorithm has 4 parameters. The principle idea of the algorithm consists in a describing the curvature by some keypoints called dominant points. Having such dominants we can connect them by lines of different orders thus having approximate contours. This could be useful when we would like to realise the compression of information presented in contours. The total number of discrete points in contours is much more than number of dominants, so the compression rate could be very high in some situations. It is very important to fix the parameters of IPAN algorithm in a way that produce dominants in the appropriate place. Normally they should be in place with high local curvature and the distance between points should be large enough to simplify matching. If the distance between any of dominants (in some feature space) is essentially more than the maximal shift of some point (for several consecutive frames) in the same feature space this should satisfy appropriate assignment. We consider the possible assignments during several consecutive frames because some dominants could disappear for some time due to contour changes.

It should be noticed that initial IPAN algorithm is not invariant to scale, i.e it is not invariant to the size of object in a video. To have dominants in appropriate place the sides of a triangle that should be placed in the internal segment of the contour depend on the size of this segment. Knowing this dependence we can make the rescaling of the triangle. Fig.**??** shows how to build the triangle inside the segment of a contour and all parameters used in the IPAN algorithm.

As we can see every triangle is characterised by coordinates of vertices p, $p+$ and $p-$. As coordinate features of a dominant point p we use (x_p, y_p) and $p-(x_{p-}, y_{p-})$. Also we use 2 angles α and the orientation angle B between side b and the mean line of the α angle of the triangle. Finally we have 6 features: 4 coordinates and 2 angles. The Euclidian distance between two dominants p_i and p_j could be found as



(a)

Figure 1: Geometrical visualisation of IPAN algorithm

$$d(p_i, p_j) = \Big(\sum_{k=1}^{N}(f_{ik} - f_{jk})^2\Big)^{\frac{1}{2}} \tag{1}$$

where $f_i = \bigcup_{k=1}^{N} f_{ik}$ and $f_j = \bigcup_{k=1}^{N} f_{jk}$ are sets of features of p_i and p_j dominants. Here we have $N = 6$

Having $d(p_i, p_j)$ we build so-called cost matrix that will be utilised for assignment using Hungarian algorithm.

3. Assignment of Points and Track Construction

A cost matrix has been built on the basis of two vectors of dominant points taken from the previous and the current frame. Dominants from the previous frame we call predicting points in sense of assignment of points on the current frame. This is because points from the previous frame have already been assigned and are the last points of each track (we assume that assignment has been taken place at previous stage). So if we have two sets of dominants s_{prev} (from the previous frame) and s_{next} (from the current frame) we can construct the cost matrix C of size $n * m$, where $n = |s_{prev}|$ and $m = |s_{next}|$:

$$C_{i,j} = d(p_i, p_j), \tag{2}$$

where p_i is the ith point from the previous set of dominants and p_j is the jth point from the current set of dominants. For finding the assignments we use the Hungarian algorithm which works on cost matrix C. After application of this algorithm we obtain the binary matrix B composed with zeros and ones. The indexes i and j of each one in the binary matrix corresponds to the dominants in the previous and the next sets that are candidates for assignment. The final decision about assignment will be made if the following condition is satisfied:

$$d(p_i, p_j) < d_{max}. \quad (3)$$

Distance d_{max} should be chosen as the maximal shift of an object (human) on the video with respect to FR. This could be done knowing maximal velocity of an object of interest with respect to the calibration parameters of video camera. It should be noticed that algorithm that builds the paths should have the following functionality:

- the assignment should be executed only for active paths. By active path we understand some path which had no assignment not more than during several last frames (this parameter could be optimised during training process). Otherwise the path becomes inactive.
- The end of the track is the moment when the track is inactive and the last points of this track will not be checked for assignment.
- The points which have not been assigned are the beginnings of new tracks.

The optimised algorithm builds paths in a way that the length of such paths is as long as possible and there are not too many paths for each separate object.

4. Some tests

We tested our algorithm on a video clip of 50 sec. with FR=25 taken from the video stream recorded from the Market Square of our town where a number of different activity actions can be registered. In Figs. **??**-**??** the contributions from two windows of the algorithm are presented. In Figs. **??**-**??** the main window with view of the Market Square from a single video camera is shown. All tracks have been built in these windows. We also give a window with dominants that shows that number of dominant points found for each person that is not too far from the camera.

In general case tracks and contours of every person should be rescaled on the basis of intrinsic and extrinsic parameters of a video camera. As seen from Figs. **??**-**??** showing windows with colored video the track building is sufficiently good. To that end we use filter on the track length. Such a filtering gives a possibility to see if the length of a given value is achieved for each person separately. As seen even for the threshold of the track length equal to 50 we can see from one to several local tracks for some persons. For threshold equal to 25 we can see tracks for all persons. For threshold equal to 0 we can see all the tracks. The length of a track as one of the main characteristics of the track builder depends on the number

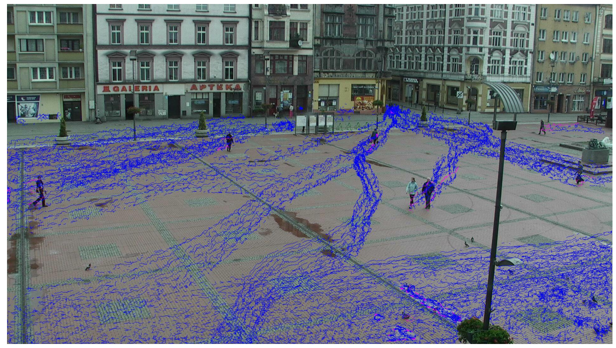


Figure 2: Complete set of tracks plotted on the initial video of the Market Square

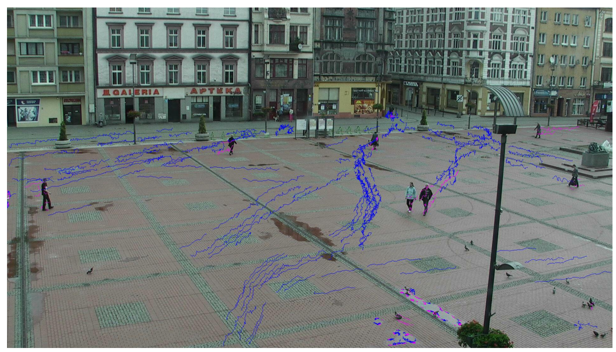


Figure 3: Filtered set of tracks with the track length threshold equal to 25 plotted on the initial video of the Market Square

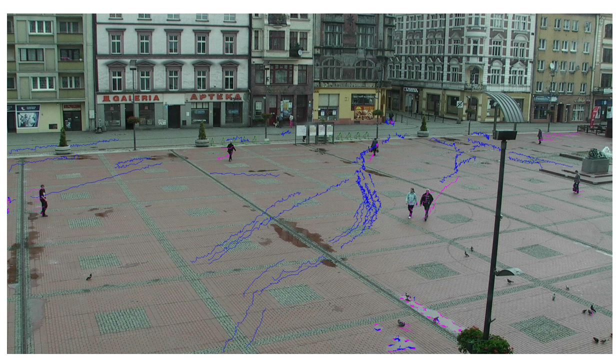


Figure 4: Filtered set of tracks with the track length threshold equal to 50 plotted on the initial video of the Market Square

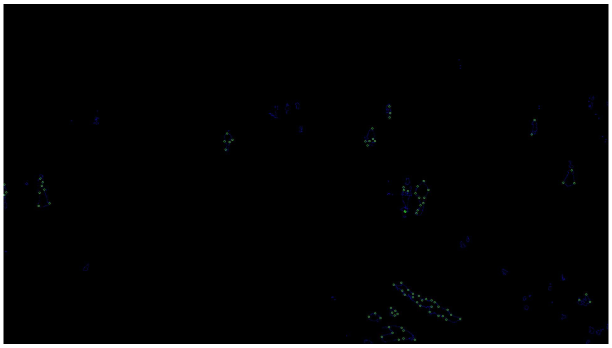


Figure 5: Dominant points plotted on filtered contours

of parameters. All of them we put on sliders or trackbars to have the possibility to control them by a human. The sliders on the Control Panel control the following parameters of the generalised algorithm:

- thresholds for the segmentation algorithm;
- size of a window for circular averaging filter;
- 4 parameters for the IPAN algorithm;
- weights on angles characterising dominants from the IPAN algorithm;
- d_{max};
- assignment gap (the number of frames where tracks are active if there is no assignment).
- window size to calculate average speed on the track end;
- filter for the track length;
- scale for the parameters of IPAN algorithm and d_{max} depending on the distance from the video camera;

5. Conclusions

We presented a generalized algorithm for video tracking that allows us to build tracks in a real-time or close to that for Full HD images. This is because it is based on geometrical approach for feature generating and fast enough assignment algorithm. A lot of things for acceleration of the algorithm could be done by changing of the parameters put on sliders. These parameters control the number of paths generated and also the length of such paths. Here improving the quality of paths (the number of paths reduction with obtaining paths of a larger length) we can speed up the algorithm.

6. Acknowledgements

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7. References

[1] Gong, Sh. and Xiang T., Visual Analysis of Behaviour: From Pixels to Semantics, Springer, London, 2011

[2] Maggio, E. and Cavallaro A., Video Tracking: Theory and Practice, Wiley, 2011

[3] Marsland, S., Machine Learning: An Algorithmic Perspective, ChapmanHall/CRC, Boca Raton, Florida, 2009.

[4] Prince, S., Computer Vision : Models, Learning and Inference, Cambridge University Press, 2012

[5] Bradski G. and Kaehler A., Learning OpenCV, O'Reilly, Sebastopol, CA, 2008

[6] Chetverikov, D. and Szabo, Zs., "A Simple and Efficient Algorithm for Detection of High Curvature Points in Planar Curves", Robust Vision for Industrial Applications 1999, Vol. 128 ,1999, p 175–184.