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KALMAN FILTER BASED MULTIPLE OBJECT TRACKING SYSTEM

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ABSTRACT

This paper presents a method for tracking multiple objects from a given video dataset. We can track many objects at a time efficiently using Kalman Filter and Optical flow algorithm. Here in this paper, we propose improved optical flow algorithm which works with high accuracy and overcomes occlusion in a video. So, improved optical flow algorithm is found to be more promising as it gives better accuracy in less computation.

KEYWORDS: Multiple Objects, Kalman Filter & Less Computation

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Original Article

INTRODUCTION

Object tracking is a crucial task within the field of computer vision. There are three important steps in video analysis:interesting moving objects detection, tracking of such objects from frame to frame, and analysis of object tracks to recognize their behaviors. The complexity of object tracking is due to different noises present in the input from the video, illumination variations in the input, unusual movement of the object and different occlusions. Most of the tracking algorithms assume that the moving object moves in smooth and no sudden change. There are two main goals in our project: to correctly recognize moving objects of interest, and to track those moving objects throughout their life span. Noise is the primary problem. Movement of the camera and background may lead to pixel movement in the image. This is of no importance. Size constraint is utilized to remove movements which are very small to contribute to the object movement.

From the input image, the subject to be tracked is to be identified. This is the next work. Conventional technique to track the system will give poor results. When the subject is in motion, we find that Template Matching give errors. Hence Template Matching andMotion detection can be used together on the objects that are moving. Results have shown this to be a robust method in both recognizing the objects as well as tracking them. The rest of the report presents a brief literature review; a description of the experiment design and the program; presentation of the results, conclusion and discussion for future work.

LITERATURE REVIEW

Motion detection and object tracking is a very rich area of research in computer vision. The main issues that make this research area difficult are:

Computational Expense

If an algorithm for detecting motions and tracking objects is to be applied to real-time applications, then it needs to be computationally inexpensive so that a modern PC has enough power to run it. Yet many algorithms in this research area are very computationally expensive since they require computing values for each pixel in each image frame.

Moving Background Rejection

Unwanted movements contributed by the tree branches and so are to be eliminated by the algorithm. If at all if the object is too small than the background then mistakes in the classifications can be done. Also the speed with which the object is moving relative to the background can lead to errors.

Method of Occlusion

Number of algorithms is available which suggest solutions for tracking under tiny occlusions, still they fail to track the object if it is occluded for a long period of time.

Modelling Targets of Interest

Many algorithms use a reasonably detailed model of the targets in objects detection and consequently require a large number of pixels on target in order to detect and track them properly. This is a problem for real-world applications where it is frequently impossible to obtain a large number of pixels on target.

Adapting to Illumination Variation

Many situations under real time have changes in the scene illumination and all the techniques should keep this in mind and try to solve this issue. If the algorithm is written which is based on the intensity technique thee is a probability that it may not work in sucha situation.

PROPOSED WORK

Kalman filter is a region based method for finding the regions of object in the next frame. The center of object is found first, and then we use Kalman filter for predicting the position of the object in the next frame. The filter we consider here will try to estimate the linear system's state and this is Gaussian distributed. The method using Kalman filteriscomposed of two steps, prediction and correction as shown in figure.1. Optimal estimate of its position, at each time of step is provided by the Kalman filter for subjects in movement which also has some unwanted noise due to this movement.

The optimality is guaranteed if all noise is Gaussian. Then the filter minimizes the mean square error of the estimated parameters (e.g. position, velocity). The

As the fresh information come they are processed immediately by the Kalman filter and also it is very useful. Here we need a linear system mixed with unknown disturbances that is dynamic to design a Kalman filter. The Kalman filter tries to estimate the state $a \in R^n$ ofthat system which is governed by the vector difference equation:

$$a_{\bar{K}} = Xa_{k-1} + Yb_k + c_{k-1}$$
$$\mathrm{t_k = Ia_k + d_k}$$

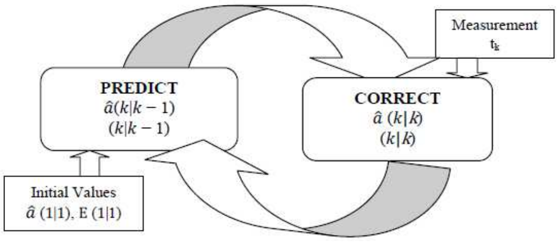


Figure: The Kalman Filter Predict/Correct Model

The random variables ck, dk represent the process and measurement noise respectively. They are assumed to be zero mean, white noise with covariance matrices respectively. The matrix A is called the state transition matrix and relates the previous state ak−1 to the current state ak, if no noise was present. The size of A is n×n. Matrix A is optional and relates the control input (if any) bk∈akto the state ak. Finally, the n×n matrix, relates the measurement tk to the state ak-1. The Kalman filter maintains the following two estimates of the state:

1. $\hat{a}(k|k-1)$,which is an estimate of the state at time-step, given knowledge of the process up to step k-1. It is an a priori state estimate at time-step 1
2. $\hat{a}(k|k)$Which is an estimate of the process state at time-step k given the measurement tk. It is a Posteriori estimate of the state at time-step k.

Below mentioned Error Covariance matrices are indeed looked after.

1. $E(k|k-1)$which is the a priori estimate error covariance of$\hat{a}\ (k|k-1)$.
2. $E(k|k)$which is the a posteriori estimate error covariance of$\hat{a}\,(k|k)$.

There are two possible steps in which Kalman filter operates

The First one is the prediction of the next state estimate(k|k− 1) using the previous one. The second is the correction of that estimate using the measurement, to obtain(k|k). Initially, (1|1) and E(1|1) are considered known. To maintain those estimates, the following operations take place. In the prediction step:

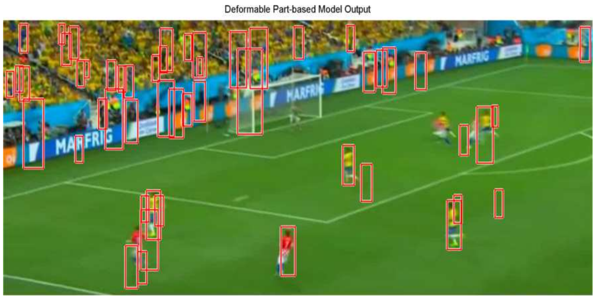
1. State prediction:$\hat{a}\ (k|k-1) = A \cdot \hat{a}\ (k-1|k-1)$
2. Error covariance prediction:$(k|k-1) = A \cdot (k-1|k-1) \cdot A^T + Q$

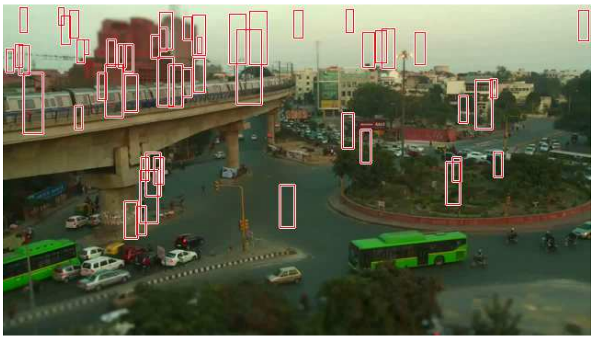
In the correction step

1. Measurement prediction: $\hat{t}\ (k|k-1) = H \cdot \hat{x}(k|k-1)$
2. Residual: $r_k = t_k - t\ (k|k-1)$
3. Measurement prediction covariance: $U_k = I \cdot (k|k-1) \cdot I^T + R$
4. Kalman gain: $C^k = (k|k-1) \cdot I_1 \cdot U^{-1}$
5. State update: $\hat{a}(k|k) = \hat{a}\ (k|k-1) + C_k r_k$
6. Error covariance update: $(k|k) = (k|k-1) - C_k \cdot U_k \cdot C_k^T$

Kalman filter is initialized by defining the state transition matrix A, The state measurement matrix 4, both covariance matrices and always this is used to feed the filter with a measurement; k [10]. Multiple objects can be tracked easily from the video dataset.

SIMULATION RESULTS





dets_cur <52x6 double>

	1	2	3	4	5	6	7
1	603.7780	392.2905	634.4624	485.1772	1	0.1323	
2	340.4167	50.4167	356.6667	100	2	-0.2345	
3	44.4003	149.9609	87.9672	281.4950	2	-0.3317	
4	979.3031	332.6664	996.7493	385.8384	2	-0.4007	
5	536.4759	15.7326	574.3492	130.1858	1	-0.4353	
6	390.2791	139.9464	410.3815	201.0869	2	-0.4416	
7	263.0608	86.5968	283.1632	147.7373	2	-0.4696	
8	493.4325	21.8521	528.7416	128.6128	1	-0.6540	
9	226.3273	76.9966	245.0556	134.0148	2	-0.6546	
10	811.2324	56.9852	834.3860	127.2792	1	-0.6785	
11	323.7500	67.0833	340	116.6667	1	-0.7014	
12	7.0833	97.0833	23.3333	146.6667	1	-0.7159	
13	265.7524	152.0371	292.4109	232.8457	2	-0.7559	
14	341.5627	16.6617	368.2211	97.4703	2	-0.7638	
15	738.0654	237.8789	762.9107	313.2481	1	-0.7819	
16	964.5508	342.5288	995.2352	435.4154	1	-0.8219	
17	778.2341	273.8313	801.3877	344.1253	1	-0.8318	
18	36.1424	7.5618	53.5887	60.7338	2	-0.8362	
19	27.0833	87.0833	43.3333	136.6667	1	-0.8468	
20	422.3237	71.1273	433.6922	106.0660	2	-0.8521	
21	414.7125	116.6216	439.5578	191.9908	2	-0.8571	
22	393.7500	27.0833	410	76.6667	2	-0.8666	
23	1.0686e+03	321.9487	1.0861e+03	375.1207	1	-0.8713	
24	160.4167	77.0833	176.6667	126.6667	1	-0.8983	
25	412.4773	23.6313	441.0790	110.2697	1	-0.9082	
26	329.7102	333.5392	348.4385	390.5574	2	-0.9082	
27	300.4167	333.7500	316.6667	383.3333	2	-0.9285	
28	207.1824	149.7475	225.9107	206.7657	2	-0.9436	

Command Window

CONCLUSIONS

In this paper, we presented a tracking method for processing video data in order to perform tracking by a machine vision system. It summarizes as multiple objects can be tracked simultaneously. It can control some problem of multi object tracking, such as appearance and disappearance of objects, and missing of an object. Amongst the methods reviewed, improved optical flow algorithm is found to be more promising as it gives better accuracy in less computation time. The present work can be extended further by using more tracking algorithms and comparing their performance accordingly to achieve more accuracy. Also we will try to test our algorithm on real time video frames.

REFERENCES

1. *ShuTian, Fei Yuan, Gui-Song Xia Multi-*objecttracking *with inter-feedback between detection and* tracking*Neurocomputing, Volume 171, 1 January 2016, Pages 768-780*
2. *Zhiyu Zhou, Dichong Wu, Zefei Zhu* Objecttracking *based on Kalman particle filter with LSSVR Optik - International Journal for Light and Electron Optics, Volume 127, Issue 2, January 2016, Pages 613-619*
3. *AslaniSepehr and NasabHomayounMahdavi, Optical Flow Based Moving Object Detection and Tracking for TrafficSurveillance, International Journal of Electrical, Computer, Electronics and Communication Engineering,* ***2013****, Vol 7 No 9.*
4. *J Berclaz, F Fleuret, E Turetken and P Fua, Multiple Object Tracking using K-Shortest Paths Optimization, IEEETransactions on Pattern Analysis and Machine Intelligence,* ***2011,*** *p. 1806-1819.*
5. *Y Zhai, MB Yeary, S Cheng and N Kehtarnavaz, An object-tracking algorithm based on multiple-model particle filteringwith state partitioning, IEEE Transactions on Instrumentation and Measurement,* ***2009****, p. 1797-1809.*
6. *BD Lucas and T Kanade, An Iterative Image Registration Technique with an Application to Stereo Vision, Proceeding ofImaging Understanding Workshop,* ***1981****, p. 121-130.*
7. *A Agarwal, S Biswas, S Singh, S Sural and AK Majundar, Object Tracking using Background Subtraction and MotionEstimation in MPEG Videos, Springer-Verlag Berlin Heidelberg, ACCV,* ***2006****, p.121-130.*
8. *Qiaona Pei, Moving Objects Detection and Tracking Technology based Optical Flow, North China University of Technology,****2009,*** *p. 11-14.*
9. *ZervosMichalis, Fua Pascal and ShitritHoresh Ben, Real Time Multi-Object Tracking using Multiple Cameras, SemesterProject, School of Computer and Communication Sciences,* ***2012.***
10. *Henrique Morimitsu, Isabelle Bloch, RobertoM. Cesar-JrExploring structure for long-term* tracking *of multiple* objects *in sports videosComputer Vision and Image Understanding, Volume 159,June 2017, Pages 89-104*