Research Paper ENGINEERING

Implementation of Multi Target Tracking Algorithm on Beagle Board-Xm

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ABSTRACT

Video tracking in real time is one of the most important topics in the field of surveillance based systems. Detection and tracking of moving objects in the video scenes is the first step in the process of information extraction . Processing a video stream to segment foreground objects from the background is a critical step in many computer vision applications. Background subtraction is a familiarly used method for achieving this segmentation. Gaussian Mixture-based Background Segmentation Algorithm and morphological operations are used for object detection and tracking. The main processing unit used in this paper for implementation process is Beagle Board-XM with Linux (Ubuntu) operating system installed with Open CV. The indexing of identified objects and automatic labeling enables the developed system suitable for surveillance applications.

KEYWORDS Background Subtraction, Open CV, Target Tracking.

INTRODUCTION

Moving Object detection and tracking is the process of segmenting the object of interest from the frames of the given video and tracking its movement. The exercise of object tracking is pertinent in the tasks like action based recognition, video indexing, human-machine interaction, monitoring of traffic, and vehicle navigation.

The underlying principle of all these methods is to detect, segment and track objects in the video. A static camera observing a scene is a common case of a surveillance system. Detecting moving objects is an important and essential step in analyzing the scene.

This work briefs object tracking from a stationary video scene. A GMM based dynamic background subtraction is first adopted to detect whether a target existing or not, and then states of merged and split targets are derived to avoid inaccurate object counting at occlusion conditions. For doing that, a modified overlap tracker is designed to complete the character label and to reach the goal of tracking characters. Additionally, the centroid distance between neighboring objects is further analyzed to achieve fairly good object tracking results in consecutive frames (V.Kamatchi Sundari, 2015). The main intention of this proposed work is to implement multiple objects tracking algorithm on Beagle Board-XM.

RELATED WORK

During the last few years, diverse researches has been undergoing for the different algorithms used for object tracking. Meanshift method, Camshift method (Afef Salhi,2012), Kalman filter (Amir Salarpour,2011), Background Subtraction(O. Barnich,2009) method are the different methods used for the tracking of the objects in the video scenes.

Target tracking papers techniques based on EM algorithms are presented by many authors.(Yan ,1999, Ari C,2012, Dawei Li,2013 and Fuxin Li ,2013) The problem of directional target tracking in a clutter free environment with unity detection probability is addressed by Fuxin Li et al. Optimal MAP state estimates is presented by R.L. Streit, and T.E. Luginbuhl, 2005 where the EM algorithm is applied to the problem of multi-target tracking, when the data origin is unclear, i.e. it is not known. The missing data are the associations discrete random variables. The E-step computes (estimates) a posteriori association probabilities while the M-step compute the MAP state sequence estimates of the target trajectories. Our proposed algorithm borrows many ideas from the algorithm which is presented by Dawei Li et al, land vehicles are not totally planar and present uphill and downhill slopes that follow the environment topography.

Our proposed scheme is another ideal state valuation algorithm for conditional mean estimation. It is also called as an algorithm of iterative expectation maximization. Gaussian Mixture Model, an active statistical model is used for background learning. Next step is the foreground detection i.e. elimination of background items by linking the valued model of background with the present video frame. Finally include the attributes of geometry information, image evidence, and temporal support with this outline. By using this, the well-defined energy minimization formulation can also exploited the core of the roads that is invariant in challenging environments.

SYSTEM OVERVIEW

A. Embedded Platform

The Beagle Board XM (Beagle Board-XM Rev C System Reference Manual, 2010) is a low-cost, low power, open source hardware single board computer produced by Texas Instrument in association with Digi-Key. Beagle Board XM is the modified version of Beagle Board which has faster CPU core (clocked at 1GHz compared to 720MHz) and more RAM (512 MB compare to 256 MB). The Beagle Board XM was designed with open source development in mind and as a way of demonstrating the Texas Instruments DM3730 system on-a-chip. The board uses up to 2 W of power and because of the low power consumption, no additional cooling and heat sinks are required. The Beagle Board XM is designed to address the Open Source Community. By eliminating all of the on-board peripherals and by providing standard expansion buses like high-speed USB 2.0, Ethernet port and HDMI port, developers and researchers can bring their own peripherals and expand the board ability what they want. It has been equipped with a minimum set of features to allow the user to experience the power of the processor.

Figure 1 shows the arrangement of major components in Beagle Board XM.

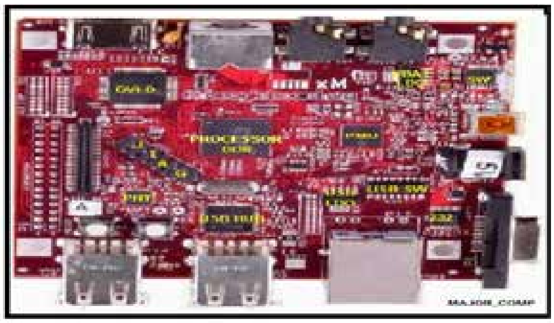

Figure 1:Beagle Board Major Components

B.OPEN CV

Open CV (Open Source Computer Vision library) (G. Bradski and A. Kaehler.2008) is a library of programming functions mainly aimed at real time computer vision developed by Intel in year 1999 and now supported by Willow Garage. It is free for use under the open source BSD license. Open CV has cross platform library function, with the avid features of its used in major activities in Motion analysis. Open CV was designed for computational efficiency and has a strong focus on real-time applications. It is written in optimized C/C++, the library can take advantage of multi-core processing. Available for C, C++, C#, JAVA, Ubunto, IOS and Python. Open CV proves to be platform independent and easily deployable in any platform. Major four advantages of using Open CV are speed, resource, portability and cost.

ALGORITHM

A dynamic background subtraction module is first measured to segment moving objects from each captured video frame. In order to overcome light variations, a dynamic threshold value connected with detecting regions of interest from the differentiated image is iteratively calculated according to the distributions of background and foreground pixels in each frame. After locating the foreground regions, four states of new, leaving, merged and split are assigned to the detected moving objects according to their appearances in the current frame. This method is briefly discussed by V Kamatchi Sundari, 2015. Figure 2 describes the overview of the proposed system.

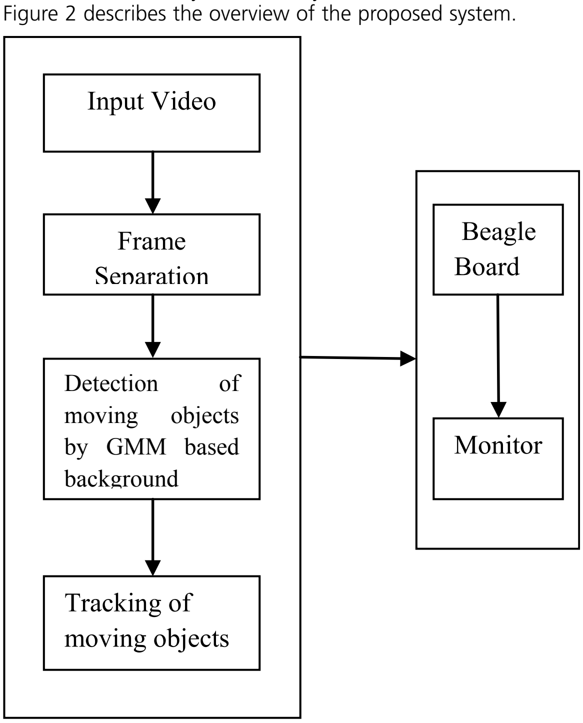

Figure 2: Overview of our proposed system

Gaussianity Process is used to measures the set of data is distributed in Gaussian. In addition to that independent difference across the frames is assumed. Hence only Gaussian noise and foreground objects remain in the difference frame Df(x, y). Under this postulation, the foreground pixels in Fp(x, y) should be non-Gaussian distributed, and the background pixels in Bp(x, y) should be Gaussian distributed.

By considering W x H centered at pixel (x, y), and the process is depends on the evaluation of the first four instantaneous of the pixel intensity differences given by,

$$(x, y) = \begin{Bmatrix} Foreground\ Pixel\ if\ H(x, y) > T \\ Background\ Pixel\quad otherwise \end{Bmatrix}$$

Expectation Process:

E step: Calculate the conditional expectancy of the whole log amplified density.

$$Q\ (X_K;\ X^{(l)}{}_K) = E\ \{\ln Fg(X_K;\ M)\ |M_{obs};\ X^{(l)}{}_K\} \qquad (1)$$

Here $X^{(l)}{}_K$ is the state estimate sequence at the l'th iteration.

Maximization Process:

M step: Calculate $X^{(l+1)}{}_K$ as

$$X^{(l+1)}{}_K = \arg\max_{XK} Q\ (X_K;\ X^{(l)}{}_K) \qquad (2)$$

The posterior density rises uniformly. This is the interesting stuff of the algorithm of EM i.e,

$Fp\ (X^{(l+1)}{}_K\ |M_{obs}) \geq Fp(X^{(l)}{}_K\ |M_{obs})$ with equivalence holding at the indigenous minima, maxima, and saddle arguments of the distribution of posterior (C.F.J. Wu,2013). The merging of $X^{(l)}{}_K$ to a fixed point, whether it is a local maximum or minimum or a saddle point which relies on the best of the opening point $X^{(0)}{}_K$. Therefore, it is recommended that the numerous EM repetitions be tried with unconnected opening points.

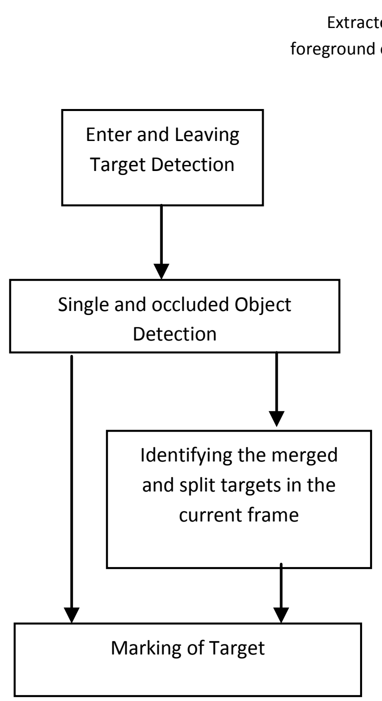

Figure 3: Processing Steps of our proposed system

To find various locations of the moving object in the video sequences, the information about the moving tracking objects is denoted by a vector state notation

$$Xt = [\ Xt,n\ |n=1,\ldots\ldots,N\ ] \qquad (3)$$

Where N is the number of moving objects at time step t .

$$X_{t,n} = [\ r,R\ ]_{t,n} \quad (4)$$

The nth component contains the (r) object centroid and the (R) Square bounding of an object, respectively. The chief concern of our system is to obtain spatial locations of substances and to observe their trajectories along with period of time. It is possible to occur in every possible of all frames or may be first itself. By effectively predicting earlier to initiate the process instantly, once started it can be functioning to the process of treating the frames in the video very effectively. The predictable design of forefront and background frames stated through our proposed method, we take the subsequent models to define the forefront and the background models.

This work defines an item out of a video scene. Particularly, the adjoin incident of objects is noticed in the adjacent frames for split and merged target states (Kangyu Pan et al, 2010). The outcome of splitting and merging target in the present frame also considers the target states by backward tracing the substances that seem in the earlier frame. Lastly tags are allotted by the chaser to discrete substances by means of locus continuity which is conserved by the identified characters in the earlier frame, this splitting and joining process could be possible MAP-posterior with EM Algorithm to achieve the target detection.

EXPERIMENTAL RESULTS

The aim of the object tracking is to track the exact position of the object frame by frame. In this section our algorithm is tested with Matlab R2013 and implements the same in Beagle Board-XM with recorded video having frame rate of 21 frames per second. The output of our system can be observed with the help of a monitor display.

Figure 4: Input Video

Figure 5: Tracking a object

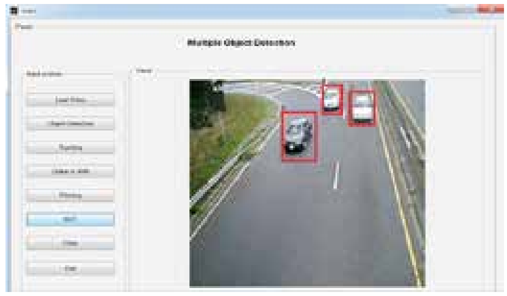

Figure 6: Tracking multiple objects

Figure 7: Snapshot of our implementation setup.

Figure 8: Snapshot obtained with Open CV

When comparing the performance of Matlab with Open CV, Matlab performance is moderate, finding false positive outside the intended objects whereas Open CV is good in finding true positives. Average number of frames processed per second is high about 18 in Open CV when compared to 5 in Matlab.

CONCLUSION

This paper concentrates on the implementation of simultaneous tracking of the multiple objects in recorded video. The objects are detected and tracked successfully in the test video.
The work presented in this paper is a part of ongoing research to realize embedded video processing platform for real time applications. In future this work is aimed to be continued in processing of live video with higher frame rate.

REFERENCES

|[1]Afef Salhi & Ameni Yengui Jammoussi.(2012), "Object tracking system using Camshift, Meanshift and Kalman filter", World Academy of Science, Engineering and Technology. |[2]Amir Salarpour, ArezooSalarpour, Mahmoud Fathi & MirHosseinDezfulian.(2011), "Vehicle tracking using kalman filter and features", Signal & Image Processing : An International Journal (SIPIJ),.2(2). |[3]O.Barnich & M. Van Droogenbroeck.(2009), "ViBe: A powerful random technique to estimate the background in video sequences," Int. Conf. Acoust., Speech Signal Process., pp. 945–948. |[4]Yan, Q, Xu, Y, Yang, X. & Nguyen, T.(1999), " Separation of Weak Reflection from a Single Superimposed Image",‖ IEEE Signal Processing Letter., vol. 21. |[5]Ari, C & Aksoy S.(2012), " Detection of Compound Structures Using a Gaussian Mixture Model With Spectral and Spatial Constraints", IEEE Transactions on Geoscience and Remote Sensing, vol. 52. |[6]Dawei Li, Lihong Xu & Goodman E.D(2013). " Illumination-Robust Foreground Detection in a Video Surveillance System" IEEE Transactions Vol.23. |[7]Fuxin Li , Carreira, J, Lebanon, G. & Sminchisescu C.(2013). " Composite Statistical Inference for Semantic Segmentation", IEEE CVPR'13. |[8]R.L. Streit, & T.E. Luginbuhl(2005). "Probabilistic multi-hypothesis tracking", Naval Underseas Warfare Center, Newport, Rhode Island, NUWC–NPT, Tech.Rep. 10428. |[9]Dawei Li, Lihong Xu , & Goodman, E(2012). "Real-Time Statistical Background Learning for Foreground Detection under Unstable Illuminations", ICMLA`12. |[10]C.F.J. Wu(2013). "On the convergence properties of the EM algorithm", Ann. Statist. |[11]Kangyu Pan, Kokaram, A., Hillebrand,J. & Ramaswami, M (2010). "Gaussian mixture models for spots in microscopy using a new split/merge em algorithm" ICIP'10. |[12]V.Kamatchi Sundari & M.Manikandan. (2015), "Intelligent Multi-Target Tracking by Communicating Two Consecutive Frames." International Journal of Applied Engineering Research, 10(9),7082-7085. |[13]Beagle Board-xM Rev C System Reference Manual, http://beagleboard.org, Revision 1.0, April 4, 2010 |[14]G. Bradski & A. Kaehler(2008), " Learning OpenCV", OReilly Publications. ||