Real-time foreground segmentation and boundary matting for live videos using SVM technique

Kajal Sangale, Prof. N.B.Kadu

Abstract— Foreground segmentation is one of the major tasks in the field of Computer Vision whose aim is to detect changes in image sequences. In this we are going to detach foreground objects from input videos. There still lacks a simple yet effective algorithm that can process live videos of objects with fuzzy boundaries (e.g., hair) captured by freely moving cameras. The key idea is that we are going to use two competing one-class support vector machines at each pixel location, which gives local color distributions for both foreground and background provides higher discriminative power while allowing better handling of ambiguities. In this using integrated foreground segmentation and boundary matting we are going to extract the object from live videos with normal and fuzzy boundaries with freely moving camera which we want using SVM technique as well as calculate near time processing speed by introducing novel acceleration techniques and by exploiting the parallel structure.

Index Terms— Foreground segmentation, video matting, support vector machine (SVM), one-class SVM (1SVM), VGA-sized videos.

I. Introduction

Video segmentation is the process of partitioning the video into multiple segments(set of pixels or subpixels). The goal of segmentation is to simplify and change the representation of the video into something that is more meaningful and easier to analyze. Video segmentation is typically used to locate objects and boundaries in videos {e.g. Film Segmentation}.

A. Foreground segmentation:

Foreground segmentation as video cutout, studies how to extract objects of interest from input videos .It is a fundamental problem in computer vision and often serves as a pre-processing step for other video analysis tasks such as surveillance, teleconferencing, action recognition and retrieval. Foreground segmentation is the extraction of the object which is at minimum distance from user or the object which is at the front. There are different methods f segmentation tri-map method, graph cut method, bilayer segmentation in this we use SVM means Support Vector machine technique.

Kajal Sangale, *Computer Engineering, Pravara Rural Engineering College, Pune University, Ahmednagar,India,9594860386.*

Prof.N.B.Kadu, *Computer Engineering, Pravara Rural Engineering College Pune University, Ahmednagar, India, 9404980016,*

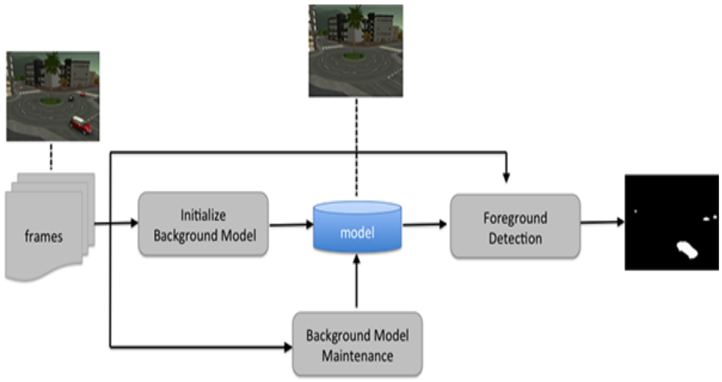

Fig 1: Foreground segmentation

B. Video Matting

Video matting is a critical operation in commercial television and film production, giving a director the power to insert new elements seamlessly into a scene or to transport an actor into a completely new location. In the matting or matte extraction process, a foreground element of arbitrary shape is extracted, or pulled, from a background image.

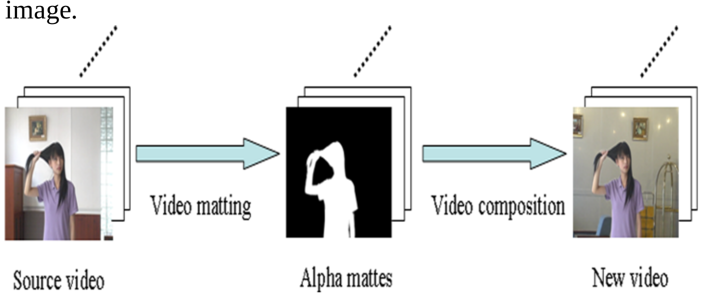

Fig 2: Video matting

Most existing algorithms are rather complicated and computationally too demanding to be operated in real-time. As a result, there still lacks an efficient and powerful algorithm capable of processing challenging live video scenes with minimum user interactions. We here present a novel integrated foreground segmentation and boundary matting approach, which is an extension to our preliminary work on foreground segmentation [8]. The algorithm is able to propagate labeling information to neighboring pixels through a simple train-relabel-matting procedure, resulting in a proper segmentation of the frame. This same procedure is used to further propagate labeling information across adjacent frames, regardless of the foreground or background motions. Several techniques are used in order to reduce computational cost. We also calculate real-time

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processing speed for VGA-sized videos for matting and without matting.
The proposed algorithm bears the following characteristics:
1. Ability to deal with challenging scenarios:
The algorithm performs a variety of challenging scenarios such as fuzzy boundaries object, motion of camera, changes of topology, and low fore/background color contrast.

2. Minimal User Interaction:
Users are nothing but the operator which is going to handle the videos. Users are only asked to handle foreground and background of the first frame with few key strokes.

3. Unified Framework for Segmentation and Matting:
The ability of C-1SVMs to train separate classifiers for foreground and background colors not only allows more robust labeling of the pixels, but also facilitates the matting procedure along object boundaries. This leads to an integrated solution for both foreground segmentation and boundary matting problems[21].

4. Easy to Implement:
The same train-relabel-matting procedure is used to segment foreground objects from input user strokes, as well as to take care of fore/background motions in the video. No additional procedure is required for obtaining trimaps or estimating scene motions.

5. Parallel Computing:
The algorithm is designed for parallel execution at individual pixel locations. Our current implementation processes VGA-sized videos in real-time using a mid-range graphics card.

6. Low Computational Cost:
The classifiers are trained using online learning, one frame the another like this execution takes place for that requires less cost.

II. RELATED WORK

In this we are going to make comparison of different algorithm and then tells how our paper is beneficial as compare to others.

L Cheng and M. Gong,In "Real time Background Subtraction from Dynamic Scenes"[1] The proposed approach is designed to work with the highly parallel graphics processors (GPUs) to facilitate realtime analysis.

A. Criminisi, G. Cross, A. Blake, and V. Kolmogorov, "Bilayer segmentation of live video,"[4] This presents an algorithm capable of real-time separation of foreground from background in monocular video sequences.

V. Kolmogorov, A. Criminisi, A. Blake, G. Cross, and C. Rother, "Bi-layer segmentation of binocular stereo video"[10] This paper has addressed the important problem of segmenting stereo sequences. Disparity-based segmentation and colour/contrast-based segmentation alone are prone to failure. LDP and LGC are algorithms capable of fusing the two kinds of information with a substantial consequent improvement in segmentation accuracy.

D. Li, Q. Chen, and C.-K. Tang, "Motion-aware KNN Laplacian for video matting," This paper demonstrates how the nonlocal principle benefits video matting via the KNN Laplacian, which comes with straight forward implementation using motion aware K nearest neighbor.

Y. Sheikh, O. Javed, and T. Kanade, "Background subtraction for freely moving cameras,"[15]These algorithm assumes a stationary cameras, and identify moving objects by detecting areas in the videos that change over time.

J. Wang and M. F. Cohen,"An iterative optimization approach for unified image segmentation and matting,"[17] Separating a foreground object from the background in a
static image involves determining both full and partial pixel coverages, also known as extracting a matte.

M. Gong and L. Cheng, "Foreground segmentation of live videos using locally competing 1SVMs,"[8] A novel foreground segmentation algorithm is proposed in this paper that is able to efficiently and effectively deal with live videos. The algorithm is easy to implement, simple to use, and capable of handling a variety of difficult scenarios, such as dynamic background, camera motion, topology changes, and fuzzy object boundaries. In contrast, SIFT features are firstly employed in Video SnapCut to estimate rigid motion, which is followed by optical flow to compute per-pixel motion. This nevertheless leads to a much more complex and computational demanding algorithm.

Our integrated foreground segmentation and boundary matting approach, which is an extension to our preliminary work on foreground segmentation. Finally, compared to our preliminary work that focuses on foreground segmentation [8], the algorithm discussed here incorporates an additional matting step into the original train-relabel procedure, allowing both foreground segmentation and boundary matting problems to be solved in an integrated manner. To properly utilize the information extracted from matting calculation, the training process has been revised and more precise report on processing time are added throughout the paper.

III. PROPOSED SYSTEM

Our working is on real-time foreground segmentation and boundary matting for live videos using SVM technique. SVM is nothing but Support Vector machine. Support Vector Machine is the supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. One-class-SVM is an unsupervised algorithm that

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learns a decision function for novelty detection: classifying new data as similar or different to the training set. Our approach is to maintain two Competing one-class Support Vector Machines (C-1SVMs) at every pixel location to supervised learning models with associated learning

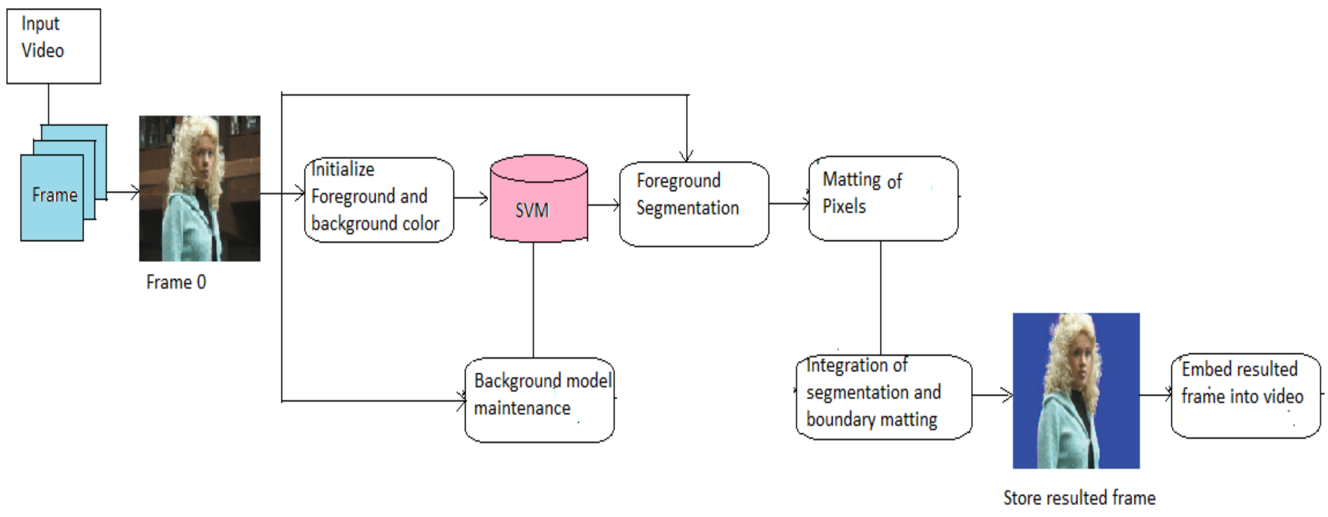

Fig: Architectural diagram of Integrated foreground segmentation and boundary matting

algorithms that analyze data and recognize patterns, used for classification and regression analysis. The two one-class Support Vector Machines (1SVMs) capture the local foreground and background color densities separately, but determine a proper label for the pixel jointly. By iterating between training local C-1SVMs and applying them to label the pixels, the algorithm effectively propagates initial user labeling to the entire image, as well as to consecutive frames. The algorithm can deal with a variety of challenging scenarios studied by the state-of-the-art methods. By using two 1SVMs to model foreground and to model foreground and background color distributions separately facilitates the matting calculation along object boundaries, making it possible to solve foreground segmentation and boundary matting problems in an integrated manner. of the above steps are further discussed in each of the following subsections.

A. Evaluation on C-1SVM:

B. Evaluation on Binary Segmentations
C. Evaluation on Matting Results
D. Perform Matting Along Foreground Boundary:
E. Processing Time
.

Advantages:
1. It is easy to implement.
2. It is simple to use.
3. It capable of handling a variety of difficult scenarios.
4. Till now we see different method of segmentation and boundary matting but this is the integrated method of both.In this we get the correct extraction of object of fuzzy boundaries(like hairs).

Applications:
1. Automated video surveillance.
2. Object tracking.
3. Object recognition.
4. 3D object recognition
5. Film making.
6. Motion capture in sports & tracking of multiple Human in Crowded Environments.

PRELIMINARY

In this section, we briefly introduce some techniques we will use in this paper fuzzy object, train-relabel-matting, Binary SVMs and C-1SVMs, Reweighting Scheme, Batch and Online Learning and Max-Pooling of Subgroups.

1. Fuzzy boundaries:
A fuzzy concept is a concept of which the boundaries of application can vary or the boundaries which are not continuous.{e.g. hairs}

2. Train-relabel-matting:
The same train-relabel-matting procedure is employed for handling temporal changes as well.

3. C-1SVMs:
We hypothesize that better performance can be achieved using two C-1SVMs. Modeling the two sets separately using the C-1SVMs produces two hyperplanes that enclose the training examples more tightly.

4. Reweighting Scheme:
The online learning algorithm does not consider the situation where a given example is used repetitively during training.

5. Batch learning:

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Training a SVM using a large set of examples is a classical batch learning problem. In batch learning we want to work on batches.

7. Online learning:
In online learning we are not going to work on batches In online learning we require minimum time.

8. Max-Pooling of Subgroups.
We divide the whole example set into *N* non-intersecting groups and train a 1SVM on each group.

CONCLUSION

The aim of foreground segmentation is to detach the desired foreground object from input videos. Over the years, there have been major amount of efforts on this topic. Nevertheless, there still lacks a simple yet effective algorithm that can process live videos of objects with fuzzy boundaries (e.g., hair) captured by freely moving cameras. This algorithm is easy to implement, simple to use, and capable of handling a variety of difficult scenarios, such as dynamic background, camera motion, topology changes, and fuzzy objects. the integrated boundary matting step can effectively pull the matte for fuzzy objects, allowing seamless composites over new backgrounds. our algorithm possesses comparable or superior performance comparing to the state-of the- art approaches designed for specifically for background subtraction, foreground subtraction and video matting. By introducing novel acceleration techniques and by exploiting the parallel structure of the algorithm, near real-time processing is achieved for VGA-sized videos. Also plan to embed the proposed algorithm into an real-time interactive video matting application, where users can see the matting results as soon as they draw the strokes.

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Kajal Sangale received B.E.(Comp) degree from Savitribai Phule University Pune,M.E. Computer Engineering Student.

Prof. N.B.Kadu received M.E. degree and Assistant Professor at PREC,Loni.

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