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Foreground Segmentation of Live Videos Using Boundary Matting Technology

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Abstract**—** This paper proposes an interactive method to extract foreground objects from live videos using Boundary Matting Technology. An initial segmentation consists of the primary associated frame of a first and last video sequence. Main objective is to segment the images of live videos in a continuous manner. Video frames are 1st divided into pixels in such a way that there is a need to use Competing Support Vector Machine (CSVM) algorithm for the classification of foreground and background methods. Accordingly, the extraction of foreground and background image sequences is done without human intervention. Finally, the initial frames which are segmented can be improved to get an accurate object boundary. The object boundaries are then used for matting these videos. Here an effectual algorithm for segmentation and then matting them is done for live videos where difficult scenarios like fuzzy object boundaries have been established. In the paper we generate Support Vector Machine (CSVMs) and also algorithms where local color distribution for both foreground and background video frames are used.

Keywords**-** Foreground segmentation, Boundary Matting, Support Vector Machine (SVMs), live videos, video frames, foreground image, background image.

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I. Introduction

Image segmentation explains how an image can be divided into multiple parts. This is used to identify things or complicated data in digital images. Segmentation subdivides a picture into its constituent regions or objects. Segmentation is a method of grouping along pixels that have similar attributes and separate out the dissimilar ones. Image Segmentation is divides an image into non-intersecting regions such that every region is consistent and also the union of adjacent regions is consistent.

Foreground segmentation, is the way to extract objects from input videos. However, a number of image sequences are restricted to be captured by stationary cameras, while others need large training datasets or sufficient user interactions. Most existing algorithms used is difficult when they are used for other surveys. As a result, there still lacks an algorithmic rule which is capable of processing difficult live video scenes with minimum user interactions. It's an elementary drawback in compute vision and sometimes is a pre-processing step for different video analysis tasks like police work, teleconferencing, action recognition and retrieval. Over the years a big quantity of techniques are planned in each laptop vision and graphics communities. However, a number of them square measure restricted to sequences captured by stationary cameras, whereas others need massive coaching datasets or cumbersome user interactions.

This paper addresses the matter of accurately extracting a foreground layer from video in real time. A primary application is live background substitution in teleconference. This demands layer separation to close lighting tricks quality, together with transparency determination as in video-matting [2, 3], however with procedure potency comfortable to achieve live streaming speed. Intended by the on top of finding, we express a unique integrated foreground segmentation and boundary matting approach.

II. LITERATURE SURVEY

In Segmentation of Live Videos Using Boundary Matting Technology comparison of different papers are been done for comparative study. In Real time Background Subtraction from Dynamic Scenes [4] a basic problem in is to identify moving foreground objects from background scenes that suggested a technique to work with the well parallel graphics processors (GPUs). It can handle complex background motion, such as flowing water and waving plants, but large camera motion cannot be handled. The frame-by-frame processing characteristics of the online approaches, on the other hand, help them further to work with live videos. Some of these approaches assume that foreground and background are properly labeled in each frame by using an existing algorithm [5], [6].

Foreground segmentation of live videos using locally competing 1SVMs [7], is a foreground segmentation algorithm suggested in this paper that is effectively deal with live videos. The above method is easy to use, implement, capable of handling dynamic background and fuzzy object boundaries. Finally, focus should be done on foreground segmentation [7], where the algorithm explains matting procedure, which allows both foreground segmentation and boundary matting problems to be solved in an integrated manner. In order to utilize the information extracted from matting calculation, the training process has been repeatedly revised and more accurate information on processing time can be calculated later.

Minglun Gong, Yiming Qian, and Li Cheng [1] propose the key plan to coach and maintain support vector machines at every basic location that form native color distributions for each foreground and background. The usage of native classifiers, as we've, provides higher discriminative power and also handles different ambiguities. By exploiting this expected machine learning technique, and by utilization each foreground segmentation and boundary matting issues in an integrated manner, our algorithmic rule is competent for live videos with advanced backgrounds from freely moving cameras. The above process can also be achieved with minimum user interactions. By introducing novel techniques and by utilizing the parallel structure of the algorithmic rule, real-time operation speed (14 frames/s without matting and 8 frames/s with matting on a midrange computer GPU) is achieved for VGA-sized videos.

M. Gong and Li Cheng [7] proposes that there is an immense body of existing work for foreground segmentation. Here we've got to focus in the foremost related ones, that area unit is classified into unsupervised [20, 17, 16, 10, 12] and the remaining as supervised [13, 11, 19, 14, 18, 8, 9] approaches. Unsupervised ones try and generate background models automatically and note outliers of the model as foreground. In background subtraction technique, assume that the input video is captured by a stationary camera background colors are modeled at every picture element [20, 17] or statistic method [16, 10]. A number of these techniques will handle repetitive background motion, like waving water and trees, however none of these will affect upon camera motion.
On the contrary, supervised ways allow users to generate training examples for each foreground and background and then use them by classifiers. Variety of essential ways [8, 11, 19] on this line are created with spectacular results, wherever multiple visual cues like color, contrast, motion are utilized in strategically different way. These area units are integrated with the assistance of structured prediction ways like restricted random fields. Though operating for video conferencing applications, these algorithms need a big set of totally annotated pictures and significant quantity of offline training set, that observe several problems once applying to completely different scene setups.

Ting Yu Cha Zhang, Michael Cohen and Yong Rui Ying Wu [21] provides a new method to segment monocular videos captured by motionless or hand-held cameras by videoing different moving non-rigid foreground items. The foreground and background objects shows three-dimensional colour Gaussian combination model (SCGMM), and segmented by means of the graph cut algorithm. By observing the modelling gap between the existing SCGMMs and segmentation task of a new frame, the key role of the a foreground/background SCGMM joint tracking algorithm is to associate this space, which significantly improves the performance in case of composite or rapid motion. Formally, they have done the combination of 2 SCGMMs into a model of the complete image, and use the joint data probability using an inhibited Expectation- Maximization (EM) algorithm. The actual proposed algorithm is established on a variety of sequences.

Liyuan Li, Weimin Huang, Irene Y.H. Gu, Qi Tian [22] states that for detection and segmentation of foreground objects from a video that contains each stationary and moving background objects and undergoes each gradual and unforeseen once-off change. A Bayes regulation for association of background and foreground from selected feature vectors is developed. Underneath this rule, different types of background objects are classified from foreground objects by selecting a correct feature vector. The stationary background object is delineating by the color feature, and also the moving background object is diagrammatic by the color co-occurrence characteristic. Foreground objects are extracted by fusing the classification results from each stationary and moving pixel. Learning methods for the gradual and unforeseen once-off background changes are projected to adapt to numerous changes in background through the video. The convergence of the training method is tried and a formula to pick out a correct learning rate is additionally derived. Experiments have shown promising ends up in extracting foreground objects from several complicated backgrounds as well as wavering tree branches, unsteady screens and water surfaces, moving escalators, gap and shutting doors, change lights and shadows of moving objects.

Yi Wang [25] described those two implementations that are capable of separating a foreground layer from video sequences. The first one is a method known as background subtraction, and the other one is resultant from Bilayer Segmentation of Live Video [13] by Criminisi et al. It is a totally unique methodology for detection and segmentation of foreground objects from a video they may be used as building blocks for 2 of the continued analysis comes within the Vision place of work, i.e., the fruit-fly and so the human action comes. The fundamental methodology of background subtraction is to match frame background with a pre-defined threshold. If the distinction of a component is larger, then classify it as foreground; otherwise, claim that it's background.

III. EXISTING SYSTEM

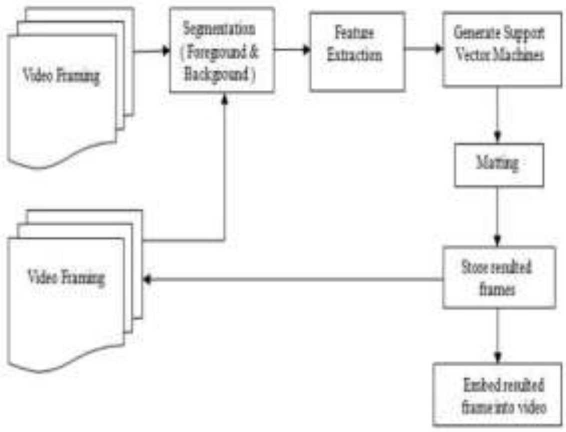

Fig.1 Segmentation & Matting Architecture

1. Video Framing:

In this, multiple frames from a single video are extracted for further processing. Video can have n number of frames depending on camera resolution settings. Frames from video gets extracted one by one frames are transferred for segmentation process.

2. Segmentation:

Frame 0 is passed as input to this step. It involves two types of segmentation that is Foreground Background segmentation.

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a. Foreground segmentation: Foreground segmentation extracts the desired foreground object from input videos. It is a fundamental problem in computer vision applications and acts as a initial step for other video analysis tasks such as teleconferencing, to recognize action and retrieval.

b. Background segmentation: The background segmentation is to extract the desired background from input videos. It is required to have clean visuals of foreground.

3. Feature Extraction:

Essential features are then extracted accordingly from these useful frames such as pixel colour, location, type. These features/attributes are required to differentiate among others. Based on these features we can generate SVMs in next phase.

4. Generate SVMs:

Based on inputs from previous steps, we generate SVMs for both background and foreground. The idea is to train and maintain two competing one-class support vector machine at each pixel location, which model local colour distributions for foreground as well as background. Once the pixels of foreground and background trained, they are used jointly to classify pixel. That is, pixel is labelled as foreground or background only if the two competing classifiers give considerable predictions, otherwise it is relabelled as unknown. The relabelling module starts by computing the scores of observation with both foreground and background pixels. Both scores are then used to compute the incurred losses of labelling pixel as either foreground or background respectively. Pixel is subsequently classified as foreground or background if the loss of pixel of foreground or background is low and the loss of foreground and background is high. This approach makes possible the detection of ambiguities, which is crucial to prevent incorrect labelling information from being propagated.

5. Matting:

Both motion blur and fuzzy foreground objects such as hair strands may cause pixels near foreground boundary having a mixture of foreground and background colours. In previous approach [19], these pixels are initially labelled as unknown and afterwards classified as either foreground or background through graph-cut based global optimization. Here we decompose the observed colours for these pixels into fore/background values and mattes, directly producing a soft segmentation for the foreground.

6. Finalize:

We stored all these processed frames this process continues to happen till video input is there. These processed frames then combine to recollect a whole video.

IV. PROPOSED SYSTEM

The core of our approach is a train-relabel-matting procedure: Competing CSVMs, Fp for foreground and Bp for background, are trained locally for each pixel p using known foreground and background colors within the local window p. Once trained, Fp and Bp are used to jointly label p as foreground, background, or unknown. Pixels along the boundary between foreground and background regions are then detected and form a matting pixel set M, on which matting operation is performed. Below steps is high level implementation of our system.

1) Train SVMs at Each Pixel Location for Color Distribution:

The support vector n machine is trained at each pixel location, which model local color distributions for both foreground and background. Hence the colors are distributed for the foreground and background segmentation with minimum human intervention. This is done accordingly so that we can easily separate out the objects from live videos.

2) Relabel Each Pixel:

Once the pixels of foreground and background trained, they are used jointly to classify pixel p. That is, pixel is labeled as foreground or background only if the two competing classifiers give consistent predictions Otherwise it is labeled as unknown. The relabeling module starts by computing the scores of observation with both foreground and background pixels. Both scores are then used to compute the incurred losses of labeling pixel as either foreground or background respectively. Pixel is subsequently classified as foreground or background if the loss of pixel of foreground or background is low and the loss of foreground and background is high. This dual thresholding strategy facilitates the detection of ambiguities, which is crucial to prevent incorrect labeling information from being propagated.

3) Perform matting along foreground boundary:

Both motion blur and fuzzy foreground objects such as hair strands may cause pixels near. Foreground boundary having a mixture of foreground and background colors. In our previous approach, these pixels are initially labeled as unknown by the aforementioned dual thresholding process and afterwards classified as either foreground or background through graphcut based global optimization. Here we decompose the observed colors for these pixels into fore/background values and the alpha mattes, directly producing a soft segmentation for the foreground.

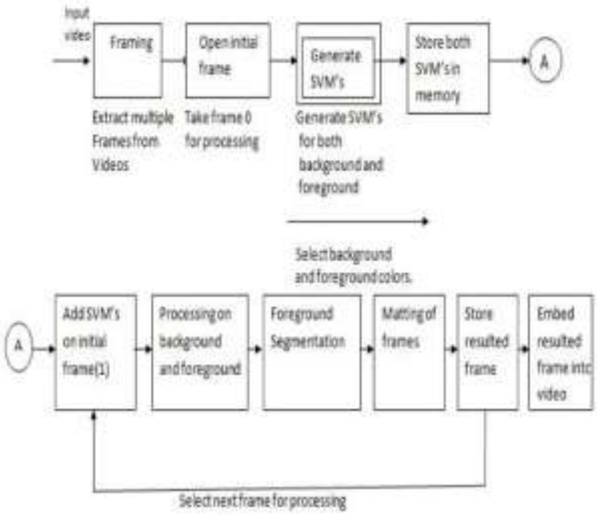

Fig.2. Proposed System

V. MATHEMATICAL MODEL

Let,
S = {I,P,R,O}
Where, S: Integrated foreground segmentation and boundary matting
I: Set of inputs
P: Set of processes
R: Rules 0: Set of outputs

Steps:
1. {i}
Where i1: Initialize camera

2. P= {p1,p2,p3,p4,p5,p6,p7,p8,p9}
p1=Framing
p2=Open initial frame
p3=Generate SVM p4=Store both SVM result into buffer
p5= Add SVMs on initial frame(1)
p6= Processing on background and foreground
p7= Foreground Segmentation
p8= Matting of frames
p9= Store resulted frame

3. R= {r1}
Where, r1 = Rules set

4. O = {o1}
Where, o1= Result

The mathematical equation is evaluated as,

O = p1 U p2 U p3 U p4 U p5 U p6 U p7 U p8 U p9

For i1= 1
and

I E r1

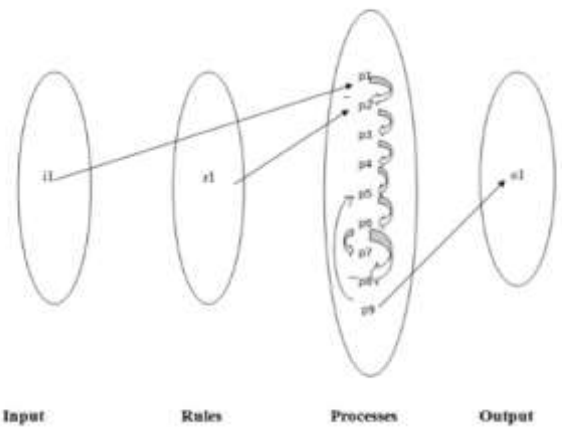

Fig.3. Mathematical Model

VI. RESULT ANALYSIS & PERFORMANCE EVALUATION

Below is the graph of the performance calculated by time in seconds w.r.t. Frames. As the time increases the number of frames which increases get processed per second.

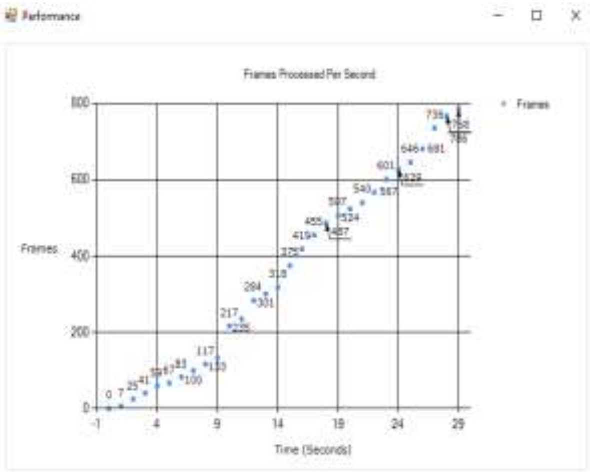

Fig. 4 Time vs Frame ratio

(a) Input frame (b) 0^{th} frame

Result frame included above, consist of the input frame where processing is done on the 0^{th} frame with the strokes given for foreground as well as background and the output is generated with the foreground extracted.

(c) 0^{th} frame with stroke (d) output

VII. CONCLUSION AND FUTURE WORK

By using the CSVM algorithm a comparable or superior performance compared for specifically foreground segmentation and video matting can be acquired. According to proposed algorithm a superior performance for frames with respect to time in seconds has been calculated. By using a good quality VGA size video foreground has been extracted as well as recorded for live videos. Also, extraction of foreground for images has been included in the paper.
For future research, we can increase processing speed by using high end graphics processor, cuda architecture hardware.

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