VIDEO SEGMENTATION USING ROBUST REGRESSION AND SPARSE DECOMPOSITION

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ABSTRACT

Segmentation of video sequences has been familiar nowadays. In terms of any crime suspect it is very helpful to get the scrupulous details concerning that instance. Sometimes there is a need to separate the background and foreground in a particular sequence because of any mismatch or crave to extract the moving object from stable and smooth background for any further use. In that time the video sequences can be converted into individual frames and then it gets processed. Here the algorithms used to separate the background and foreground by fixing the background pixel values to the smooth block. This is based on two techniques as follows robust regression and sparse decomposition. In the first technique robust regression, the inlier pixels are considered as the background and all the remaining pixels (outlier pixels) are considered as foreground. Then using the second technique called sparse decomposition, background and foreground gets exhibited based on the sparse components. These techniques are not only effective in the case to segment the video sequences but also for the numerous applications like text abstraction from the screen content image and also in medical image segmentation.

Keywords- Robust regression, Random Sample Consensus (RANSAC) and sparse decomposition.

I INTRODUCTION

Real foreground detection is frequently the major pace in video processing claims. Its output is usually as an input to a higher level process, such as object categorization, tracking or action recognition, making it as a life-threatening part of the system. Although various techniques have been proposed for moving Objects recognition, it is still a puzzling problem when the Background scenes are vibrant.

In the scale and orientation invariant text segmentation [7], the authors proposed a two stage procedure where in the first step, a coarse segmentation layer for textural regions is mined based on the intensity variation dissemination of text typescripts. There could be a uncommon pictorial regions in the segmentation output of the first phase. In the second stage, a textual connected component (TCC) based enhancement is anticipated to disregard the persisted pictorial expanses. This methodology is primarily based on morphological operations, and since it is premeditated based on a lot of hypothesis on the essential text in the foreground, it cannot be used for segmentation of other foreground (such as line graphics patterns) in screen content images this will be featured in some of the video sequences which consists of textual components.

Background subtraction is the usually used practice for background parting. It consists of two steps, one is conserving the background model, and the other is withdrawing the new frame from the background model and thresholding the difference value to define the foreground. Based on this many different methodologies have been offered.

This methodology expected the probability density of each pixel unswervingly without any spreading assumptions. But these procedures are not robust adequate in dynamic sections. Recently, other styles that did not rely on the monotonous practice of trying to model the background have been paid much courtesy. The method viewed foreground objects as sparse corruption signals and estimated them by the sparse recovering method. However, the sparse assumption on the total error in dynamic scenes may be inaccurate which degrades its detection routine.

In this paper, we recommend a new approach that senses the foreground objects based on robust linear regression model as a first technique. In this model, we regard foreground objects as outliers and consider that the surveillance error is composed of foreground outlier and background noise. In order to constantly guess the coefficients, we should robustly eradicate the outlier and noise. Thus, the foreground detection duty has been renewed into an outlier estimation problem. Based on the statement that foreground outlier is sparse [1] and background noise is isolated in maximum cases, we suggest a novel objective function that concurrently estimates the coefficients and thin foreground outlier. We then transform the purpose to fit our problem through only analyzing the foreground outlier and provide the solution technique. Experimental results determine the usefulness of our technique. The rest of the paper is ordered as follows. We familiarize the linear regression technique, and then we intend our linear reversion model for foreground recognition and give the solution technique. Then foreground recognition method is presented.

Background subtraction [2],[3] is commonly observed as a current process for extracting the foreground. Though, the background in a composite atmosphere may include disrupting motions and hence makes accurate segmentation puzzling. In the past era, great evolution in enlightening the performance of foreground detection has been stated. Background subtraction is a main procedure used to perceive moving parts by deducting them from the reputable background. This means that video frames firstly are likened with a background model, and then fluctuations are acknowledged as the foreground.

Foreground object segmentation from a video brook is an efficient, essential and critical step for many great level computer visualization tasks, such as traffic control, object-based video encoding, and social signal processing and human machine collaborations. The precision of segmentation can expressively disturb the global performance of the solicitation commissioning it. Background subtraction is largely observed as an active method for take out the foreground. However, the background in a compound atmosphere may comprise disrupting gesticulations and henceforth marks accurate dissection puzzling. In this work, we intend two segmentation algorithms, one trusting on the robust regression procedure and the other one using sparse decomposition. These algorithms flabbergasted some of the above problems, and to the best of our acquaintance they have not been scrutinized formerly. In the robust regression based approach, we try to catch a smooth model that can fit the background pixels perfectly. One significant fact is that, when the smooth prototypical is tailored to the image, it should not be exaggerated by the foreground pixels. This is consummate through the RANSAC (Random sample consensus) process, which diminishes the number of pixels which exceeds the certain threshold level. In the further approach, which practices sparse decomposition (SD)[4], the background and foreground part of the video frames are exhibited with a smooth element and a sparse element, respectively. Meanwhile we do not know in advance how many basis tasks to be included for the background portion, the routine picks from a huge set of bases that we think are sufficient to represent the most "complex" background, while decreasing coefficient $_1$ norm to avoid super imposition of the smooth model on the foreground pixels.

The arrangement of this paper is as follows. Section II presents the main impression of the proposed segmentation procedures. The Section II-A briefly designates the first projected arrangement constructed on the RANSAC algorithm. The succeeding anticipated system based on sparse decomposition is described in Section II-B. Section III provides the experimental results for these algorithms. And lastly the paper is resolved in Section IV.

II PROPOSED METHODS

In the existing technique the images contains graphics or the text regions gets segmented as background and foreground using these same techniques. As a proposed method we are going to use the same techniques on the real time video frames for the further applications.

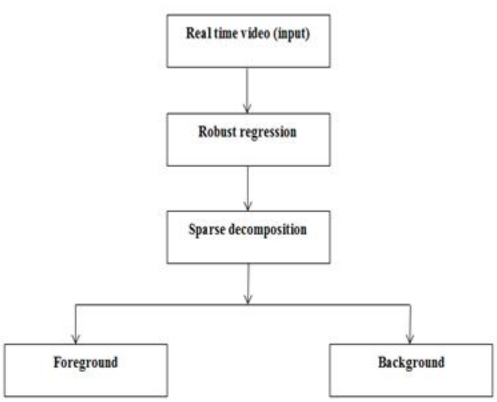

Fig 1.Proposed method

A. Robust regression based segmentation

Robust regression is a practice of regression exploration, which is established to flabbergast some restrictions of outdated processes. The act of maximum of the outmoded regression systems can be ominously exaggerated if the conventions about principal data-generation method are despoiled and they are decidedly complex to the occurrence of outliers. The outlier can be assumed as any data-point or reflection which does not monitor the same arrangement as the rest of interpretations. The robust regression algorithms are premeditated to find the accurate model for a dataset even in the existence of outliers. They principally try to eradicate the outliers from dataset and custom the inliers for model prophecy.

RANSAC is a common robust regression algorithm. It is a repetitive tactic that accomplishes the factor approximation by diminishing the number of outliers (which can be thought as minimizing the $_0$-norm). RANSAC recaps two iterative processes to discover a model for a set of data. In the first step, it precedes a subset of the data and arises the parameters of this model only using that subset. The cardinality of this subset is the minutest adequate number to define the model bounds. As a second step, it checks the model resulting from the first step in contradiction of the total dataset to see how many samples can be modeled consistently.

A model will be measured as an outlier if it has a fitting error higher than an onset that explains the extreme endorsed abnormality. RANSAC reiterations the method a static number of times and at the conclusion, it picks the model with the principal consensus set (the set of inliers) as the ideal model. There is a correlation amid our segmentation structure and model fitting in RANSAC. We can consider the foreground pixels as outliers for the smooth model on behalf of the background. Consequently RANSAC can be used to execute foreground segmentation mission.

The proposed RANSAC algorithm for foreground/ background segmentation of a block of size $N \times N$ is as follows,

1) Select a subset of K randomly chosen pixels. Let us denote this subset by $S = \{(xl , yl), l = 1, 2, . . . , K\}$.
2) Fit the model_$\sum_{k=1}^{k} \alpha k\, Pk\, (x, y)$ to the pixels $(xl , yl) \in S$ and find the αk's. This is done by solving the set of K linear equations $\sum_k \alpha k\, Pk\, (xl , yl) = F(xl , yl)$ $l = 1, ..,, K.$
3) Test all $N2$ pixels $F(x, y)$ in the block against the fitted model. Those pixels that can be projected with an error less than ϵ_{in} will be considered as the inliers.
4) Save the consensus set of the existing iteration if it has a larger size than the largest consensus set identified so far.
5) If the inlier ratio, which is the ratio of inlier pixels to the total number of pixels, is more than 95%, stop the algorithm.
6) Repeat this procedure up to M_{iter} times.

Fig 2.Segmentation using RANSAC algorithm

The ultimate result of RANSAC can be distinguished by refurbishing over all inliers once again and defining all pixels with error less than $\epsilon_{in.}$ To enhance the speediness of the RANSAC system, we stopover once we found a consent set which has an inlier ratio additional than 0.95. The segmentation outcome by RANSAC is generally very noble, but it is computationally challenging. For blocks that can be straightforwardly segmented using various methods.

B. Sparse decomposition

This method has been recycled for uncountable solicitations in recent years, including super-resolution; face recognition, denosing, image restoration morphological component analysis, and sparse coding. In this effort, we explored the application of sparse decomposition for image segmentation. As we mentioned earlier, the smooth background regions can be well represented with a few smooth basis functions, however the high-frequency element of the image belonging to the foreground cannot be represented with this smooth model. But using the fact that foreground pixels dwell in a moderately small percentage of the images we can model the foreground with a sparse component overlaid on background.

Consequently it is autonomously consistent to think of assorted content image as a superposition of two components, one level and the supplementary one sparse, as shown below

$$F(x, y) = \sum_{k=1}^{K} \alpha_k P_k(x, y) + S(x, y)$$

Where $\sum_{i=1}^{K} \alpha_i P_i(x, y)$ and $S(x, y)$ relate to the smooth background segment and foreground pixels harmoniously. Therefore we can use sparse decomposition procedures to discrete these two contraptions. After decomposition, those pixels with enormous value in the S component will be measured as foreground. We will symbolize this algorithm as "SD", for code succinctness.

To have an accompanying abridged symbolization, we will look at the 1-D version of this problem. On behalf of the 1-D description of $S(x, y)$ by s, can be written as

$$f = P\alpha + s.$$

Now to accomplish image segmentation, we want to inflict some erstwhile familiarity about background and foreground to our optimization problem. Since we do not know in advance how many basis occupations to embrace for the background part, we allow the archetypal to pick from a huge set of bases that we deliberate are appropriate to epitomize the most "complex" background, while minimizing coefficient $_0$ norm to avoid over fitting of the smooth archetypal on the foreground pixels [6]. Since if we do not control the parameters, we may end up with a state of affairs that even some of the foreground pixels are symbolized with this prototypical (imagine the case that we use a complete set of bases for background representation). Consequently the number of nonzero workings of α should be small (i.e., α_0 should be small). On the further hand we think the mainstream of the pixels in each block to be in the accurate place to the background component, therefore the quantity of nonzero components of s should be small. And the preceding but not the least one is that foreground pixels stereotypically form associated components in an image, therefore we can supplement a regularization duration which encourages the connectivity of foreground pixels. Here we used entire dissimilarity of the foreground component to castigate lonely points in foreground [12]. Positioning all of these priors altogether we will get the succeeding optimization problem:

$$\text{Minimize}_{\alpha,s} \; \|\alpha\|0+\lambda_1\|s\|0+\lambda_2 TV(S)$$

$$\text{Subject to } f = P\alpha + s.$$

where λ_1 and λ_2 are some constants which prerequisite to be regulated. For the leading two terms since $_0$ is not rounded, we use its approached $_1$ variety to have a convex unruly. Aimed at the total variation we can practice either the isotropic or the anisotropic version of 2-D total variation. To mark our optimization problem modest, we have used the anisotropic version in this process, which is defined as

$$TV(s) = |S_{i+1,j} - S_{i,j}| + |S_{i,j+1} - S_{i,j}|.$$

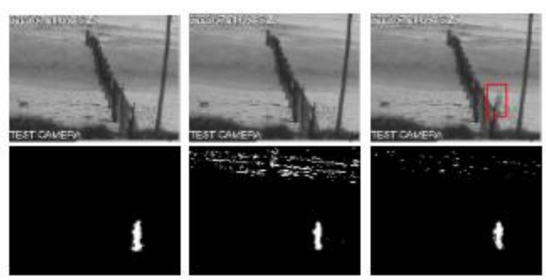

Fig 3. Segmentation using sparse decomposition

As soon as a block does not mollify any of the above environments, RANSAC/SD will be applied to isolate the background and the foreground. If the segmentation is accurate, the ratio of background pixels over the total number of pixels should be impartially huge (greater than at least half). When the proportion is slight, the background of the block may be too composite to be accessible by the espoused smooth function model. This may also materialize as soon as the block is seated at the connection of two smooth backgrounds. To overwhelm these complications, we smear the proposed method recursively by means of a quadtree arrangement. When the inlier proportion of the current block is less than $€_2$, we split it into four minor blocks and smear the proposed algorithm on every smaller block, until the smallest block size is extended.

The global segmentation algorithm is shortened as follows:

1) Preliminary with block size N = 64, if the standard deviation of pixels' intensities is less than $_1$ (i.e., pixels in the block have very analogous color intensity), then affirm the total block as background. If not, go to the next step;

2) Accomplish least square fitting by means of all pixels. If all pixels can be prophesied with an error less than $€_{in}$, assert the total block as background. If not, go to the next step;

3) If the number of unalike colors (in terms of the luminance value) is less than T_1 and the intensity array is above R, affirm the block as text/graphics over a constant background and find the background as the color in that block with the maximum calculation of pixels. If not, go to the next step;

4) Practice RANSAC/SD to detach background and foreground by means of the luminance component merely. Confirm that the equivalent chrominance components of background pixels can also be fitted using K basis functions with an error less than $€_{in}$. If several of them cannot be fitted through this error, eliminate them from inliers set. If the fraction of inliers is more than a threshold $_2$ or N is equal to 8, the inlier pixels are selected as background. If not go to the next step;

5) Molder the contemporary block and run the segmentation process.

To indicate the benefit of quad tree disintegration, we afford an illustration of the segmentation plan without and with quad tree decomposition; we get ample better result associated to the case with no decomposition. When we do not permit a 64 × 64 block for further separated, only a small percentage of pixels can be characterized well by a smooth function, parting many pixels as foreground. It is price declaring that the gray area on the top of the image is measured as foreground in the segmentation outcome deprived of using quadtree decomposition. This is because the first row of 64 × 64 blocks contains two smooth background regions with moderately equal size.

III EXPERIMENTAL RESULTS

To permit demanding evaluation of various algorithms, we have engendered an interpreted dataset containing 328 image blocks of size 64 × 64; removed from sample frames from HEVC [5] check sequences for screen content coding. The ground truth foregrounds for these images are mined physically and then distinguished autonomously by alternative expert.

Previously showing the segmentation outcome of the suggested algorithms on the test imaginings even in video sequences, we illustrate how the segmentation result varies by changing different constraints in RANSAC algorithm. The sparse decomposition algorithm would also have the same behavior. To calculate the effect of the falsification threshold, $_{in}$, for inlier pixels in the final segmentation result.

For unassuming cases where the background has a contracted color range that is quite different from the foreground, both DjVu and the proposed methods will work well. On the other hand, SPEC does not work well when the background is fairly homogeneous within a block and the foreground text/lines have varying colors.

It also accomplishes well in extrication the foreground from the background even when the involvement 3d videos [8]-[11] have common background. Nevertheless, this is proficient at the disbursement of unembellished over-segmentation of both the foreground and the background so that when the foreground comprehends dissimilar parts, it implements poorly in terms of assembling the different amounts of the object which are having different color intensities.

On behalf of the RANSAC algorithm, the maximum number of reiteration is preferred to be 200. For the sparse decomposition algorithm, the weight parameters in the objective function are tuned by challenging on a substantiation set and are set to be λ_1 = 10 and λ_2 = 4.

Fig.4 Separated as background and foreground by our proposed method

Since the RANSAC method is considerably faster than SD and produced very analogous segmentation precision, the RANSAC method is desired for practical presentations. The proportions of blocks administered by diverse steps of the projected segmentation algorithm (for the images in our dataset). Note that the constraints used to categorize the first three types of blocks can be preferred to accomplish the anticipated transaction among the segmentation accuracy and computation time. The scarcer blocks will want to go through the RANSAC or SD algorithm, which will condense the overall computation time.

IV CONCLUSION

This paper includes two techniques which are capable of segmenting the video sequences separately as background and foreground. One of the techniques used is robust regression which decides the outlier pixels as foreground by using the special algorithm called Random Sample Consensus (RANSAC) algorithm which effectively solve this problem in a proper way such that the further implementation will be easier. Our second technique is Sparse Decomposition (SD) which is used to separate the smooth background from the sparse foreground layer. For an effective segmentation of the video sequences these two techniques are used because the techniques are well suited and simple to execute and produce the output for real time video sequences which is fed as a input in order to use those sequences for the further use. These algorithms are tested on several test images and compared with three other well-known algorithms for background/foreground separation and the proposed algorithms show significantly better performance for blocks where the background and foreground pixels have overlapping intensities.

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