TEXTUAL CONTENT REMOVAL SCHEME OVER VIDEO STREAM

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Abstract— This paper introduces a novel framework for Text detection and Removal. We present a two stage framework for automatic video text detection and make the frames and remove embedded video text. Then fill-in their remaining regions by Similar Pixel or regions. Text locations in each frame are found via an unsupervised clustering Algorithm performed on the connected components produced by the stroke width transform. Many different types of image in-painting algorithms already in the literature. Image in-painting is filling in damaged or destroyed regions in an image with similar pixels or regions. Explore the use of the proposed approach to image text detection and perform in-painting and show promising results. Another contribution of this paper is used SWT. SWT needs an accurate edge map. The algorithms are analyzed in both theoretical ways, which have made the suitability of these image in-painting algorithms over different kinds of applications in image processing areas. We use most popular canny edge detector which advantage from the geometric features revealed by the bandlet transform. The detected video text regions are removed, and then the video is restored by an in-painting algorithm scheme. The proposed video in-painting approach uses spatio-temporal geometric flows extracted by bandlets to recover the missing data.

Keywords— In-Painting; Stroke Width Transform; In-painting Connected Components, Support Vector Machine;

I. INTRODUCTION

Embedded text in an exceedingly video sequence provides valuable data. Texts sometimes seem as logos, subtitles, captions or banners within the video sequence. Such data embedded texts are often mostly found within the news and different standard TV and in [1] most of time in Cricket broadcastings. That text could obstruct necessary parts of a video. There ought to be the way to erase the unwanted text from the video. Roughly speaking associate degree automatic video text removal theme involves 2 main stages: i) associate degree automatic video text detection and ii) Good video completion/restoration when the text removal. Existing video text completion techniques seldom cowl each of those aspects in an exceedingly on single platform. The planned video in-painting approach applies spatio-temporal geometric flows extracted by bandlet transform to reconstruct the missing information. The bandlets network used to reconstruct the missing image information. Regularization algorithmic program, that takes advantage of bandlet bases in exploiting the eolotropic regularities, is introduced to hold out the in-painting task. The planned ways in, for example, contend with solely the restoration stage from the video in-painting algorithm perspective .The planned theme in [2] utilizes a support vector machine (SVM)-based text detection technique to localize texts within the video. The video text detection is performed by a multilayer perceptrons theme and genetic algorithms. We have a tendency to propose a video text completion approach that consists of associate degree correct video text
localization technique and a best restoration stage.

II. II . LITERATURE SURVEY

A. SINGLE FRAME TEXT DETECTION CONNECTED WORKS

Text in video, particularly the superimposed text, is that the most reliable data to be thought-about in video compart mentalisation analysis work. Several analysis works have addressed the task of extracting text regions from videos [3]. Our planned video text detection approach relies on pursuit the detected texts in every frame . In such tracking-based text detection ways, the accuracy of detected text locations in every frame considerably affects the performance of the video text detector. To avoid this limitation, we have a tendency to develop during this paper associate degree correct single frame (image) text detector because the base of our video text detection approach. Existing image text detectors is also generally classified into 2 main teams : texture (also known as region) based mostly and CC based ways. Texture-based ways scan the image at variety of scales and think about the embedded text as a selected texture pattern that's distinguishable from different elements of the image and its background. Basically, options of assorted regions of the image area unit preserved. Then, the presence of text is known by either a supervised or associate degree unsupervised classifier. Finally, the neighboring text region candidates area unit incorporated supported some geometric options to come up with text blocks. As samples of such ways, the technique introduced in [4] applies Sobel Edge detector altogether Y, U, and V channels, and then invariant options like edge strength, edge density, and edge's horizontal distribution were thought-about. The strategy given in [3] produces a statistical-based feature vector mistreatment the Sobel edge map and applies k-means formula to classify image regions into text and non-text elements. Assuming that the horizontal gradient worth of text regions is above that of alternative components of the image, the tactic in thresholds the variance of gradient values to spot text-regions. A support vector machine (SVM) classifier is employed in to come up with text maps from the gray-level options of all native areas. The method extracts the features through each layer of image pyramids. The technique in additionally takes advantage of image pyramids to notice native thresholds to observe text areas. The frequency domain is shown to be practical in text-region classifications. For example, classification is applied in wavelet domain in and in order to detect aligned texts in an image. In the same vein, the proposed method in applies frequency domain coefficients obtained by the discrete cosine transform (DCT) to extract features. By Thresholding filter responses, text-free regions are discarded and the remaining regions are grouped as segmented text regions CC-based methods stem from the observation that text regions share similar properties such as pixel color and different geometric features. At the same time, text regions have close spatial relationship. thus based mostly on such properties they square measure classified along and kind CCs. the tactic introduced in finds candidate text regions by utilizing cagy edge detector, then a region pruning step is carried out by means of an adjacency graph and some heuristic rules based on local components features. Candidate CCs are extracted by the tactic

B. VIDEO IN-PAINTING RELATED WORKS

i) TEXTURE SYNTHESIS AND BLOCK APPLYING ALGORITHM

Chan and Shen developed a new in-painting called Curvature Driven Delusion (CDD), and in a later paper remarkably showed how the Euler elastic encapsulate both CCD in-painting and transportation in-painting. Many additional types of in-paintings methodologies were proposed subsequently, including textural in-painting which relies on texture matching and replication, or global image statistics, or templates matching functional. The matching process of the texture inside the whole region can be speeded up through Principal Component Analysis (PCA) and Vector Quantization (VQ) based techniques[2]. The variants of this approach are discussed below:

ii) TEXTURE SYNTHESIS

E fros and Leung [6] have given an effective and simple algorithm for highly connected problem of texture synthesis. It is based on Markov Random Field and texture synthesis is done by pixel by pixel. The pixel is compared with the neighboring pixel randomly. This algorithm is very slow because the filling-in is being done pixel by pixel. Criminisi et.al [1], [12] introduced another algorithm for texture synthesis and priority is given for filling the edges [2], [5].

iii) PIXEL SYNTHESIS

S. E. Chen and L. Williams [39] used "Pixel Synthesis by non parametric Sampling". It is based on pixel data. Jing Xu and Jian Wu, et al. [11] implemented 8-neighborhood Fast Sweeping Method to remove the text and hidden errors on video.

iv) MULTI- SCALE PYRAMIDS DECOMPOSITIONS

Mohammad Faizal, et introduced this algorithm for improving the blurring image done by single scale algorithm is affected by the effect of blurring. S.Roth and MJ. Black presented a technique based on prior models. The diffusion technique is used for denoising approaches and was changed and applied to repair the damaged images. Elad. Developed an approach by separating the image into cartoon texture layers and sparsely represented two layers by two incoherent over complete transforms.

v) BLOCK REPLICATING METHOD

E Fros and Freeman [6] set pixel by pixel texture synthesis method. It is used to find a minimum error boundary cut between the existing texture pixel and new block to be replaced. Chen and Williams extended the idea to 3D by calculating a linear warp held between corresponding 3D points of two scenes, and interpolated for views in between. Their research tries to deal with both holes and visibility ordering.

III. III. EXPERIMENTAL RESULTS

1. ALGORITHM VIDEO TEXT DETECTION

The frame text detector is an image text localization technique based on CCs that benefits from SWT and a k-means clustering which in turn requires accurate edge locations. The scheme contains three main stages as follows: 1) Edge detection, 2) SWT and generating CCs, and 3) k-means clustering of the CCs In this section, We first define the notion of a Stroke Width Transform grouping pixels into letter can describe the mechanism for gr constructs of words and line

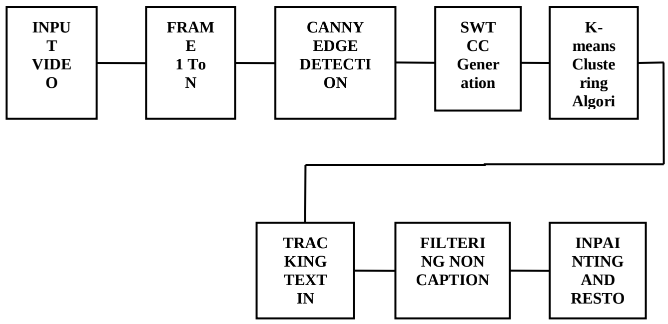

Fig 1. Main stages of the proposed video text detection and removal

2 THE STROKE WIDTH TRANSFORM

The Stroke Width Transform image operator which computes most likely stroke containing the SWT is an image of size equal image where each element associated with the pixel. We contiguous part of an image that constant width, as depicted in assume to know the actual width recover it background pixels. p is a pixel Searching in the direction of the gr the corresponding pixel on the o th pixel along the ray is assigned by value and the found width of the initial value of each element In order to recover strokes, image using Canny edge gradient direction. The text detection algorithm. stroke and then explain the), and how it is used for candidates[1] Finally, we grouping letters into biggest which enables further of the algorithm is shown on (SWT for short) is a local per pixel the width of the pixel. The output of the a SWT to the size of the input contains the width of the stroke we define a stroke to be a at forms a band of a nearly.

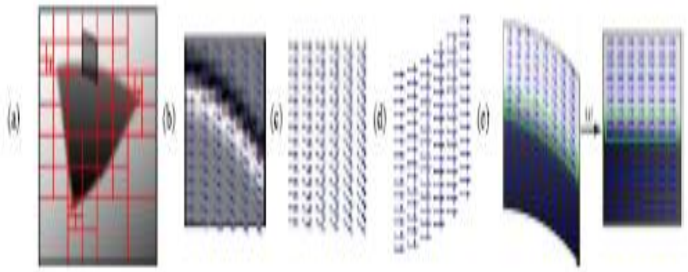

Fig .2. Bandlet Transform (a) Dyadic segmentation based on local directionality of the image (b) A sample bandlet segmentation square that contains a strong regularity function shown by the red dash.(c) Geometric flow and sampling position (d) Sampling position adapted to the warped geometric flow (e) Illustration of a warping example

1) EDGEDETECTION VICTIMIZATION BANDLETS

As mentioned earlier, the bandelet rework effectively represents the pure mathematics of an image. we have a tendency to make the most of this illustration and propose a edge detection algorithmic rule that may be used effectively in text detection techniques. On the opposite hand, it's been that finding native maxima of ripple rework coefficients is analogous to the multi-scale cagy edge detector operator. Since the image coefficients area unit all crooked on native dominant flows within the bandlet transform, the ultimate square and rabbet coefficients generated for every segmentation sq[2]. S have the shape of approximation, and high-pass filtering values seem within the ripple rework of a 1D signal. we have a tendency to get pleasure from the bandlet-based ensuing 1D high-pass frequency coefficients that area unit tailored to the radial asymmetry of the sting that exists in every segmentation sq. S so as to search out a binary map of the sting positions within the image. The square and rabbet rework is performed on the initial image, and for every segmentation sq. S the square and rabbet coefficients area unit generated. For each S, the ensuing coefficients area unit classified in low-pass (approximation) and high-pass filtering results kind of like the 1Dripple rework. Since the approximation half consists of coarse data of the initial signal, we have a tendency to discard it and solely method the high-pass coefficients. The first-order derivatives of the fine-detail square and rabbet coefficients area unit computed. By applying a discourse filer, we discover native maxima of the ensuing gradient signal since several meaningful edges are often found within the native maxima of the gradient not solely within the world maxima. Then, so as to boost the standard of the sting image a 2 level thresholding is utilized. for every point xi within the gradient signal, we have a tendency to check if xi may be a native most and its price is bigger than a threshold TG. If so, xi is unbroken as an edge purpose constant otherwise it'll be discarded. Hence, a window with size 2L +1 centered at xi is ready. Then, the binary indicator of edge points within the gradient signal is generated as follows:

Mi = 1 if gi > TG ∧ gi > g j , ∀ j ∈ [i − L, i − 1] ∧ gi > g j , ∀ j ∈ [i + one, i + L]
0 otherwise

gi represents the gradient price for xi and g j indicates gradient price of neighboring pixels of xi that exist is that the window. M may be a map of native maxima of the gradient signal. The corresponding locations of zero's of M within the bandlet fine (high-pass) coefficients area unit set to 0, for all the square and rabbet squares S. Then, the inverse square and rabbet rework is performed so as to own the ultimate edge locations of the initial image. Obviously, the standard of the sting map depends on the worth of the edge TG. so as to confirm a top quality, a two-level thresholding is utilized. First, the sting detection is performed employing a low price for TG and also the edge image El is made. The algorithmic rule is performed once more utilizing the next value for TG to come up with the sting image Eh. Apparently, El includes additional edge pixels than Eh , that solely includes vital edges. Also, all the sting pixels of Eh exist in El . a mix of Eh and El ends up in additional reasonable results. for every edge element Ceh that exists in Eh we have a tendency to examine El and check if there's a foothold element Cel in El that overlaps Ceh. If so, Cel is taken from El and saved within the final image edge map. Considering the square and rabbet rework structure strictly adapted to sturdy native picture element flows through a geometry-based II segmentation, this edge detection theme reveals reliable edge pixels. Moreover, since the regions consisting of thin singularities like noisy and foliage pixels, and also the regions with numerous picture element intensities area unit eliminated within the bandlet geometric segmentation, the ensuing edges area unit quite acceptable to localize text-edges embedded within the image. shows the results of 4 completely different edge detection strategies as well as Sobel, Prewitt, Canny, ripple and also the planned bandlet-based technique. The input image includes a text and noisy pixels. Our planned approach shows significantly higher results compared to the opposite strategies.

(a)

(a)

(b)

(c)


(d)

Fig.3.Output results of video text detection. (a) Original frame. (b) Video text detection result. The video text objects are differentiated from the other text objects by another color. (c) Detected video text is removed and masked(d)Inpainted frames

Several video sequences are used to evaluate the proposed video text removal method. The set of videos contains sequences captured from TV, movies and video games. The resolution of each video sequence is 320 × 240. In the implementation of the text detector and the video inpainting scheme, the following settings are used:

- Gray-scale values of the RGB frames are found by (R+G+B)/3 whenever needed.
- In order to reduce the size of the inpainting volume instead of performing the inpainting task on the entire video volume for a text which has a bounding volume size of w × _× h, the bounding box is confined to w+50 × + 10 × h + 50 (w and h, respectively, represent width and height of the volume in pixels and _ represents the number of frames in the volume).

IV. IV. CONCLUSION

We presented an video text removal scheme which involves an automatic video text detection and in-painting stage. The video text detection technique strictly relies on an accurate text detector for single frames. We proposed connected component-based image text detection developed as an unsupervised clustering algorithm scheme. A feature vector based on properties extracted from stroke width transform connected components, distinct characteristics of text components that exist in the extracted image and their general geometry and introduced a canny edge detection approach which is quite adapted to edge locations of texts embedded in various types of images. The detected text regions in all the frames are tracked in the entire video sequence in order to locate the video text and distinguish it from the other given parts of the video. The text is removed and the video is restored using the proposed in--painting technique which performs 3D regularization in the bandlet transform domain. Like the text detector, the in-painting scheme takes advantage of geometric flows and texture structures revealed by the bandlet bases. The video in-painting is performed by enforcing the sparseness of the bandlet image representation through a minimization over the bandlet coefficients. The minimization is done in the video extracted frames by an iterative soft-Thresholding scheme. Unlike many existing video completion methods, our video in-painting approach does not require complicated background-fore ground , motion layer segmentation, or optical flow. The survey results indicate a high performance of our video in-painting approach and crucial is formed. Since the accuracy of the image text detector depends on precise edge locations to generate the connected components, we employed the properties of bandlet transform.in representing local image geometry and introduced a new edge detection approach which is quite adapted to edge locations of texts embedded in various types of images. The video text detection technique strictly relies on an accurate text detector for single frames.

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