ISSN: 2321-8169
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Content Aware Video Retargeting using Seam Carving

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Abstract: Video retargeting method achieves high-quality resizing to arbitrary aspect ratios for complex videos containing diverse camera and dynamic motions. Video retargeting from a full-resolution video to a lower resolution display will inevitably cause information loss. While retargeting the video the important contents must also be preserved. Seam carving works well for images without straight lines or regular patterns like landscape images but may cause distortions if used for images with straight lines. Our approach combines Seam Carving method along with Hough transform to preserve the originality of the video.

***Keywords**: Hough Transform, Energy Mapping, Seam Carving, Video Retargeting.*

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I. Introduction

All the video devices such as mobile phones, mobile video game devices, TVs, and Internet video players, should support the video playback with varying formats, resolutions, sizes, and aspect ratios. Solutions to this requirement include scaling, cropping, letterboxing and warping. All those solutions are basic and not very effective, uniform scaling will distort the salient object, cropping may cut the important part, letterboxing will waste the space on the screen and partially warping will not properly handle the situation when the salient objects move to the sides of the screen. In order to convert the video to a new target resolution or aspect ratio while preserving the salient content, video retargeting has recently played a more and more significant role. Video Retargeting
Is a method that makes the video to better suit the target display, minimizing the important information lost. In video retargeting removal or carving of non salient regions may cause some degree of distortion or discontinuousness of video content, which would lead to artifacts both temporally and spatially. The artifacts should be reduced by considering the salient content in the target video and enforcing spatial and temporal coherence at the same time. However, spatial and temporal coherence may contradict to each other in some situations. In this paper an algorithm for video retargeting is based on the Seam carving approach and Hough transform.

II. Related Works

Retargeting problem is achieved by employing motion information and by distributing distortion in both spatial and temporal dimensions. The novel cropping and warping operators are combined, where the cropping removes temporally-recurring contents and the warping utilizes available homogeneous regions to mask deformations while preserving motion. Variational optimization allows finding the best balance between the two operations, enabling retargeting of challenging videos with complex motions, numerous prominent objects and arbitrary depth variability. The best detection methods are sometimes confused by noise and lighting, therefore the motion of irrelevant parts of the content is preserved. The automatic cropping method may be ineffective for extreme camera motion, since prominent objects are cropped forever. As the computational cost is high, this method is limited in length and resolution of the videos it process. This method suffers from temporal incoherence.

A CRF model was learned and evaluated on a large image database containing 20,000+ well-labelled images by multiple users. A set of novel features, including multiscale contrast, centre surround histogram, and color spatial distribution, to describe a salient object locally, regionally, and globally. A conditional random field is learned to effectively combine these features for salient object detection.

The spatiotemporal approach combines the spatial saliency by computing distances between ordinal signatures of edge and color orientations obtained from the centre and the surrounding regions and the temporal saliency by simply computing the sum of absolute difference between temporal gradients of the centre and the surrounding regions. The proposed method is computationally efficient, reliable, and simple to implement and thus it can be easily extended to various applications such as image retargeting and moving object extraction.

Video retargeting is a structure-level video adaptation technique that resizes a video from one resolution to another lower resolution without severely deforming major content. An ideal video retargeting method has to preserve major visual content and avoid critical visual information loss while resizing the visual content. Maintaining the spatio-temporal coherence of a retargeted video is very critical on visual quality. Although several content-aware image

International Journal on Recent and Innovation Trends in Computing and Communication ISSN: 2321-8169
Volume: 2 Issue: 2 376 – 379

retargeting methods have proven to achieve good visual quality in resizing a single image, directly extending these image-based retargeting methods to video applications usually causes severe temporal incoherence artifacts.

III. Seam-Carving Based Video Retargeting

Seam Carving supports content-aware video resizing for both reduction and expansion. A seam is an optimal 8-connected path of pixels on a single image from top to bottom, or left to right, where optimality is defined by energy function. By repeatedly carving out or inserting seams in one direction we can change the aspect ratio of an image. By applying these operators in both directions we can retarget the video to a new size. The selection and order of seams protect the content of the frame, as defined by the energy function. Seam carving can also be used for image content enhancement and object removal.

A. Line Detection

The Canny operator is used to compute the gradient of the image

$$G_X = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

$$G_Y = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A$$

Where A Fig. 1 denotes the source frame, and * here denotes the 2-D convolution operation. The *x*-coordinate is defined as increasing in the "down"-direction, and the *y*-coordinate is defined as increasing in the "right"-direction in this paper. Gx and Gy denote the gradient components on *x*- and *y*-directions, respectively. At each point in the image, Fig. 2 the resulting gradient value can be combined to give the gradient magnitude, using

$$G = \sqrt{G_X^2 + G_Y^2}$$

Where G denotes the gradient magnitude.

The Hough transform method is introduced for detection of lines Fig. 3 in frame in order to avoid deformation of objects. The Hough Transform is a global method for finding straight lines hidden in larger amounts of other data. For detecting lines in images, the image is first binarised using some form of thresholding and then the positive instances catalogued in an examples dataset.

Each point (d, T) in Hough space corresponds to a line at angle T and distance d from the origin in the original data space. The value of a function in Hough space gives the point density along a line in the data space. The Hough Transform utilises this by the following method.

For each point in the original space consider all the lines which go through that point at a particular discrete set of angles, chosen a priori. For each angle T, calculate the distance to the line through the point at that angle and discretise that distance using an a priori chosen discretisation, giving value d.

The discretisation of the Hough space is made and this will result in a set of boxes in Hough space. These boxes are called the Hough accumulators. For each line we consider above, we increment a count (initialised at zero) in the Hough accumulator at point (d, T). After considering all the lines through all the points, a Hough accumulator with a high value will probably correspond to a line of points.

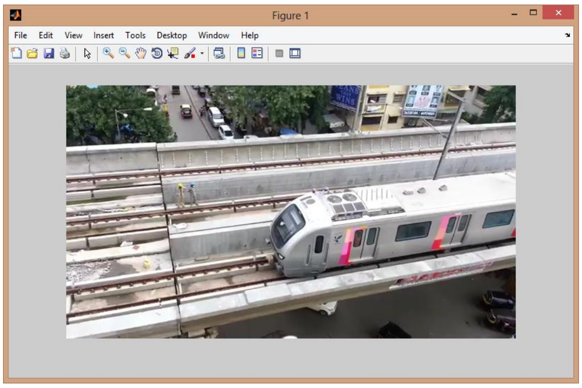

Fig. 1: Original Frame

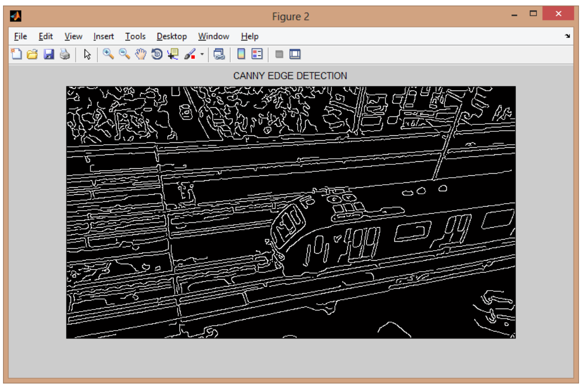

Fig. 2: Edge Detection

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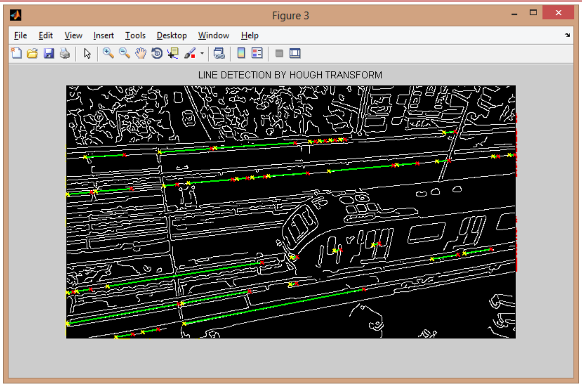


Fig. 3: Line Detection

In fact for uniformly distributed points, each Hough box should have a Poisson distributed count with mean given by the length of the line times discretisation width times uniform point density. Some Hough boxes will correspond to longer lines than other, resulting in the pattern seen in the star/galaxy data transform below. A count which is in the tail of the relevant Poisson distribution is unlikely to be the result of the underlying uniform data, and hence more likely to be the result of some line of points. Giving some prior model for the number of points in a line will allow a proper Bayesian assessment of whether there is a line at the relevant angle and distance from the origin.

B. Energy Mapping

Energy Mapping consists of gradient, which is based on canny operator and saliency of every pixel. The saliency is computed by Itti's algorithm. For the first frame in a scene, a seam could be found by any image seam-carving method. The positions of the seam for i^{th} frame could be denoted by a set *Si* in

$$Si = \{(1, p1), (2, p2) \ldots (H, pH)\}$$

Where H denotes the height of the image, *pk* denotes the *y* coordinate of the point on the *k*th row of the seam. As a result, (*k*, *pk*) denotes the coordinate on the *k*th point of the seam. Then, the seam is vertically and equally divided into several parts, and the points having the maximum energy value in their parts are selected as key points (KP)

$$Ri = \{x \mid (i-1) \times H/ N_{KP} < x \leq i \times H/N_{KP},\ x \in N\}$$

$$i \in 1, 2, \ldots N_{KP}$$

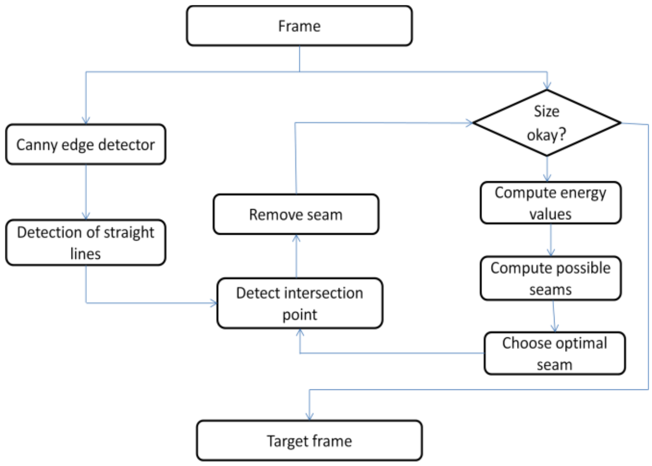
Where N_{KP} denotes the number of key points, which is set to 10. N denotes the integer domain. R*i* defines the intervals on the *x*-dimension, so R1 to RN_{KP} vertically and equally divide the seam into N_{KP} parts. Then, by selecting the maximum energy point on the seam in each interval, the coordinates of the key points are determined, using

$$KPi = \{ (xj, yj) | 1 \leq j \leq N_{KP}, (xj, yj) \in Si, xj \in Rj, \forall (xk, yk) \in Si, xk \in Rj : EM(xj, yj) \geq EM(xk, yk)\}$$

Where *EM*(*x, y*) denotes the value of EM of the source image at the coordinate (*x, y*). As a result, the points on the seam with the maximum energy value in each interval R*i* are selected as key points. We define the *k*th key point in *i*th frame as *kpi*, *k* = (*kpxi, k, kpxi, k*), from top to bottom.

C. Seam Carving

The Seam Carving method belongs to the category of pixel removing. The basic idea is to remove paths of low energy pixels (seams) from top to bottom or from left to right which are not so important for the understanding of the image content. The removal of each seam causes a reduction of the frame size by one where vertical seams reduce the width and horizontal



Architecture of video retargeting

Seams reduce the height. Valid seams which are included in all frames of a shot are used for size adaptation.

Based on the energy mapping and line detection, low energy seams are removed from the frame to adapt the target display. The intersection point of seam and the line is determined to prevent the removal of adjacent pixels which are located on a line. This leads to avoid deformation of objects and line.

IV. Conclusion

We have studied the problem of video retargeting. We observed that camera and object motion cause feature correspondences to deviate from temporally adjacent pixels, easily causing flickering or waving artifacts. The proposed methodology consists of seam carving along with line detection. Seams are computed as the optimal paths on a single frame and are either removed or inserted from an image. Our proposed work uses Hough transform algorithm to detect lines and Seam Carving for resizing the videos. Experimental result shows that the video retargeting is achieved better in our proposed method than the existing system.

ISSN: 2321-8169
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BIOGRAPHY

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