RESEARCH ARTICLE OPEN ACCESS

A Real Time Video Colorization Method with Gabor Feature Space

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ABSTRACT
Video colorization has become one of the most challenging tasks for multimedia Technologists. The present method of video colorization requires high processing costs and will induce temporal artifacts in a video space. A new approach for video colorization in a spatio temporal manner with optimization in rotation with gabor feature space. The work is implemented on graphics hardware Platform which is parallel to achieve real time performance of color optimization. This can be achieved with real time color propagation by clustering video frames and then extending gabor filtering to optical flow computation. Temporal coherence is further refined through user scribbles in video frames. This approach was demonstrated with appropriate video examples and observed most qualified colorized videos.
Keywords- Gabor features space, parallel optimization, user strokes, video colorization**,** Temporal Coherence.

I. INTRODUCTION

Now-a-days most of the multimedia users has been devoting a great effort for video colorization because of highly processing costs and there is no suitable method for efficient video colorization. There are plenty number of researchers who have proposed a new methods for video colorization. The existing video colorization methods propagate colors from key frames to subsequent frames easily by using an optical flow. But this will introduce artifacts in certain frames and will be reflected in video colorization results. These errors cannot be eliminated because the optimization used by most of these methods based on one pass linear system solver. This paper introduces a more efficient color optimization method with parallel color propagation. Color propagation assigns similar pixels with matching colors. The Smooth function of higher dimensional feature space is approximated with spatio temporal sub graphs in the feature space. Compared to previous methods it requires a very large linear system, and this method iteratively propagates the colors among the pixels in graphs to achieve greater refinement and parallel acceleration. Temporal coherence should be maintained by using gabor flow between frames and optimization of color is possible through gabor filtering. A New feature space is used in this method to provide rotation feature with gabor filtering. In this feature space similarity with color and pixel is performed. Consecutively gabor flow is used to perform temporal connectivity between the pixel and sub graphs. Two noticeable contributions are made in this paper. i) A method for maintaining temporal color coherence using optimized gabor flow ii)a parallelized method for fully solving the optimization of video colorization.

II. EXISTING SYSTEM

In present colorization methods, colorization is done by using user color scribbles onto gray scale images. The colors of all remaining pixels are optimized by using these scribbles as constraints. The other colorization methods include learning techniques and gray scale intensities. The color scribbles drawn by the user are utilized in other techniques. The colors of these scribbles are then distributed algorithmically over an entire video space. Recently, a colorization approach based on gabor feature space is proposed suitable for single image domain. Color distribution is done across the entire image but this method does not scale well to video data. To solve this problem, color propagation in temporal video space is not merely in 2D space of unrelated image.

III. PROPOSED SYSTEM

In the proposed system, Gabor filters are used to extract the features, and the whole features are combined with Gabor feature space. The proposed system involves the following steps:

i) Establishing pixel similarity in video gray scale through rotation wears Gabor filtering
ii) Cluster the feature space adaptively to form sub graphs.
iii) Gabor flow is used to establish temporal correspondences between sub graphs.
iv) Color optimization can be approximated easily through pixel per linear iteration in the feature space.

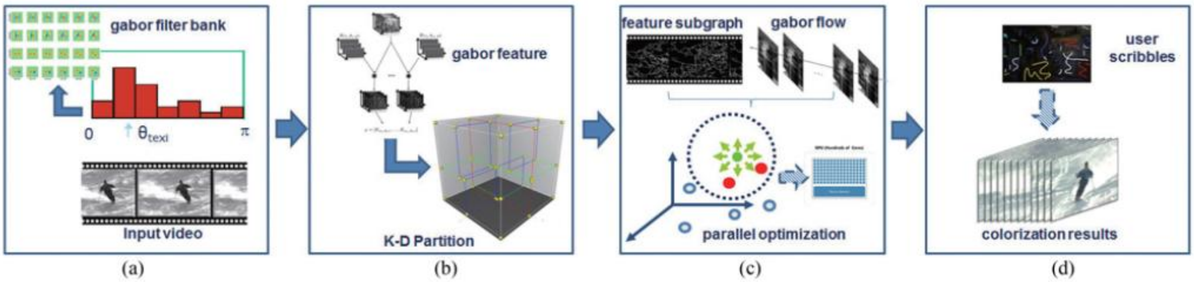

Fig.1:Pipeline for colorization approach.(a)Given a set of source of video frames,total set up rotation aware gabor filtering for texture discrimination and resolution detection.(b)Feature space generated by gabor filtering is then adaptively partitioned into K-D tree subgraphs (c) Gabor flow is constructed to represent temporal correspondance among different sub graphs.(d) The colors are propagated directly to the pixels of these subgraphs in parallel.

Fig.2: Colorization results of the river bank video using parallel optimization in the Gabor feature space

1. Creating Gabor Feature Space

By using Gabor filters it is easy to express pixel similarity. The output bank of 24 gabor filters (4 scales,6 orientations) is used to produce a feature space. These filters represent scale and orientation of texture locally. This approach of pixel similarity works well, but in some cases such as the two pixels lying in the same texture or object with different orientations is different even they are in the same neighborhood. This often occurs in natural images. It can define a texture as function $R(x,y) = \beta_{tex}$ representing texture direction in the position (x,y). By adjusting each filter's orientation β_n according to the texture direction, it can create a set of rotation aware gabor filters for pixel i

$$B_n = (n\pi+\beta_{texi}) / R \qquad \text{.....(1)}$$

By substituting the above equation into the gabor filter formulation, the rotation ware gabor filters are constructed to generate feature vectors based on fourier transformation.

2. Clustering In Feature Space

The pixels with high similarity are located very close to each other which is usually called gabor feature space. To propagate colors to the neighborhood in feature space, the connectivity of pixels in the neighborhood is determined. The computation of neighborhood in a feature space is expensive; therefore the clustering methods are used for neighbor computation in the gabor feature space.

The feature space is further subdivided by K-D tree at higher dimensions to build connectivity and neighborhood for the pixels. The tree is built in a top down way which hierarchally reflects the pixel similarity. The generated feature space is then transformed into a set of connected sub graphs.

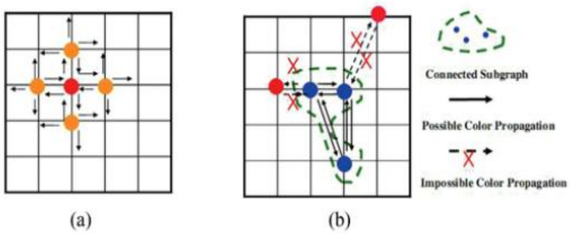

Fig.3: comparison of color propagation in 2-D image space with that in Gabor feature space.(a) color propagation in image spatial space (b)color propagation in our feature space

3. Temporal Coherence with Gabor Flow

Color propagation is performed across the entire feature space by enabling connected sub graphs. If the feature space is not fully connected there is a need of additional user input to maintain atleast one color assignment per sub graph. To maintain temporal coherence, the temporal connectivity of pixels in different sub graphs is preferred, so that color is spread automatically across the feature space. Temporal connectivity indicates to what degree the colorization is temporally coherent and therefore it is resistance to flickering effects.

To check similarity over time, a new flow field called gabor flow is introduced. To identify pixel color correspondences, a discrete parallel match algorithm was used based on rotation ware gabor filters. The basic task is to find robust color correspondences among unconnected clusters in the gabor feature space. A pixel's filter banks consists of elements $F_{k,}$ k=1 . . . . . . P which is used to define gabor flow energy as

$$E_{GF}(u,v) = \sum ((F_k)_x u+(F_k)_y+(F_k)_t)^2 \qquad (2)$$

$$\begin{pmatrix} (F_1)_x & (F_1)_y & (F_1)_t \\ (F_2)_x & (F_2)_y & (F_2)_t \\ . & . & . \\ . & . & . \\ (F_p)_x & (F_p)_y & (F_p)_t \end{pmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = 0 \qquad (3)$$

Where u and v are the x and y components of gabor flow. By replacing the system entries in (3) with the components of vector valued gabor features the task is reduced. The resulting linear system can be solved by estimating gabor flow with the least mean square method.

4.Color Propagation In Feature Space

There are many energy formulations for color propagation. In this paper, the neighborhood is determined by minimizing the energy in comparison with the well known eight neighbor area in the image space. By using gabor flow, for pixel i its neighbors in the gabor feature space are ($N_F(i)$) within one sub graph, and its temporal correspondences are determined by gabor flow. After formulation of neighborhood and the intensity values of user scribbles are known,the values of components U and V should be estimated. As the methods to estimate U and V are similar, it can find only the component U

$$E(U) = \sum_i (U(i) - \sum_{k \in N_F(i)} W_{ki} U(k))^2 \qquad (6)$$

where W_{ki} is a weighing function that sums to 1 and it is larger when its feature space is identical to that of pixel i.k and i are neighboring pixels in the feature space and their weighing functions are computed on the basis of feature distances between pixel i and its neighbors.

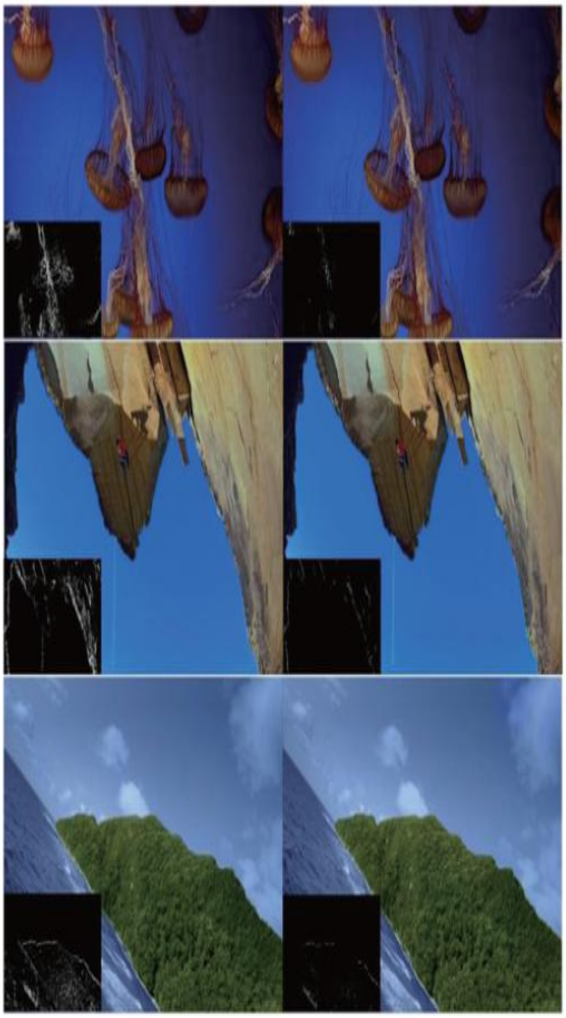

Fig 4: color propagation comparisons (a) using optical flow (b) using gabor feature. Note that the high error region(indicated by white pixels) produced using optical flow is much larger than that produced using gabor feature space

IV. RESULTS AND DISCUSSION

Figure 4 shows the comparison of the colorization of various videos using optical and gabor feature space. From this it can be observe that the texture regions are determined accurately by using gabor feature space. Figure 7 demonstrates colorization propagation based on the texture similarity. Fig 5 & 6 shows video colorization results for various video sequences. Note that in all these examples, colors are accurately are assigned based on a small number of input color scribbles

Fig 5: colorization of gray scale image through user color scribbles marked on the gray scale image

Fig 6: colorization results of birthday video (a)gray scale frame 1 (b) user inputs on the gray scale frame 1 (c) colorized frame 5

Fig 7: colorization using optimization feature space.(a) Input strokes (b) colorization result

Fig 8: colorizing texture with multiple colors (a) input scribbles (b) our colorization result. Note that red boxes indicate where colors have been improperly blended in texture similar regions

V. LIMITATION

The colorization approach fails to colorize properly with scribbles when the pixels with high texture similarity did not have similar colors. This is due to inherent restriction of gabor filters that results in over propagation using optimization. This limitation can be done by establishing a larger feature space by combining texture features and image spatial positions.

VI. CONCLUSION

The core challenges of colorization are to assign similar colors to texture similar regions. In this approach a novel method to video colorization is presented, which uses the gabor feature space to achieve good matching results, In spite of significant differences in appearance and spatial layout of video frames. This method is highly parallelizable and adaptive. It is applicable to various data, especially the videos of natural scenes. In future, the use of more sophisticated monochrome texture descriptors in video sequences can be done and further the color propagation capabilities can be improved.

VII. Acknowledgements

First and Foremost thanks to Annamacharya Institute of Technology & Sciences, Rajampet for providing me the facilities to pursue my work and special thanks to my guide for the successful completion of my work.

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