A NOVEL APPROACH FOR VIDEO RESTORATION USING GROUP-BASED SPARSE REPRESENTATION

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***Abstract*— Video restoration for blurred images is the significant challenge in Image processing. The video is restored using group based sparse representation. Video restoration is the operation of taking a corrupted/noisy video and estimating the clean original image. A Restoration method includes a motion-compensated de-noising. Digital compression artifacts and de-blocking are suppressed or masked. The group consists of non-local patches with similar structures and establishes a novel sparse representation modelling called Group Based Sparse Representation. Group Based Sparse Representation sparsely represents images in a unified framework. Thus this simultaneously enforces the local and non-local sparsity of self-similarity in images. For dictionary learning DCT technique is used for efficient restoration. Group Based Sparse Representation modelling performs peak signal-to-noise ratio. An experimental results show the performance of the proposed system. Thus this method is good in the video restoration concepts.**

***Index Terms*—** Denoising, image restoration, sparse representation, deblurring, inpainting.

I INTRODUCTION

Digital technology manipulates multi-dimensional signals with systems ranges from digital circuits to parallel computers. Image Processing, Analysis and Understanding are three main goals of manipulation. Three steps for restoration are: (1) purifying video signal, (2) quality to capture with a good capturing device and (3) filtering the video.

A. Video Restoration

Video restoration is the operation of taking a corrupted/noisy video and estimating the clean original image. Corruption occurs in different forms such as motion blur, noise, and camera misfocus. Video restoration removes or minimizes some known degradations in the video.

B. Group Construction

The video is divided into small frames. These images are divided into patches. Each patch is denoted as x_k. The patches are used to form the matrix. All the patches with similar structures in the matrix are called as a group. By averaging all the groups, the image is recovered from the group.

C. Group-Based Sparse Representation

The GSR model assumes that each group can be represented accurately by a few atoms of dictionary learning. The entire image is sparsely represented by a set of sparse codes in the group domain. In the dictionary any atoms can be picked. In the block or structured sparsity model the atoms are picked individually and from that groups of atoms are to be picked. Thus these groups can be overlapped by varying size. It is used to represent sparse in the number of groups selected.

II RELATED WORKS

Takeda H., studied the field of nonparametric statistics and presents a generalization of developing tools which results in image processing and reconstruction. In general, reconstruction techniques which adapts and expands kernel regression ideas which is used in image denoising, up scaling, interpolation, fusion, and more. Furthermore, it includes the recently popularized bilateral filter; it is the special cases of the proposed framework [9]. Ji H., [5] presented a new patch-based video restoration scheme. Grouping similar patches in the spatiotemporal domain, formulates the video restoration problem as a joint sparse and low-rank matrix approximation problem. The resulting nuclear norm and norm related minimization problem can be solved by numerical methods.

In the proposed system video restoration scheme is illustrated effectively on two applications: video denoising is done in the presence of random value noise, and video inpainting is done for archived films. Dong [3] presented the sparse representation, as an image patch which models the code as a linear combination of atoms from which few atoms is chosen out from a complete dictionary, and shows the promising results in various video restoration applications. Degradation occurs in the observed image (e.g. Noisy, Blurred), for reconstruction of sparse representations in conventional models it may not be accurate for the original image. Efficiency is improved in

ISSN: 2278 – 1323

sparse representation by the concept of sparse code noise. Image restoration is used to overwhelm the sparse coding noise. The non-local self-similarity is used to obtain the good estimation of the coefficients of sparse coding of the original image and coefficients of sparse coding of the observed image are centralized to those estimates.

III PROPOSED SYSTEM

Creation of dictionary is difficult in existing work. To avoid this drawback Group based Sparse Representation (GSR) is used. First, a group is constructed. Then the group based sparse representation modelling is used to enforce the intrinsic local sparsity and non-local self-similarity of videos simultaneously in a unified framework, which restores the video. Thus DCT based dictionary learning is used to directly identify the same groups in the video.

IV SYSTEM MODEL

System model includes many processes. First the video is chosen and then convert the input video into frames, thus the noisy image is created. Then group based sparse representation is done. The DCT technique is used for dictionary learning. DCT is known as Discrete Cosine Transformation. Then dictionary grouping is done. Grouping is done by gathering the same pixel value. The pixel which has less noise is grouped. After grouping denoising is applied. Thus the image which is affected by noise is removed. Finally the frames are converted into video. Fig1 explains about the overall process of proposed system. The proposed system increases the performance and efficiency. The proposed work is very efficient to restore the video.

V IMPLEMENTATION

A. Video Acquisition

Video capturing which electronically captures, records, processes, stores, transmits and reconstructs still images in sequence which represents scenes in motion. First the video is chosen.

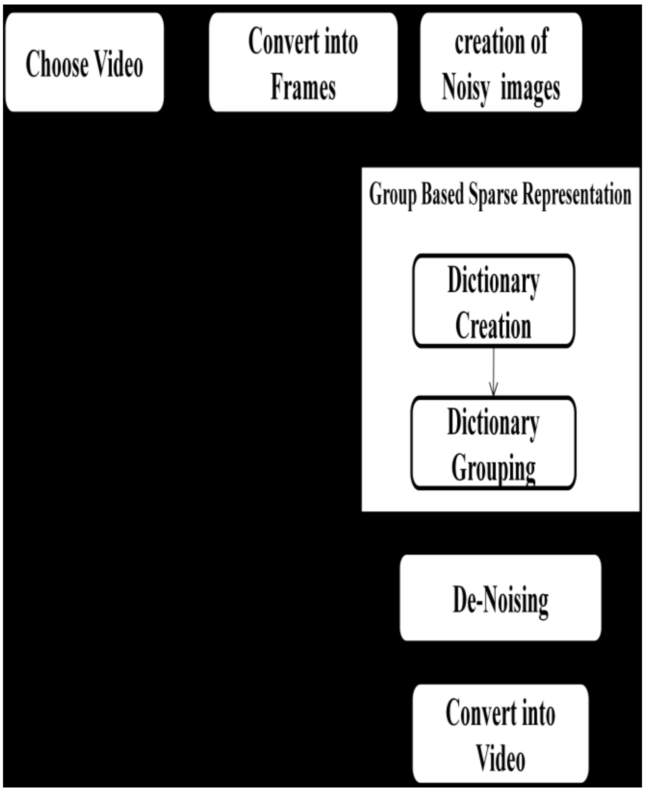

Fig1. System Architecture

B. Conversion of Frames

The video given as the input is divided into small frames. These frames are given to the input of the next step. The number of stills per unit of time for video, ranges from six to eight frames per second. These frames are saved and processed consequently.

C. Creation of Noisy Image

Noisy image is the random variation of brightness or colour information in images, and it is an aspect of electronic noise. Sensor and the circuitry of a scanner or digital camera produce it. A typical model of noisy image is Gaussian and additive which is independent at each pixel and independent of the signal intensity caused by thermal noise including the noise which arise from the noise of capacitors. "Impulsive" noise is also called as salt-and-pepper noise or spike noise. Salt-and-pepper noise will have dark pixels and bright pixels in dark regions and in bright regions that is black and white pixels. Quantization noise is the noise obtained by pixels quantization of a sensed image to number of discrete levels. It adds uniform distribution approximately and adds the noise in the original image.

D. Dictionary Creation

ISSN: 2278 – 1323

The image is divided into patches. Each patch is denoted as x_k. Next the patches are used to form the matrix. All the patches in matrix with similar patches are named as a group. By averaging all the groups, the image is recovered from the group. The proposed works links the patch pair and the blur constraint in a dictionary.

E. Dictionary Grouping

For each group DCT based dictionary learning is done. Then Group-Based Sparse Representation is done for entire image.

F. Denoising

Image de-noising is the process of removing the noise which occurred in the image. After Dictionary grouping the noise should be removed.

G. Restored Video

To generate a video from a set of sequences or set of frames, starts with the number zero. Frames are converted into video. Thus the Video is restored. Rescaling is used to manage the size of the video in the desired resolution.

VI RESULT

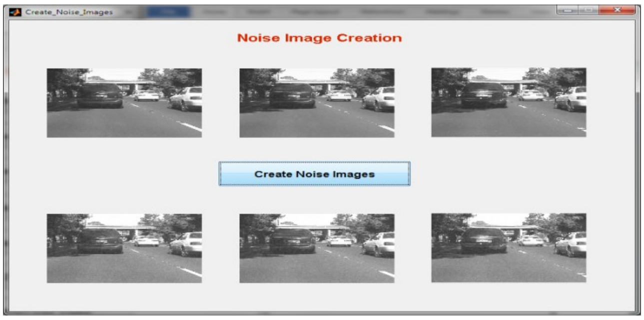

Fig.2 Noisy Image

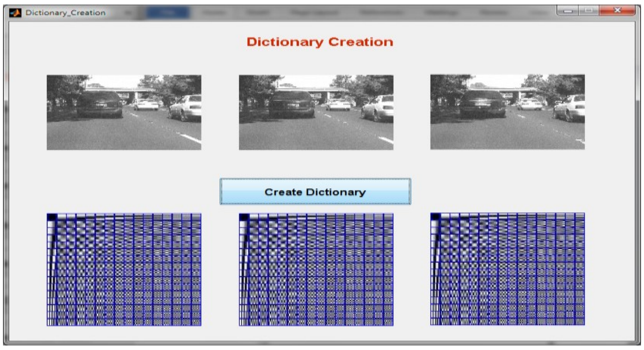

Fig.3 Dictionary Creation

Fig.4 Denoising

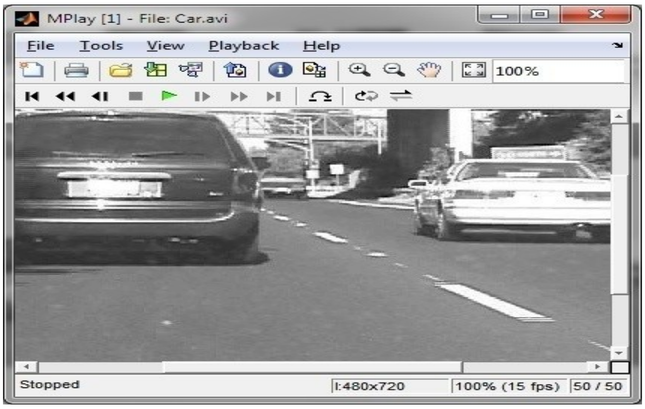

Fig.5 Restored Video

VII CONCLUSION

The proposed system is designed with the DCT based dictionary learning. The proposed method is very efficient to achieve low complexity and restore the video accurately.

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ISSN: 2278 – 1323