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A Structural Patch Decomposition Approach for MME- Image Fusion Technique using Video

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Abstract*: *Removal of shadows from one image could be a difficult drawback. Manufacturing a high-quality shadow-free image that is indistinguishable from a replica of a real shadow-free scene is even tougher Shadows in pictures area unit generally full of many phenomena within the scene, as well as physical phenomena like lighting conditions, kind and behavior of shadowy surfaces, occluding objects, etc. Additionally, shadow regions might endure post acquisition, image process transformations, e.g., distinction sweetening, which can introduce noticeable artifacts within the shadow-free pictures. We dispute that the assumptions introduced in most studies arise from the quality of the matter of shadow removal from one image and limit the category of shadow pictures which might be handled by employing a Modified Multi-exposure image fusion (MMEF) technique. Experimental results showing definitively the capabilities of our algorithmic rule are given. The difference is that HDR reconstruction works in the radiance domain where the value is linear w.r.t. the exposure, while MMEF works in the intensity based domain. Compared with object motion, camera motion is relatively easy to tackle via either setting a tripod or employing some registration techniques.

***Index Terms*: Index Terms - SPD-MMEF, Image fusion, Ghost Removal Algorithm, Pixel - level based image Fusion. Image enhancement..**

I. INTRODUCTION

The objective of Image Fusion (IF) is to integrate reciprocal multisensor, multitemporal and multiview data into one new image containing data the standard of that can't be complete otherwise. The consolidated image contains bigger data content for the scene than anybody of the individual image sources separate. The dependability and overall detail of the image is inflated, thanks to the addition of analogous and complementary data. Image fusion requires that images be registered first before they are fused. Data fusion techniques mix information from totally different sources along. The main objective of using fusion is to supply a united result that has the foremost elaborated and reliable data attainable. Fusing multiple data sources along additionally produces an additional economical illustration of the information. Produce a single image from a set of input images. To produce one image from a collection of input pictures. The investigation image ought to have additional complete info that is an additional helpful for human or machine perception.Design of Image Fusion is extracting all the helpful info from the supply pictures and don't introduce artifacts or an inconsistency which is able to detract Human observers.

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II. RELATED WORK

In this part many reference papers and ideas of several authors are given to get knowledge about image fusion using the image enhancement technique. Since early introduced in 1980's, MEF has been attracting significant interest from each academia and business. Most existing MEF algorithms are a unit pixel-wise strategies that, but suffers from a main disadvantage. The weight map is commonly too shouting and should end in numerous artifacts if straight applied to the fusion method. Thus, ad-hoc remedies have been proposed to post-process the weighting map by either smoothing or edge preserving filtering [2].[17].

Despite the demonstrated success, typical MEF algorithms require the input source image sequence to be perfectly aligned and there is little object motion in the scene. In practice, however, a small displacement due to handheld cameras or object motion (such as ripples and human movement) would neutralize the advantages brought by MEF and cause artifacts referred to as "ghosting', as exemplified [4].

While MEF works in the intensity domain (after applying CRF to the radiance value). Compared with object motion, camera motion is relatively easy to tackle via either setting a tripod or employing some registration techniques[5]. As a result, substantial efforts have been put to develop ghost removal algorithms with an emphasis on object motion. Many existing deghosting algorithms require pixel- or patch-level motion estimation, and their performance is highly dependent on the motion estimation accuracy. One problem shared by these design principles is that they suffer from higher computational burden, which may not be affordable by mobile devices [3],[7].

Most current MEF algorithms are pixel-wise systems to post-process the weighting map by either smoothing or edge preserving filtering. The locale weights via angle based distinction maximization and image prominence detection. Some other algorithms also assume that the background dominates the scene and moving objects only appear in one exposure in order to simplify the ghost removal process [9].[13]. The existing work divided input images into several non-overlapping patches and selected the ones with the highest entropy as the winners. The blocking artifacts were minimized by a integrate function[10].

The above mentioned pixel-wise MEF methods need to deliberately take into account the noisy characteristics. Post-processing is a must to produce a reasonable fused image, which is a main drawback of this type of methods. Moreover, the mostearly method MEF algorithms are a unit solely verified mistreatment restricted examples, while not comprehensive verifications on databases that have enough variations of image information [11],

The disadvantages are weighting map is often too noisy and may result in various artifacts if straight tested to the fusion technique. Most existing ghost removal algorithms that deliver state-of-the-art performance require motion estimation in an iterative optimization framework, which suffers from substantial computational complexity and is not suitable for mobile devices [20].

III. PROBLEM STATEMENT

In this work, we tend to enumerate the varied issues and challenges associated with the task of image fusion. It is price, noting that a given image doesn't essentially embrace all of the phenomena mentioned below, and indeed, in several of the photographs we tend to explored solely a set of phenomena happens. However, so as to improve powerful Modified Multi-exposure image fusion (MMEF) that's strong to ghosting impact.

We dissolve a picture patch into 3 parts area unit signal stability, signal network and mean intensity. Algorithms which may effectively pictures beneath completely different conditions and of the various image or video varieties. Any noise eliminates algorithms ought to account for the varied kinds of potential phenomena which cannot have an effect on the ultimate sharp image.

IV. PROPOSED SYSTEM

In this fig.1, we detail the proposed Structural Patch Decomposition (SPD) approach for MMEF. We first describe a baseline version that works for static scenes, and then extend it to dynamic scenes by adding a structural consistency check, resulting in the robust SPD-MMEF algorithm. First, as critical most pixel-wise MMEF strategies, the projected rule doesn't need post-processing steps to boost visual quality or to decrease back spatial artifacts. Second, it uses RGB color channels put together, and so produces united pictures with the additional vivid color look. Third and most significantly, the direction of the signal structure element within the patch vector area provide ideal data for ghost removal.

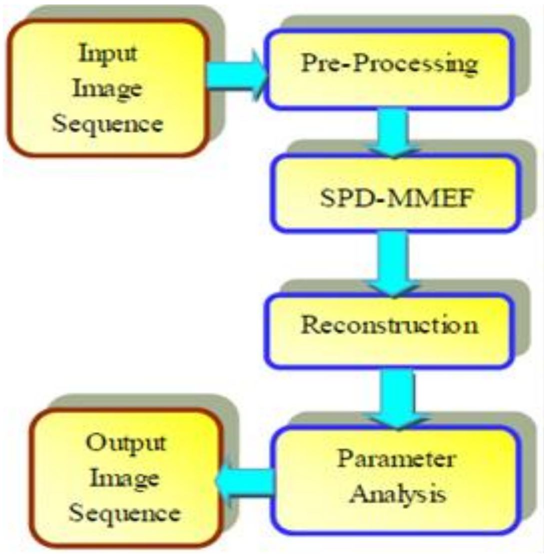

Fig .1 Proposed approach block diagram

A. Baseline SPD-MMEF

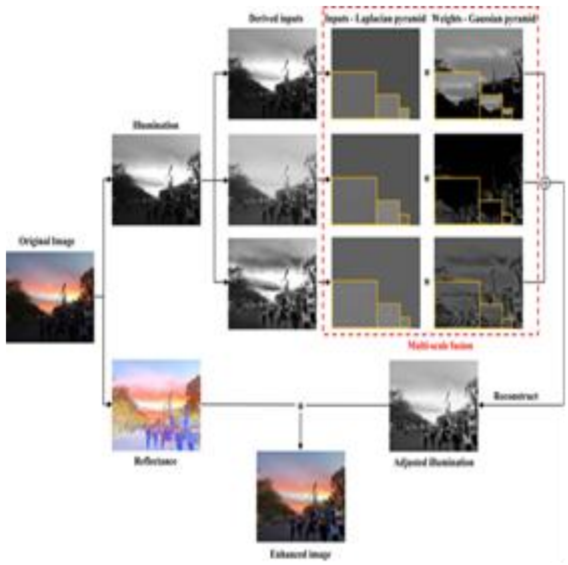

Fig.2 Base line SPD-MMEF

In this above fig.2 shows the $\{xk\}=\{xk|1 \leq k \leq K\}$ be a group of color image patches separate at identical spatial position of the supply sequence that have K multi-exposure pictures. Here xk for all k are column vectors of C N2 measure, where C is that the no of the color channels of the input image and N is that the spatial volume of a square patch. Every access of the vector is one among the 3 intensity values in RGB channels of a pixel within the patch. Given a color patch, we have a tendency to initial decompose it into 3 components: signal structure, signal strength and mean intensity. As such, the matter of constructing a patch within the united image is born-again to process the 3 parts individually and so inverting the decomposition.

We start the process of the component of signal strength. The visual ness of the local patch arrangement for the most part depends on local distinction, that is directly associated with signal strength. Considering that everyone input image patches as practical capturing of the image, the patch that has the very best distinction among them would correspond to the most effective visibility. Therefore, the specified signal strength of the amalgamated image patch is set by the very best signal strength of all input image patches. Where C is that the range of the color channels of the input pictures and N is that the spatial size of a square patch. Each passage of the vector is one of the 3 intensity values in RGB channels of a pixel in the patch. Given a color patch, we have a tendency to initial decompose it into 3 components: mean intensity, signal structure and signal strength.

$$\begin{aligned} \mathbf{x}_k &= \|\mathbf{x}_k - \mu_{\mathbf{x}_k}\| \cdot \frac{\mathbf{x}_k - \mu_{\mathbf{x}_k}}{\|\mathbf{x}_k - \mu_{\mathbf{x}_k}\|} + \mu_{\mathbf{x}_k} \\ &= \|\tilde{\mathbf{x}}_k\| \cdot \frac{\tilde{\mathbf{x}}_k}{\|\tilde{\mathbf{x}}_k\|} + \mu_{\mathbf{x}_k} \\ &= c_k \cdot \mathbf{s}_k + l_k, \end{aligned} \tag{1}$$

Where || . || Stand for the l2 norm of a vector, µxk is the mean value of the patch, and ˜xk = xk−µxk denotes a mean-eliminated patch. The scalar ck = ||xk|| the unit-length vector sk =˜xk / ||˜xk||, and the scalar lk = µxk represent the mean intensity, signal structure and signal strength components of xk, commonly. All patches may be unambiguously decomposed into the 3 parts and therefore the method is invertible. As such, the matter of constructing a patch within the consolidated image is born-again to process the 3 elements individually and so inverting the decomposition.

We initial method the element of signal strength. The clarity of the local patch structure mostly depends on local variation, that is directly associated with signal stability. Considering that everyone input supply image patches as practical capturing of the image, the patch that has the best distinction among them would correspond to the simplest visibility. Therefore, the specified signal strength of the consolidated image patch is set by the very best signal strength of all supply image patches

$$\hat{c} = \max_{1 \le k \le K} c_k = \max_{1 \le k \le K} \|\tilde{\mathbf{x}}_k\|. \tag{2}$$

Different from signal strength, the unit-length structure vector Sk points to a unique direction in the CN2 dimensional area. The specified structure of the consolidated image patch is predicted to best represent the structures of all input image patches. A plane fulfillment of this link is given by

$$\hat{\mathbf{s}} = \frac{\bar{\mathbf{s}}}{\|\bar{\mathbf{s}}\|} \quad \text{and} \quad \bar{\mathbf{s}} = \frac{\sum_{k=1}^{K} S(\tilde{\mathbf{x}}_k)\, \mathbf{s}_k}{\sum_{k=1}^{K} S(\tilde{\mathbf{x}}_k)}, \tag{3}$$

Where S(•) may be a coefficient perform that determines the contribution of every input image patch within the structure of the consolidated image patch. Naturally, the improvement should increase with the stability of the image patch. A straight forward access that conforms to such an inspiration is to apply a power weighting activity is given by

$$S(\tilde{\mathbf{x}}_k) = \|\tilde{\mathbf{x}}_k\|^p, \tag{4}$$

Where p ≥ 0 is a parameter, with varied decisions about the worth of p this general formulation results in a family of the coefficient functions with completely different physical meanings. The larger the p is a lot of stress is placed on the patches that have comparatively better strength.

$$\hat{l} = \frac{\sum_{k=1}^{K} L(\mu_k, l_k)\, l_k}{\sum_{k=1}^{K} L(\mu_k, l_k)}, \tag{5}$$

where L(•) is a carry function that takes the global mean rate µk of the color image Xk and the local mean value of the present patch xk as inputs. L(•) evaluate the good possibility of xk in Xk so that big cost is given when Xk and/or xk are under or over-exposed. We adopt a 2 dimensional mathematician profile to determine this measure.

$$L(\mu_k, l_k) = \exp\left(-\frac{(\mu_k - \mu_c)^2}{2\sigma_g^2} - \frac{(l_k - l_c)^2}{2\sigma_l^2}\right) \tag{6}$$

represent the structures of all supply image patches.

Due to the development of the xk that stacks RGB channels of a patch into one vector, inherently take under consideration color distinction and structure. An example is shown. For smooth patches (such as the door frames in the middle of the image) that contain little structure information, SPD-MMEF prefers those within the image that contain robust color data than gray ones that typically result from under/over-detection. By distinction, MMEF algorithms that treat RGB channels one by one might not build correct use of color data and provides patches across exposures similar sensory activity importance for fusion.

$$\hat{\mathbf{X}}(i) = \sum_{k=1}^{K} \mathbf{W}_k(i) \mathbf{X}_k(i), \tag{7}$$

The MMEF method is pixel-wise patch decompositions that typically follow a weighted summation n frame work. wherever K is that the range of the input pictures within the burden and intensity values at the ith element within the kth showing image, severally, represents the consolidated image. A simple extension of this way in transform domain is to interchange Xk (i) with transform coefficients. The weighting map Wk usually carries data relating to structure maintenance and visual significance of the kth input image at the pixel level.

With specific models to measure this data, existing MMEF algorithms take issue in the main within the computation of Wk and the way it's going to adapt over an area or scale supported image content.

The above mentioned pixel-wise MMEF methods need to deliberately take into account the noisy characteristics of the Wk. Post-processing is a must to produce a reasonable fused image, which is a main drawback of this type of methods. Moreover, most present MMEF algorithms are a unit only verified victimization restricted examples, while not comprehensive verifications on databases that contain sufficient changes of image content.

B. ROBUST SPD-MMEF

We extend the baseline SPD-MMEF to account for dynamic scenes in the presence of the camera and view motion. We assume that the input source sequence is aligned, for example by setting a stand or some image enrollment algorithms. This assumption is mild because the camera motion is normally small and comparatively uniform.

Within the framework of the proposed SPD, it is very convenient to detect inconsistent motions across exposures by making use of the structure vector Sk. To be specific we compute the inner product between the reference signal structure Sr and the signal structure's Sk of another exposure.

$$\rho_k = \mathbf{s}_r^T \mathbf{s}_k = \frac{(\mathbf{x}_r - l_r)^T (\mathbf{x}_k - l_k)}{\|\mathbf{x}_r - l_r\| \|\mathbf{x}_k - l_k\|}. \quad (8)$$

ρk lies in [−1, 1] with a larger value indicating higher consistency between sk and sr. Since sk is constructed by mean removal and strength normalization, it is robust to exposure and contrast variations. We make an additional modification on Eq. (8) by summing a low constant € to both the numerator and the denominator.

$$\rho_k = \frac{(\mathbf{x}_r - l_r)^T (\mathbf{x}_k - l_k) + \epsilon}{\|\mathbf{x}_r - l_r\| \|\mathbf{x}_k - l_k\| + \epsilon}. \quad (9)$$

The constant is to ensure the robustness of the structural consistency to sensor noise. More specifically, in the darkest areas where signal strengths are weak, when the structure vector sr is scaled to unit length, it will mainly contain amplified noise structures, making the structural consistency check in Eq. (8) unreliable. Fortunately, this issue can be well addressed by adding to both the denominator and the numerator as in Eq. (9).

We first create K −1 latent images by mapping the intensity values of the reference image to the rest K−1 exposures and compute the absolute mean intensity difference of identifying patches in the kth exposure and its corresponding latent image. We again threshold the difference

$$\bar{B}_k = \begin{cases} 1 & \text{if } |l_k - l'_k| < T_m \\ 0 & \text{if } |l_k - l'_k| \geq T_m \end{cases}, \quad (10)$$

Where l'k is the mean intensity of the co-located patch in the kth latent image created from the reference image and Tm is a pre-defined threshold. We define the final structural consistency measure w.r.t. a reference patch by multiplying

$$B_k = \tilde{B}_k \cdot \bar{B}_k \quad (11)$$

In general, ¯Bk mainly works as a supplement to ˜Bk to more conservatively fill in the under or over-uncovered regions of the concern image.

C. IMPLEMENTATION DETAILS

Geometric functions allow us to analyze the overall characteristics of an image by Computing the Mean or variance, deciding the intensity values on a line section, displaying a picture bar chart and plotting a sketch of intensity values. We make, for the primary time for the most effective of our data, a multi-scale multiple exposure image dataset that contains small-contrast images with totally different exposure scales and their comparable high-quality relevance image. The created dynamic scene makes end-to-end particular learning about high performance of the proposed MMEF ways attainable. It additionally provides a platform for quantitatively value, a minimum of to some extent, the execution of various contrast improvement algorithms. With the created dataset, a well-designed dynamic scene is prepared for the proposed method. Our work provides a new solution for high performance of dynamic image fusion.

The two thresholds Ts and Tm are crucial for SPD-MMEF to work with dynamic scenes in the presence of camera and object motion. Both Ts and Tm have the same range [0, 1]. Ideally, the structural consistency map should be able to reject inconsistent motions w.r.t. the reference exposure while incorporating as many consistent patches as possible to make full use of all valid information for fusion.

Modified Multi-Exposure image fusion (MMEF) will turn out an image with High dynamic range (HDR) impact by fusing many images with completely different exposures. The normal MMEF strategies need important pre/post-processing steps to boost the visual quality by reducing spatial artifacts. These

methods may produce unwanted artifacts because of the limited processing power of mobile devices and complexities of real scenes.

D. IMPLIMENTATION OF SPD- MMEF ALOGRITHM

We summarize the proposed SPD-MMEF approach in Algorithm 1.

Input: Input image sequence {Xk} = {Xk | 1 ≤ k ≤ K}

1. Check the reference image Xr and create the K – 1 latent image {X' k} = { X' k | k ≠ r } of Xr using IMF
2. for each reference patch xr do
3. Extract its image re-located patches {Xk, X' k | k ≠ r }
4. Verify the structural consistency of {Xk} using Bk
5. Neglect the inconsistent xk compensated by X'k
6. Compute ĉ, ŝ and î separately
7. Reconstruct the fused patch ĥ = ĉ • ŝ + î
8. end for
9. Aggregate fused patches into Ĥ

Output: Fused image Ĥ

1) A small positive constant

2) The exponent parameter p to determine the weight of the structure Vector component,

3-4) two Gaussian spread parameters to determine the weight of the mean Intensity component,

5-6) two thresholds Ts and Tm that binarized the structural consistency Map and

7-8) The patch size and its associated stride.

In these details, we run comprehensive experiments to confirm the performance of SPD-MMEF. Throughout the project we apply the proposed robust SPD-MMEF algorithm to all test sequences (both static and dynamic) with fixed parameter settings. We compare SPD-MMEF with state-of-the-art and representative MMEF and deghosting algorithms that are specifically designed for static or dynamic scenes. Finally, we perform complexity analysis of state-of-the-art deghosting algorithmic and report their average execution time on source sequences.

SPD-MMEF METHOD ADVANTAGES

SPD-MMEF generates little noise the weighing map and makes better use of color information during fusion. HDR restoration to produce high standard HDR images with Low Ghosting Artifacts. SPD techniques are useful in image quality assessment of contrast- Changed and Stereoscopic images.

E. GHOST REMOVAL ALGORITHM

The MMEF methods may produce ghosting artifacts in the presence of camera and object motion. To reduce such artifacts during fusion, a quality of ghost removal algorithms have been designed. In the radiance domain, the linearity between the sensor radiance and the exposure time has been well exploited either directly or through some mathematical models such as energy minimization and low rank minimization.

The assumption here is that the linearity should only be broken when the scene changes due to moving objects, provided that the alignment and CRF estimation are perfect. In addition, Eden et al. selected one radiance rate out one of the input images for each spatial location as an attempt to eliminate ghosting artifacts. However, moving object duplication or deformation may appear.

V. SIMULATION RESULTS

The following is the analysis of the simulation results of the introduced algorithm (SPD-MMEF). The execution of the algorithm is evaluated with the performance metric PSNR for different bit rates. As the system aims mainly to give better performance at low bit rate, the algorithm tested for a standard Horse sequence of image.

A. *HORSE IMAGE ANALYSIS*

In the presence of work, we practically implemented the execution of the image fusion method of SPD- MMEF algorithms as mentioned in fig. 3

Fig. 3 Input Horse Image Comparisons

Table.1 shows the PSNR value obtained from a Horse Sequence of image from both existing systems and from the proposed system. The average PSNR value in the SPD–MMEF methods improvement compared to the existing systems. This indicates clearly that the proposed algorithm outperforms. The Analysis of PSNR results in Horse image are plotted in fig.4

Table. 1 Average PSNR Value Horse Image Sequence Size 683 × 1024

METHODS	PSNR VALUE
SEN -12	10.93
PECE-10	11.45
QIN-15	15.68
SPD - MEF	18.15
SPD-MMEF	18.95

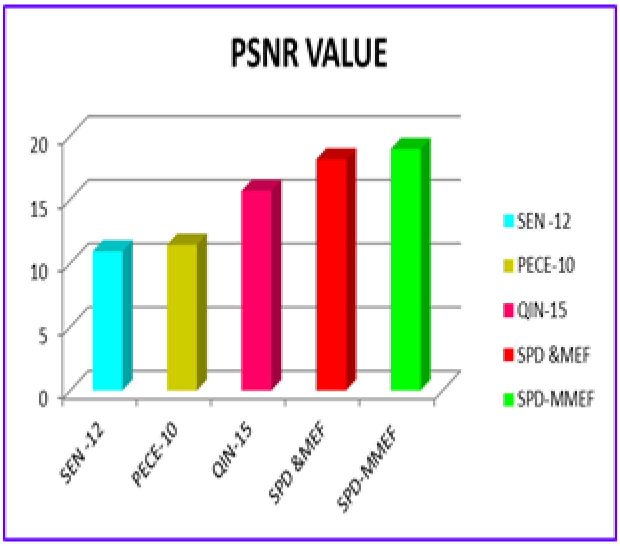

Fig .4 Analysis of PSNR value of Horse image

The image fusion method of SPD- MMEF algorithms applied in the Horse image sequence, the output of the horse image as shown below in fig.5

Fig. 5 Fused Horse Image Output

Table.2 Horse image-Execution time

METHODS	TIME in Sec.
SEN -12	75.28
PECE-10	46.41
QIN-15	40.93
SPD &MEF	36.91
SPD & MMEF	32.72

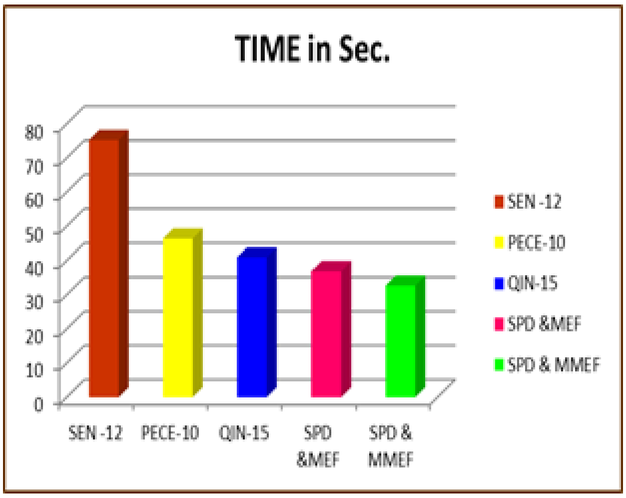

Fig.6 Execution time -Horse Image Output

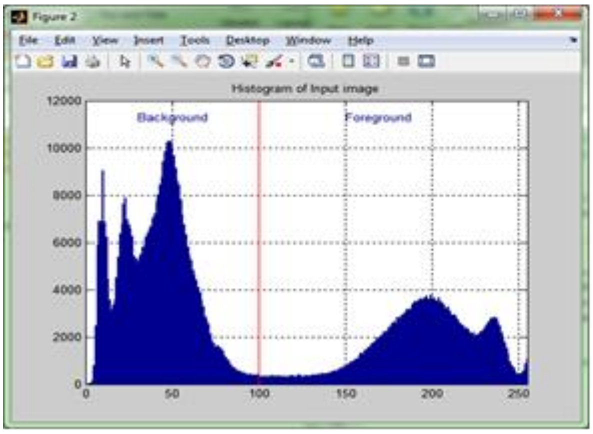

Fig.7 Input Horse Image Histogram

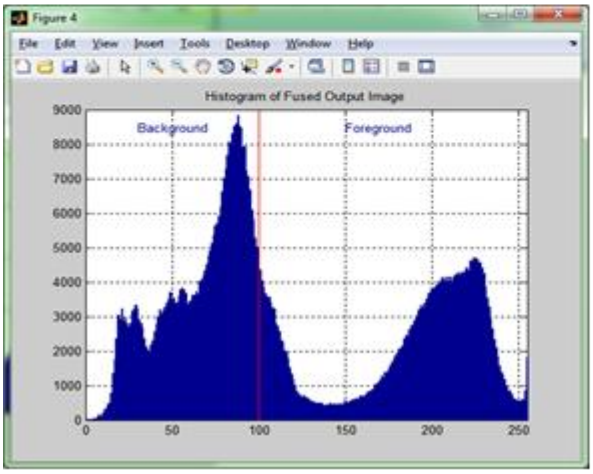

Fig.8 Histogram of Horse output image.

B. HILLS VIDEO INPUT FRAME– RESULT ANALYSIS

In this section, the system evaluation is done with the results obtained from simulation. They are compared with existing Fusion methods. The average PSNR is calculated over the image frames.

The image fusion SPD-MMEF technique applied all the Hills video frames. The input and output Horse image in fig.7 and 8. The input and output Hills video frame as shown in fig.9 and Histogram chart of the input Hills video frame as shown in fig.10.Thereconstructed Hills video output frame as shown in fig.11 and output Histogram chart of Hills video frame as shown in fig.12 ,Comparison of input, noise - image and output image Hills video sequence frame as shown in fig.13.

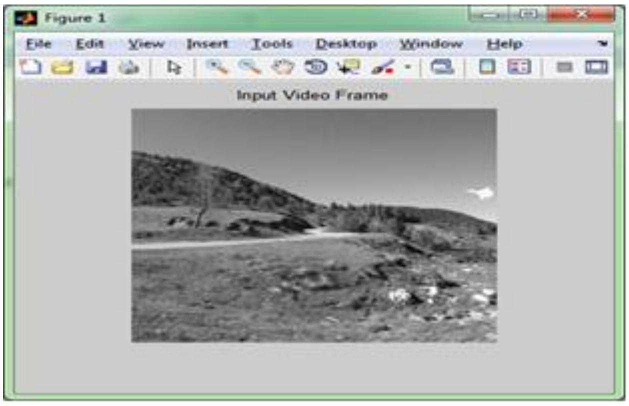

Fig. 9 Hills input video frame

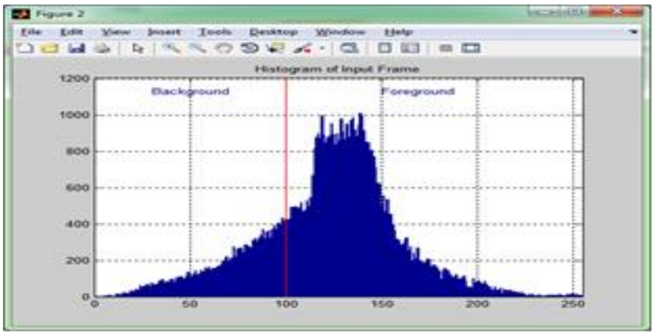

Fig.10 Histogram of Hills input Video Frame

Fig. 11 Output Video Frame

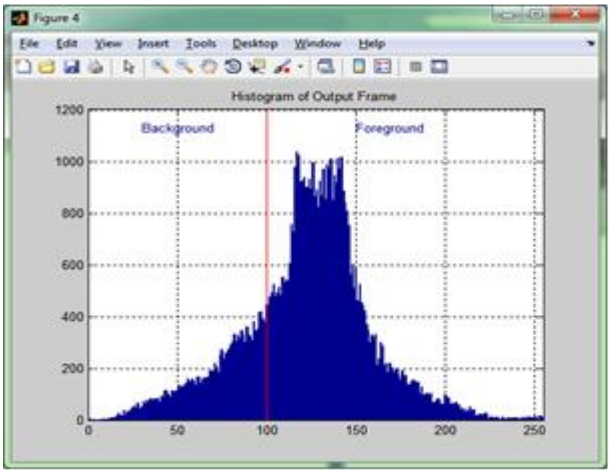

Fig.12 Histogram of Hills output Video Frame

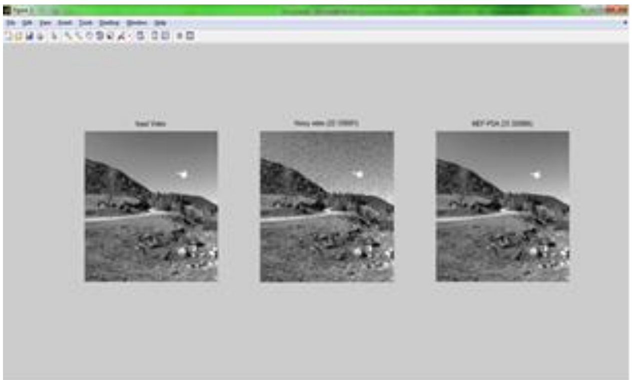

Fig.13 Comparison of input and output Hills video sequence frame

Table.3 shows the PSNR value obtained for Hills video Sequence of image from both existing systems and from the proposed system. The average PSNR value in the SPD–MMEF methods improvement compared to the existing systems. This indicates clearly that the proposed algorithm outperforms. The Analysis of PSNR results in Hills video frame image are plotted in fig .14

Table.3 Hills Video-PSNR Calculation

METHODS	PSNR VALUE
SEN-12	23.32
PECE-10	27.52
QIN-15	29.96
SPD &MEF	32.78
SPD-MMEF	33.82

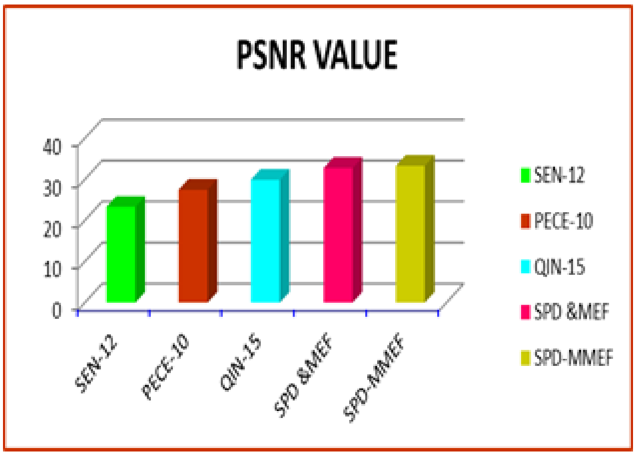

Fig.14 Analysis of PSNR value of Hills video frame image

Table.4 shows the average execution time of the new technique and the existing approach for the Hills video frame image sequence shows at every value of rate in bits per dimension, the execution is better in the proposed system. The out performance of the system during analysis of Execution time (Hills output fused image) Fig.15

Table.4 Execution Time Calculation (20 frame Hills video)

METHODS	TIME in Sec.
SEN-12	356.7867
PECE-10	347.4532
QIN-15	313.3987
SPD &MEF	286.9876
SPD &MMEF	266.3998

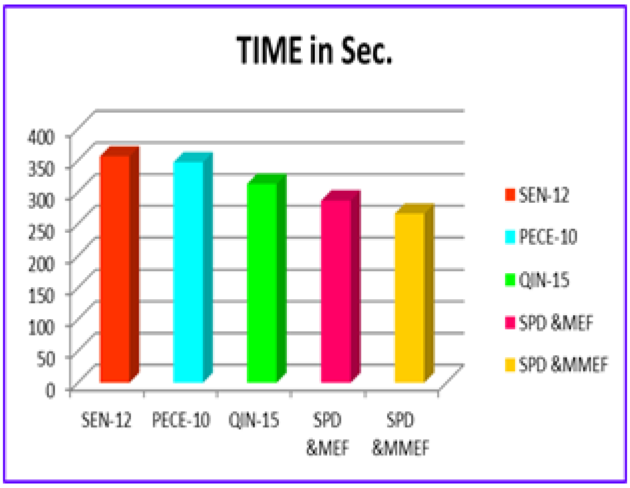

Fig.15 Analysis of Execution time Fused Hills video Output

VI. CONCLUSION

In this paper, we proposed a novel structural patch decomposition (SPD) approach for MMEF. Different from most pixel wise MMEF methods, SPD-MMEF works on color image patches exactly by decomposing that into 3 conceptually separate components and by processing every component separately. As a result, SPD-MMEF generates little noise in the weighing map and makes better use of color information during fusion. Furthermore, reliable deghosting performance is achieved by using the direction information of the structure vector. Comprehensive experimental results demonstrated that SPD-MMEF produces MEF images with smart information, vivid color image and little ghosting artifacts while maintaining a manageable computational cost.

The proposed video fusion technique by combining the SPD- MMEF standard and SPD with MMEF is discussed. 1.5dB improvement in average PSNR is inferred across various methods for Hills Video frame Sequence.

12% improvement Hills video frame image in PSNR value and 22% improvement in execution time for Hills video frame image sequence of the proposed system.Similarly,8% improvement Horse image in PSNR value and 24% improvement in execution time for Horse image sequences from the proposed system.

The performance of the system provides with better improvement than the previous systems. The performance of the Histogram processing results shows that the improvement of Mean, Median and standard deviation values using two video sequences (Hills video and Horse image) frames.

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