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Modified Wavelet Image Fusion Based On Svd

Bijitha S R, Lekshmi Mohan, Megha M Kartha, Asha P Kurian, K P Soman
Centre For Excellence in Computational Engineering and Networking
Amrita Vishwa Vidyapeetham, Amrita School of Engineering, Coimbatore-641112

ABSTRACT

Image fusion is a concept of combining multiple images into composite products which gives more visual information than individual source image. Image fusion had its beginning with the concept of simply averaging the intensities of the corresponding pixels of the set of input images, thus producing a fused image. A lot of advancement have happened in the field of image fusion by employing wavelet based image fusion techniques like Haar wavelet method .In this paper a new image fusion method is proposed based on daubechies wavelet and SVD. Here wavelet decomposition of input images is done and SVD is applied only to the approximation coefficients. Image fusion is performed using the modified input images. Singular values have been changed to observe variation in the quality of output image. The performance discriminators used here are PSNR, NAE, MSE, SE, NC.

Keywords

Image fusion, SVD, Wavelet decomposition

1. INTRODUCTION

Image fusion is the process of combining information from two or more input images to form a more informative image. The image fusion can be performed at different levels such as pixel level, feature level, signal level and decision level. Wavelet analysis deals with analysing the signal with short duration finite energy functions called as wavelets.

In initial studies, image fusion has been applied to different fields such as pattern recognition, visual enhancement, object detection and area surveillance [1].The widely used image fusion methods include Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS), high pass filtering, multiresolution analysis based methods (pyramid algorithm and wavelet transform), Artificial Neural Network etc [2]. The image fusion methods like IHS, PCA and Brovery transform operate under spatial domain which may produce spectral degradation. As the introduction of multiresolution analysis, the wavelet transform has become a very useful tool for image fusion. It has been found that wavelet based image fusion is advantageous than spatial and spectral fusion techniques [3-5].

The different wavelet type includes Haar, Meyer, Daubechies, Shannon, Cofman wavelet etc. Fusion methods based on Discrete Wavelet Transform (DWT) was introduced in [6]. The DWT based image fusion outperforms the standard fusion methods. A new image fusion scheme based on wavelet based contourlet transform (WBCT) was explained in [7]. Here WBCT is used to perform decomposition of each image and coefficients of fused image are constructed using different fusion rules. A fusion method based on SVD was applied to multispectral face recognition [8]. SVD is applied inorder to enhance the super resolution images by converting the reference image in to SVD domain and the images' singular values are fused before performing interpolation [9].

In the proposed approach, SVD is applied on wavelet based image fusion and it is compared with standard wavelet based image fusion. SVD captures the variation of data and it is used to perform the fusion by various singular values. The performance is evaluated using various quality measures such as Peak Signal to Noise Ratio(PSNR), Normalized cross correlation(NC), Structured Content (SC), Mean Squared Error(MSE) and Normalized Absolute Error(NAE).

The rest of the paper is organized as follows. Section 2 introduces image fusion methods. The performance discriminators to determine the quality of image is explained in Section 3. The proposed method is introduced in Section 4. Simulation results are presented and discussed in Section 5 and concluded in Section 6.

2. IMAGE FUSION METHODS

Image fusion is a framework where a composite image can be produced which contains enhanced information using some methods. Here mainly wavelet and SVD based fusion methods are taken in to consideration.

2.1 WAVELET DECOMPOSITION

Wavelet function does not play any role directly in the computation of signal expansion coefficients. Our aim is to establish this relationship between expansion coefficients at a lower scale and expansion coefficients at a higher scale. Haar scaling and wavelet function is used to interpret the result.
The refinement relation is,

We have $$\phi(t) = \sum_{n=0}^{N-1} h(n)\sqrt{2}\phi(2t-n)$$

$$= \sum_{n}^{N-1} h(n)\phi_{1,n}(t)$$

Here, N is the number of coefficients in the refinement relation. For Haar, N=2, and the relation is

$$\phi(t) = h(0)\sqrt{2}\phi(2t) + h(1)\sqrt{2}\phi(2t-1)$$
$$= h(0)\phi_{1,0}(t) + h(1)\phi_{1,1}(t)$$

Note that $h(0)$ and $h(1)$ are normalized coefficients. For Haar, $h(0) = \frac{1}{\sqrt{2}}$ and $h(1) = \frac{1}{\sqrt{2}}$,

We aim at relating *jth* level ϕ with the next higher level scale level *j+1*, so we write

$$\phi(2^j t - k) = \sum_{n=0}^{N-1} h(n)\sqrt{2}\phi(2(2^j t - k) - n)$$

$$=\sum_{n=0}^{N-1} h(n)\sqrt{2}\phi(2^{j+1}t-2k-n)$$

By putting $m=2k+n,$ we have

$$\phi(2^{j}t-k)=\sum_{m=2k}^{2k+N-1} h(m-2k)\sqrt{2}\phi(2^{j+1}t-m)$$

Similarly,

$$\psi(2^{j}t-k)=\sum_{m=2k}^{2k+N-1} g(m-2k)\sqrt{2}\phi(2^{j+1}t-m)$$

V_j can be denoted as,

$$V_j=\underset{k}{Span}\left\{\overline{2^{j/2}\phi(2^{j}t-k)\}}\right\}$$

Then

$$f(t)\in V_{j+1}\Rightarrow f(t)=\sum_{k} s_{j+1}(k)2^{(j+1)/2}\phi(2^{j+1}(t-k)$$

That is, $f(t)$ is expressed as a linear combination of bases in V_{j+1} . At this scale, wavelets are not coming to picture.

Since $V_{j+1}=V_j\oplus W_j$, to represent same signal, in the next lower scale, we require the help of wavelets. So we have

$$f(t)=\sum_{k} s_j(k)2^{j/2}\phi(2^{j}t-k)+\sum_{k} d_j(k)2^{j/2}\psi(2^{j}t-k)$$ The $2^{j/2}$ terms maintain the unity norm of the basis functions at various scales.

To find $s_j(k)$ project $f(t)$ on to the corresponding normalized base $2^{j/2}\phi(2^{j}t-k)$. That is

$$s_j(k)=\left\langle f(t),\phi_{j,k}(t)\right\rangle$$

$$=\int f(t)2^{j/2}\phi(2^{j}t-k)dt$$

$$s_j(k)=\sum_{m=2k}^{2k+N-1} h(m-2k)\int f(t)2^{(j+1)/2}\phi(2^{j+1}t-m)dt$$

The integral in ( ) is basically projection of $f(t)$ on to the normalized base $2^{(j+1)/2}\phi(2^{j+1}t-m)$ and according to previous equations , it is $s_{j+1}(m)$

Therefore

$$s_j(k)=\sum_{m=2k}^{2k+N-1} h(m-2k)s_{j+1}(m)$$

The corresponding relationship for the wavelet coefficients is

$$d_j(k)=\sum_{m=2k}^{2k+N-1} g(m-2k)s_{j+1}(m)$$

The Haar wavelet fusion is performed based on the above process. The proposed approach uses Daubechies wavelet. The daubechies wavelets are a family of orthogonal wavelet which defines a discrete wavelet transform. It is characterized by a maximal number of vanishing moments. The concept of daubechies wavelet is similar to Haar and differs in how scaling and wavelet functions are defined [10].The proposed approach is compared with the Haar wavelet based fusion[11]

2.2 SVD

SVD is a technique which factorises matrix A into three matrices u , v and $\sum$ such that $A=u\sum v^{T}$. According to Pythagoras theorem the sum of the squares of the lengths of all data points is equal to the sum of squares of all the elements of the matrix A [12].

Consider two unit norm vectors $e_1=\begin{bmatrix}1\\0\end{bmatrix}$ and $e_2=\begin{bmatrix}0\\1\end{bmatrix}$

Ae_1 and Ae_2 represents x_1 and x_2 coordinates of all data points.

Let S represent the total variation of the data.

$$S=(Ae_1)^{T}(Ae_1)+(Ae_2)^{T}(Ae_2)$$

$$S=e_1^{T}A^{T}Ae_1+e_2^{T}A^{T}Ae_2$$

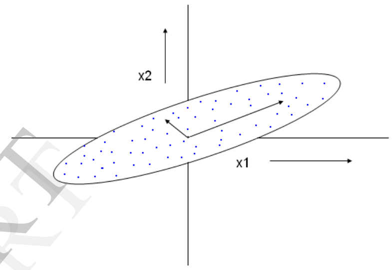

Fig 1-Geometrical approach of SVD [12]

The principal axis of the ellipse represents the direction along which data is distributed. The remaining variation is along an axis perpendicular to yhe principal axis. A 2-d vector can be decomposed into two components in any two orthogonal direction. Consider two orthogonal unit vectors v_1 and v_2 and project data onto those vectors.

$$S=v_1^{T}A^{T}Av_1+v_2^{T}A^{T}Av_2$$

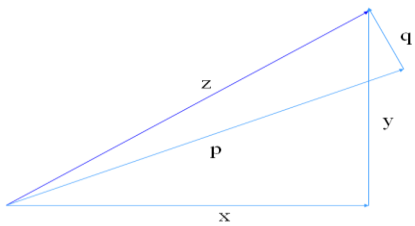

Fig 2-Pythagoras theorem [12]

$$z^2=x^2+y^2 \text{ and } z^2=p^2+q^2$$

Consider two unit norm orthogonal vectors v_1 and v_2 such that maximum variation along v_1 axis which is at 45 degree to the x axis.

$$v_1 = \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$$

The variation along this direction is

$$(Av_1)^T (Av_1) = v_1^T A^T A v_1$$

This is obtained by solving an optimization problem.

$$\max v_1^T A^T A v_1$$

$$subject\,to\, v^T v = 1$$

Taking Lagrangian and applying first order optimization condition.

$$L(v,\lambda) = v^T A^T A v - \lambda(v^T v - 1)$$

$$\frac{\partial L}{\partial v} = 2A^T A v - 2\lambda v = 0 \Rightarrow A^T A v = \lambda v$$

The direction is given by eigen vector of $A^T A$. Choose the eigen vector corresponding to largest eigen value λ represent variation along direction v.

$$v^T A^T A v = v^T \lambda v = \lambda v^T v = \lambda$$

Let $Av_1 = a_1 u_1$. Av represent the component of each data point. Similarly $Av_2 = a_2 u_2$.

$$A\begin{bmatrix} v_1 & v_2 \end{bmatrix} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix}$$

$$AV = U\Sigma$$

Since the columns of V are orthonormal, $V^T V = I$

$$A = U\Sigma V^T = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \end{bmatrix}$$

The dimensions of each matrix can be

$$A_{m\times 2} = U_{m\times 2} \Sigma_{2\times 2} V_{2\times 2}^T$$

Applications of SVD includes system identification [13], order determination [14], image coding [15] etc.

3. PERFORMANCE EVALUATION

The quality of the proposed image fusion method is evaluated based on certain parameters such as Peak Signal to Noise Ratio(PSNR), Normalized cross correlation, Structured content, Mean Squared Error(MSE), Normalized absolute error(NAE) [11,16]

Mean Squared Error (MSE): It is the average of the squares of errors. Error is the amount by which the value implied differs from the original value. The image quality decreases as MSE increases.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[I(i,j) - K(i,j) \right]^2$$

Peak Signal to Noise Ratio (PSNR): It is the ratio between the maximum possible power of a signal and the power of noise that affects the fidelity of the output. The image quality increases as PSNR increases.

$$PSNR = 20\log_{10}\left(\frac{MAX_i}{\sqrt{MSE}}\right)$$ where MAX_i is the maximum possible pixel value of the image.

Normalized cross correlation (NC): Cross correlation is the measure of similarity of two images. In image processing applications the brightness of the image can vary due to exposure conditions, so images can be first normalized. The image quality increases as NC increases.

$$NC = \frac{1}{n} \sum_{x,y} \frac{\left(f(x,y) - \bar{f}\right)\left(t(x,y) - \bar{t}\right)}{\sigma_f \sigma_t}$$

where n is the number of pixels in $t(x,y)$ and $f(x,y)$, $\bar{f}$ is the average of f , σ_f and σ_t are standard deviations

Structured Content (SC): It is the ratio between the content of the both the expected and the obtained data. Practically, it is the ratio between the net sum of the square of the expected data and the net sum of square of the obtained data.

$$SC = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(A_{ij}\right)^2}{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(B_{ij}\right)^2}$$

Where *m* is the height of the Image implying the number or pixel rows, *n* is the width of the image, implying the number of pixel columns. *A(i,j)*being the pixel density values of the perfect image. *B(i,j)* being the pixel density values of the fused image. The quality of the image increases while SC decreases.

Normalized absolute error (NAE): It is a metric where the error value is normalised with respect to the expected data..

$$NAE = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(\left|A_{ij} - B_{ij}\right|\right)}{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(A_{ij}\right)}$$

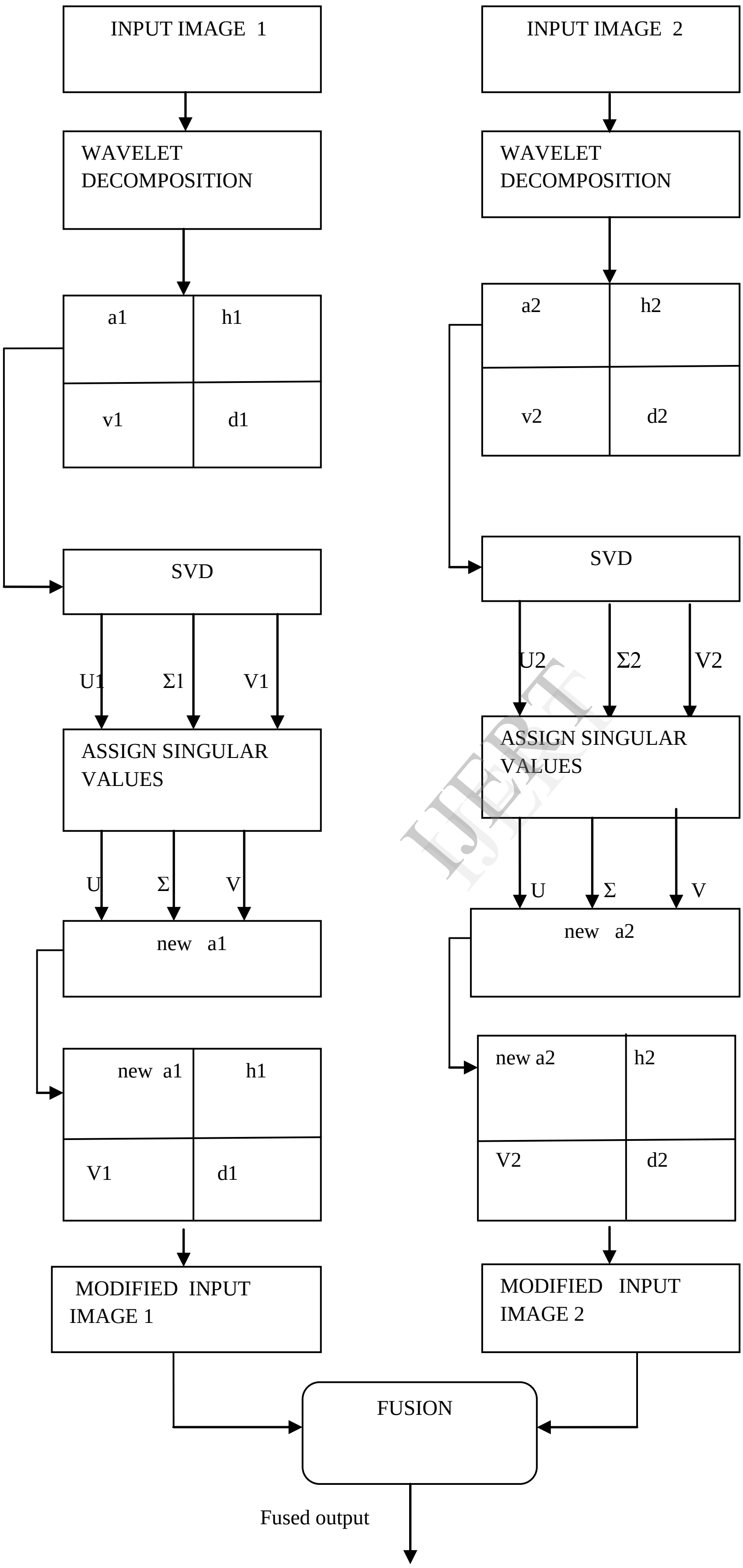

Fig 3.BLOCK DIAGRAM OF PROPOSED APPROACH

4. PROPOSED METHOD

In this method image fusion is carried out in two blurred input images. The block diagram of the proposed method is given figure 3. As the first step, wavelet decomposition is applied to the input images and thereby decomposing the image into components namely, a,,h,v and, d. which represents approximation, horizontal, vertical, detail coefficient respectively. In this method, approximation coefficient is taken alone for applying the following technique. This is achieved by applying Singular value decomposition to the input images that would make the good information in each of the image prominent. In this method, image is decomposed into 3 components U, $\sum$ and V^T which contains its information. In this, U&V are orthonormal matrices and Σ represents a diagonal matrix,which gives the values of variations of data points. Columns of V are eigen vectors of matrix $A^T A$. Columns of U are projections of A (or data points which are rows of A) on to columns of V .Σ is a diagonal matrix and diagonal elements are square root of variation of data points along the columns of V. This new approximation coefficients is inserted into the place of old approximation coefficient along with h,v and d. . By this approach fused output can be obtained by taking only certain components. Here, assigning different singular values means taking reduced number of components from each matrix U, $\sum$, V by preserving the actual image size. After that image fusion is performed using this reduced number of components and thus obtained the fused output .

5. RESULTS AND DISCUSSION

In this section, the performance of proposed method of SVD based wavelet image fusion is tested using one standard data set which contains two blurred images. These results are compared with the results of fusion carried out by the method of Haar wavelet based image fusion on the same set of input images.

The SVD based wavelet approach is tested using different values of singular values, k as 10 to 150. Table 2 shows the different image quality parameters for different values of k, i.e. for different singular values. On the other hand Table 1 shows comparison of image quality parameters of the proposed approach and Haar wavelet based image fusion with the same input image set.

Here Fig 4,5and6 shows the datasets which contains input images for fusion &the reference image respectively. Fig 7 to fig 10 illustrates the output images for different singular values from 10 to 150. Fig 11 gives the image resulted from Haar wavelet based image fusion. From input images it is understood that some parts of input images are blurred, which reduces the visual information. The perfect image shown in fig 6, act as the reference image for deciding the image quality measures of the output image. Simulation results part displays the various output images for various singular values using the proposed SVD based wavelet fusion method. Based on these output images Table-1 is created, which gives the various image quality discriminators. From fig 7 to fig 10, it is understood that output image quality is varied according to the change in singular values,k. As the singular value is getting changed from 10 to 150, the image quality has increased and high quality image is obtained. The detailed analysis can be done by using the table-2. In this, values of various image quality parameters as PSNR(peak signal to noise ratio),MSE(mean square error),NCC(normalised cross correlation),SC(structural content), andNAE(normalised absolute error) are measured with reference to the perfect image is given.

The value of PSNR(Peak Signal to Noise Ratio) is always having a high value for good quality images. In the table it is seen that the PSNR value is 23.64 when singular value (k) is 10.It has reached 31.21 for k=150.from this it can be concluded that the image quality is very good& high for higher values of k. Similarly M.S.E which indicates the mean square error of two images hose value should be very low for good quality visual images. Here M.S.E has changed from 280.7252 (for k=10) to 49.149(for k=150).This indicates that the value of error is very low for higher value of k ,ie singular value and image quality of output image is high and give more information. When coming to the case of NC (Normalised Cross Correlation), it is well understood that its value is quite high for good visual images with reference to perfect image. It canbe observed that here, when the singular values has increased from k=10 to 150 the value of NC also gets increased from 0.9502 to 0.9861.This gives us an indication about good image quality of the fused output through the proposed approach. Similarly while considering the case of SC(Structural Content), it should be low for good visual images. In When looking in to that,it is seen that it is decreased from 1.0564(for k=10) to 1.02(fork=150).It indicates the good quality output image with high information content for high singular value ,k=150.

As a last factor NAE(Normalised Absolute Error),) is considered.It is known NAE should be low for high image quality.Here it is observed that it decreases from 0.1840(for k=10) to 0.0488(for k=150. So it can be concluded that the output image obtained by the proposed svd based wavelet fusion is yielding higher quality for higher singular value.

The simulation results are shown below.The outputs for various singular values are given. It is depicted in the plots given in Fig 12 to fig 16-, which indicates the variation of different parameters with singular value,k.

In fig 11 the output obtained by Haar wavelet based image fusion is given. Table 1 shows the values of image quality measures for the outputs obtained by Haar wavelet and SVD based wavelet fusion. In this it is seen that the value of PSNR is 31.20 for the proposed method while it is 24.75 for haar wavelet based method. Here SVD based wavelet method gives good result as explained earlier. Similarly other parameters also indicate that SVD based fusion gives better results than Haar wavelet based fusion.

5.1 Observed results

Fig 4 – Input image1

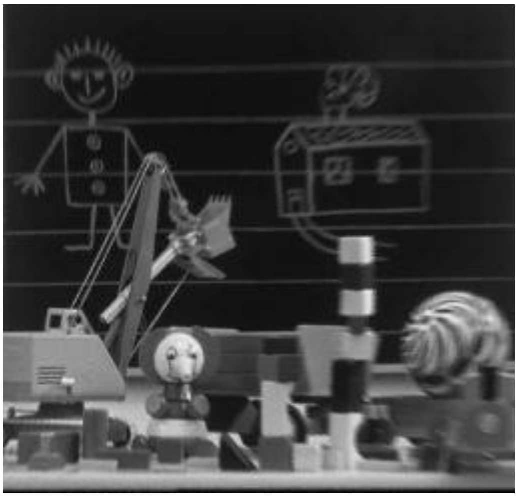

Fig 5- Input image2

Fig 6-Reference image

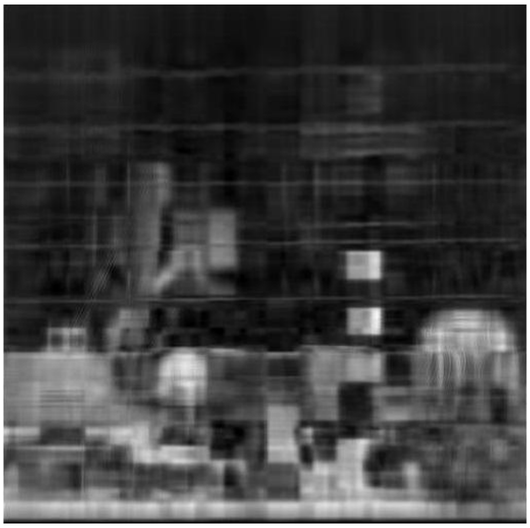

Fig 7 - Output image(k=10)

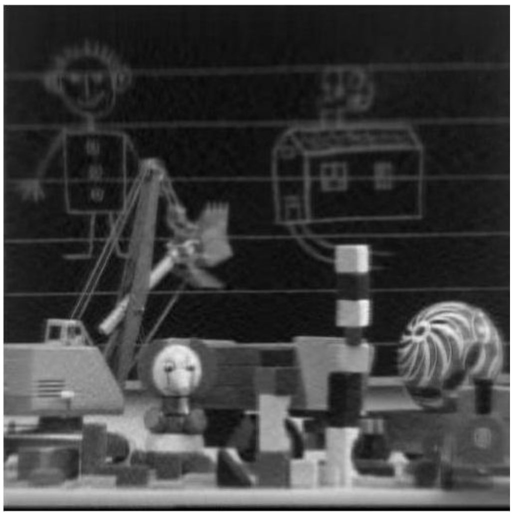

Fig 8- Output image(k=50)

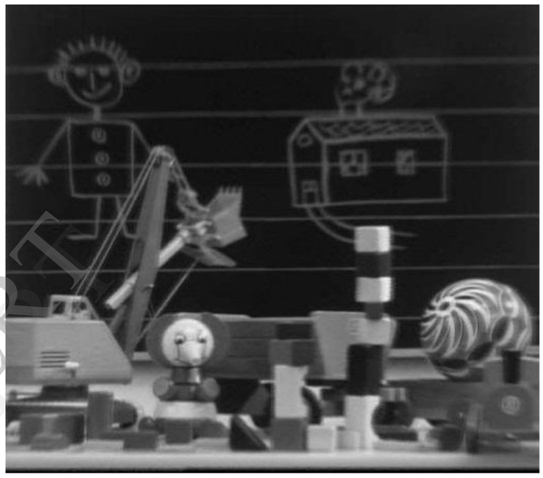

Fig 9- Output image(k=100)

Fig 10- Output image(k=150)

Fig 11- Output image for wavelet based fusion

5.2 Comparative study of outputs

The performance discriminators of output images of SVD based wavelet fusion for different singular values are computed& tabulated as follows. This helps for the comparison of two methods.

Table 1, Comparison of SVD and PCA Based Fusion

Parameters	SVD with k=150	Haar wavelet based fusion
PSNR	31.2157	24.75
MSE	49.1490	217.25
NC	0.9861	1.0206
SC	1.0201	0.9285
NAE	0.0488	0.1017

Table 2, performance of SVD for different values of k

K	PSNR	MSE	NC	SC	NAE
10	23.64	280.7252	0.9502	1.0564	0.1840
20	26.44	147.5162	0.9714	1.0340	0.1269
30	28.14	99.61	0.9784	1.0275	0.0993
40	29.25	77.24	0.9818	1.0242	0.0825
50	30.03	64.55	0.9836	1.0226	0.0717
60	30.54	57.39	0.9847	1.0216	0.0641
70	30.84	53.56	0.9853	1.0210	0.0591
80	31.01	51.49	0.9856	1.0206	0.0558
90	31.11	50.31	0.9858	1.0204	0.0535
100	31.16	49.74	0.9860	1.0203	0.0520
110	31.19	49.40	0.9860	1.0202	0.0509
120	31.20	49.28	0.9861	1.0202	0.0501
130	31.21	49.20	0.9861	1.0201	0.0495
140	31.2145	49.16	0.9861	1.0201	0.0491
150	31.2157	49.14	0.9861	1.0201	0.0488

6. CONCLUSION

An SVD (singular value decomposition)based wavelet image fusion approach was implemented in this paper. This can be used to fuse two low clarity input images to increase the clarity of the output image and to increase the visual perception. This method is implemented by the proposed approach by performing the wavelet decomposition of input images and taking approximation coefficient alone. Then SVD is applied to approximation coefficient &choosing certain components of SVD (U, Σ and V) of the input images based on a singular value. Thus approximation coefficient is replaced by the modified one. Then fusion of those images is performed. The quality of the images was assessed by the use of various image quality measures like PSNR, NC, SC, NAE and MSE. The quality of this output image was keeping on increasing as the singular value (k) increases and by the prposed method, output images of good clarity was obtained. After that SVD based fusion was compared with Haar wavelet based fusion. The comparative study of image quality discriminators point towards a conclusion that SVD based wavelet image fusion gives higher quality output&more visual information compared with Haar wavelet.This indicates a new method to obtain good output images by the fusion of blurred images.

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