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Comparative Analysis of Different Image Fusion Techniques for Sensor Application

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ABSTRACT

Image processing is one of the hot research topics for the researchers where processing/transformation of the images are done. Image fusion is the part of image processing where the unwanted data or redundancy in the sensed information is eliminated in the order to reduce the energy consumption and bandwidth of the sensor nodes present in the WSN. The output obtained from image fusion is having very high quality information about the object then compare to images sensed by the image sensor. In this paper different and one of the effective image fusion techniques i.e. image fusion using Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), Complex Wavelets (CWT) and Laplacian Pyramids are implemented and compared. Different performance parameters are used for the evolution of performance. The result shows that PCA leads with greater remark in most of the times, sometimes DWT and CWT depending upon the decomposition levels. Worst performance by the Laplacian pyramid.

Keywords: Image Fusion, Redundancy, PCA, Wavelet transform, Pyramids, Standard Entropy, Image Sensor.

1. INTRODUCTION

Image Processing is a technique to enhance raw images received from sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications for which they were first developed. The result obtained by processing is having greater quality with clear visibility of the objects present sensed image. There are two types of images, analog image and digital image. Now days we all preferring digital image processing as it is having more advantages than compare to analog image processing (Anil, 1989). Some of the fundamental steps involved in image processing are image representation, image preprocessing, image enhancement, image restoration, image analysis, image reconstruction and image data compression (Gonzalez, 1992). Image processing can be used in

remote sensing, medical imaging, forensic studies, textiles, material science, military, graphic arts, printing industry, etc.

On the other hand image fusion is a process where unwanted data in the sensed image are removed and only required information which is more informative is sent to the controller or to the base station (Elmenreich, 2002). In other way image fusion reduces the amount of data and creates new images which are more suitable for human observation or further processing of images. Image fusion improves the reliability (by redundant information) and capability of the images (by redundant information), (Lehigh University). The image fusion can be used in target reorganization, object detection, military applications, medical imaging, Industrial applications, computer vision and robotics (Haghighat et al. 2011; Hong et al. 1999).

Figure 1 shows the image fusion system. Here it combines two images which are having same object information but some of the information is not clear in image 1 but those information's are clear in image 2 so instead of sending two images here fusing of the images is done, the type of fusing technology is dependent on the user's desire. The fusion methodology can be averaging the images or addition of the images or subtraction of the images or minimum of two images or maximum of two images (Eduardo Fernandez Canga, 2002).

Some of the popular image fusion techniques are Principal Component Analysis, Simple Averaging, Pyramid Based Image fusion, image fusion using wavelets, IHS Transform based image fusion, pair-wise spatial frequency matching and high pass filtering techniques (Deepak Kumar Sahu and Parsai, 2012). These image fusion techniques try to enhance the digital image without spoiling it. The fusion is performed at three different levels i.e pixel level image fusion, feature level image fusion and decision level image fusion. In this paper different image fusion techniques like Image Fusion using PCA, DWT, CWT and Laplacian Pyramid are simulated and are compared by using some standard performance parameters like Root Mean Square Error (RMSE), Signal to noise Ratio (SNR), Peak signal to noise ratio (PSNR), Mean Absolute Error (MAE), Entropy and Standard Deviation. The organization of the paper is as follows, section II presents explanation about different image fusion techniques, section III describes the simulation of different image fusion techniques, section IV gives results and discussion finally section V concludes the paper.

2. IMAGE FUSION TECHNIQUES

Image fusion is a tool to fuse multisource images using advanced image processing techniques. Image fusion aims at the combination of disparate and complementary data to improve the information visible in the images as well as to increase the reliability of the analysis. This leads to more accurate data and improved utility. There are various methods that have been developed to perform image fusion. Some of the popular and known image fusion techniques are listed below.

1. Principal Component Analysis (PCA) based Fusion
2. Intensity Hue Saturation transform (IHS) based fusion
3. High-pass Filtering method
4. Pyramid Method
 - a. Gaussian Pyramid
 - b. Laplacian Pyramid
 - c. Gradient Pyramid
 - d. Morphological Pyramid
 - e. Ratio of Low Pass Pyramid
5. Wavelet Transform
 - a. Discrete Wavelet Transform (DWT)
 - b. Stationary Wavelet Transform (SWT)
 - c. Multi-wavelet Transform (MWT)
 - d. Complex Wavelet Transform (CWT)
6. Curvelet Transform

In this paper we are concentrating on four popular image fusion techniques i.e image fusion using PCA, DWT, CWT and Laplacian Pyramid.

2.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is mainly used in image compression and image classification techniques. Principal Component Analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis in other words PCA transform the number of correlated variables into uncorrelated variables called principal components. The main advantage of PCA is, when its data size is compressed as well as if dimensions are altered then there is no much loss of information at the output image (Metwalli et al. 2009; Yue-Hao

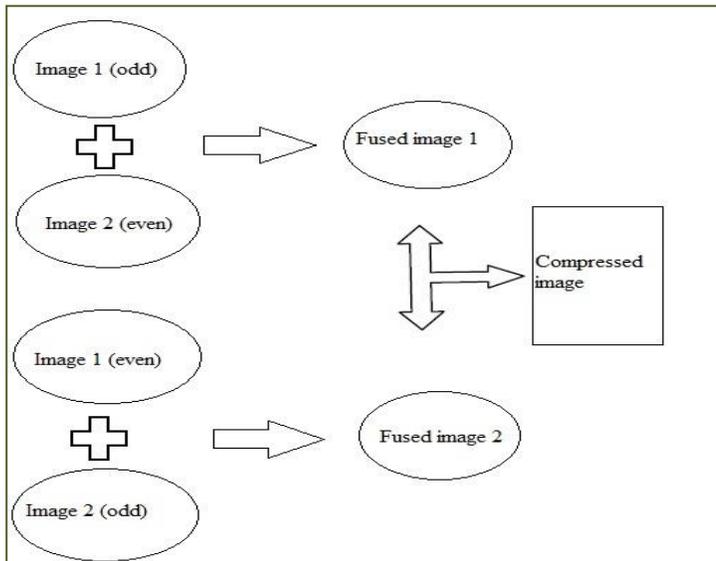


Figure 1
Image Fusion System

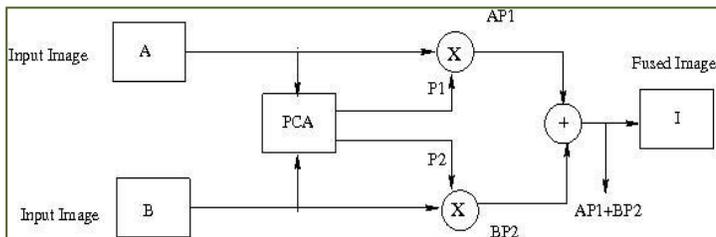


Figure 2
Image Fusion using Principal Component Analysis

LL	LH ¹	Low High ²	1
HL	HH		
High Low		High High	Low High
High Low		High High	

Figure 3
2-D DWT for Image

et al. 2012). The fusion is achieved by weighted average of images to be fused. The weights for each source image are obtained from the Eigen vector related to the largest Eigen value of the covariance matrices of each source. It computes a compact and optimal description of the data set. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set. PCA can also be called as Hotelling Transform or Karhunen-Loève transforms (Anjali Malviva and Bhirud, 2009).

In this the first principal component is taken along the direction of the maximum variance. The second principal component is forced to lie in the subspace vertical (perpendicular) of the first. Within this subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace vertical to the first two and so on (Naidu and Raul et al. 2008). The image fusion using Principal component analysis is represented in Figure 2. The information flow diagram of PCA-based image fusion algorithm is shown in Figure 2. The input images (images to be fused) A (x, y) and B (x, y) are arranged in two column vectors and their empirical means are subtracted. The resulting vector has a dimension of $n \times 2$, where n is length of the each image vector. Compute the eigenvector and eigenvalues for this resulting vector are computed and the eigenvectors corresponding to the larger eigenvalue obtained. The normalized components P1 and P2 (i.e., $P1 + P2 = 1$) are computed from the obtained eigenvector. The fused image is: $I = AP1 + BP2$.

2.2. Discrete Wavelet Transform (DWT)

In discrete wavelet transform an image signal can be analyzed by passing it through analysis filter banks followed by decimation operation. This analysis filter bank, consisting of low pass and high pass filters at each decomposition stage is commonly used in image compression. When the signal is passed through this filter it corresponds to an averaging operation, extracts the courser information of signal. The high pass filter corresponds to a differencing operation, extracts the finer information of the signal. The outputs of the filter are then decimated by a factor of two (Bahram Jayidi, 2006). Finally, the image is split into four bands denoted by LL, HL, LH and HH after one-level decomposition. Further decompositions can be achieved by acting upon the LL sub band successively and the resultant image is split into multiple bands as shown in the figure 3.

In images fine information content is generally found in the high frequencies where as the courser information content in the

low frequencies. The wavelet transform uses its multiresolution capability to decompose the image into multiple frequency bands (Wang et al. 2002). First the wavelet transforms of the images are computed. The wavelet transform contains the low-high bands, the high-low bands and high-high bands of the image at different scales. Since large absolute transform coefficients correspond to sharper brightness changes, a good integration rule is to select, at every point in the transform domain, the coefficients whose absolute values are higher. In this way the fusion takes place in all the resolution levels and the more dominant features at each scale are preserved in the new multiresolution representation. Subsequently a new image is constructed by performing an inverse wavelet transform. The process of 2 Dimensional DWT based image fusion is as shown in figure 4.

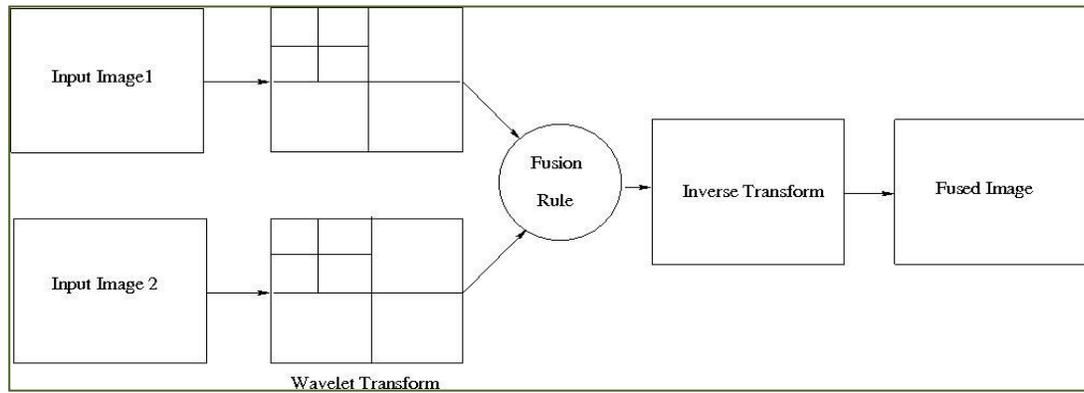


Figure 4
2-D DWT Image fusion

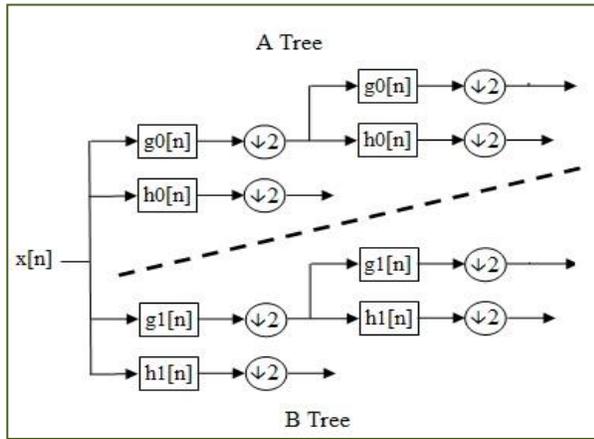


Figure 5
2-Level Dual Tree CWT

2.3. Complex Wavelet transforms (CWT)

The complex wavelet transform (CWT) is a complex-valued extension to the standard discrete wavelet transform (DWT). It is a two-dimensional wavelet transform which provides multi-resolution, sparse representation, and positive characterization of the arrangement of an image. The areas of the images more in focus give rise to larger magnitude coefficients within that region. A simple choose maximum scheme is used to produce the combined coefficient map. The resulting fused image is then produced by transforming the combined coefficient map using the inverse complex wavelet transform. The wavelet coefficient images show the orientated nature of the complex wavelet sub-bands

(Kingsbury et al. 1999; Neumann and Steidl, 2003). The motivation for using the DT (Dual-Tree)-CWT (Selesnick et al. 2005) for image fusion is its shift invariance together with its reduced over completeness when compared with the shift invariant discrete wavelet transforms (SIDWT). The improved directional selectivity of the DT-CWT should also provide improved result over the SIDWT. The complex wavelet transform was used with the filters given in designed for improved shift invariance. The Block diagram of 2-level Dual Tree CWT is as shown in figure 5.

2.4. Laplacian Pyramid

Image pyramids have been initially described for a multi-resolution image analysis and as a model for the binocular fusion in human vision. An image pyramid can be described as collection of low or band pass copies of an original image in which both the band limit and sample density are reduced in regular steps (Yaonan Wang et al. 2000). Burt and Adelson introduced the Laplacian algorithm in 1983 as a technique of image encoding (Burt and Adelson, 1983). However, it is not the encoding itself what is interesting for this research but the capability of multi-resolution pyramid transformation. A multi resolution pyramid transformation decomposes an image into multiple resolutions at different scales. A pyramid is a sequence of images in which each level is a filtered and sub-sampled copy of the predecessor. The lowest level of the pyramid has the same scale as the original image and contains the highest resolution information. Higher levels of the pyramid are reduced resolution and increased scale versions of the original image. Laplacian pyramid of an image is a set of band pass image; in which each is a band pass filtered copy of its predecessor. Band pass copies can be obtained by calculating the difference between low pass images at successive levels of a Gaussian pyramid. In Laplacian fusion method the following steps are involved: 1) Find the Gaussian pyramid, 2) generation of fused pyramid from Laplacian pyramid, 3) Decoding of the fused image. Fusion is done by considering the average values of the each pyramid level of the corresponding input images $I_1(x, y)$ and $I_2(x, y)$. They are added to obtain fused pyramid. Fused image is obtained by expanding and then summing all the levels of the fused pyramid (Burt and Adelson, 1983). The Following figure 6 shows the block representation of the Laplacian Algorithm.

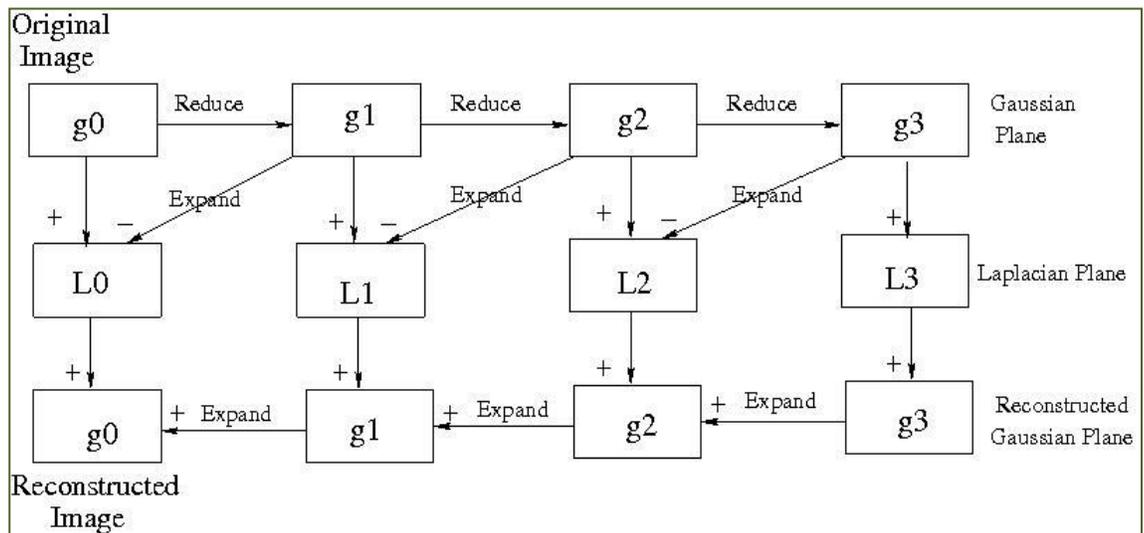


Figure 6
Block Representation of the Laplacian Algorithm

3. SIMULATION

In this case we are considering four image fusion techniques i.e image fusion using PCA, DWT, CWT and Laplacian Pyramid. The techniques are simulated in MATLAB 7.8 (2009R) version. The steps required in the simulation of each of the techniques are mentioned below.

3.1. Algorithm for Image Fusion using Principle Component Analysis

Let the input images (images to be fused or source images) be arranged in two-column vectors. The steps followed to project this data into 2-D subspaces are (Hui Zou et al. 2004; Naidu and Raol. 2008):

1. Organize the data into column vectors. The resulting matrix Z is of dimension 2 x n.
2. Compute the empirical mean along each column. The mean vector **Me** has a dimension of 1 x 2.
3. Subtract the empirical mean vector **Me** from each column of the data matrix Z. The resulting matrix X is of dimension 2 x n.
4. Find the covariance matrix C of X that is $C=XX^T$ mean of expectation = cov(X)
5. Compute the eigenvectors V and Eigen value D of C and sort them by decreasing Eigen value. Both V and D are of dimension 2 x 2.
6. Consider the first column of V which corresponds to larger Eigen value to compute P1 and P2 as

$$P_1 = \frac{V(1)}{\sum V} \quad P_2 = \frac{V(2)}{\sum V}$$

At normalization $P_1+P_2=1$.

7. Fused Image I= A(x,y)P1+B(x,y)P2

3.2. Image Fusion using Laplacian Pyramid

1. Compute the reduced resolution approximation of level g_0 of the input image A and image B. This is done by filtering by using 5X5 Gaussian filter and down sampling the filtered result by the factor 2. Place the resulting image at the level g_1 of the approximation pyramid.
2. Create an estimate of the level g_0 input image from the reduced resolution approximation of the step1.This is done by up sampling and filtering the generated approximation .The resulting prediction image is the will have the same dimension as the level g_0 input image, which is a laplacain Pyramid .
3. Compute the difference between the predicted image of step 2 and the input of step 1.Place the result in level g_0 of the prediction residual pyramid.
4. Take the mean of Pyramid A which is resultant of image A and Pyramid B which is resultant of image B and add weighted average of these two Pyramid, resulting Pyramid is the fused Pyramid of each corresponding level.
5. The original image can be recovered exactly by expanding, then summing all the levels of the Fused Pyramids.



Figure 7
Reference Image $I_r(x,y)$



Figure 8
Source Image $I_s(x,y)$



Figure 9
Source Image $I_2(x,y)$



Figure 10
PCA fused image



Figure 11
DWT fused image



Figure 12
CWT fused image



Figure 13
Laplacian pyramid fused image

Table 1
Performance evaluation metrics to evaluate image fusion algorithm

	Laplacian	PCA	DWT	CWT	Referred original image
RMSE	33.915	27.606	46.487	41.579	Yes
SNR	12.863	9.962	27.276	28.212	Yes
MAE	0.86	1.95	3.932	3.696	Yes
PSNR	40.212	73.44	63.874	65.744	Yes
PFE	1.147	1.87	1.376	1.38	Yes
SD	69.043	73.40	73.935	74.63	No
Image quality	Average	GOOD	GOOD	BETTER	

3.3. Image Fusion using Discrete Wavelet Transform

Apply the DWT to Images A and B (geometrically registered images).

1. Take the average of the approximate coefficients of two images repetitively and store the resultant in one matrix.
2. Apply the binary decision map tree in order to choose the detail coefficients between the two images detail coefficients and store the result in the matrix.
3. Apply the IDWT to get the fused image.

3.4. Image Fusion using Complex Wavelet Transform

1. Take Test Images
2. Apply Dual Tree CWT to each of the test images
3. Set the decomposition level (Here we have considered 3 level decomposition)
4. Combine the complex wavelet coefficients (Magnitudes)
5. Applying inverse Dual Tree CWT (Reconstruction)
6. Generating Final fused images.

4. RESULTS

Two scenes are considered here. For each scene two image sensors are used. Captured images from both image sensors are applied to all the four techniques. Six performance parameters are considered here namely, RMSE, SNR, MAE, PSNR, Standard Deviation and Image Quality to check the performance of each of the techniques. The results and their performance analysis are as represented below.

Nomenclature:

X_{obs} = Observed Values, X_{model} = Modeled Values, I , I_f , I_s , I_h , I_r : Representation of the source, fused, LPF, HPF, and reference images, y_i =True Value, e_i = Absolute Errors, f_i =Prediction, h_{if} = Histogram of Fused Image. h_{ir} = Histogram of Reference Image, I_1 , I_2 = Input Images, M , N : sizes of the image, L = Total gray levels,

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs, i} - X_{model, i})^2}{n}}$$

Where X_{obs} and X_{model} values at time/place i .



Figure 14
Reference Image $I_r(x,y)$



Figure 15
Source Image $I_s(x,y)$



Figure 16
Source image $I_2(x,y)$



Figure 17
PCA fused image



Figure 18
DWT fused image



Figure 19
CWT fused image



Figure 20
Laplacian pyramid fused image

Signal-to-Noise Ratio (SNR):

$$SNR = 20 \log_{10} \left(\frac{\sum_{i=1}^n \sum_{j=1}^n (I_r(i,j))^2}{\sum_{i=1}^n \sum_{j=1}^n (I_r(i,j) - I_s(i,j))^2} \right)$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^n |f_i - y_i| = \frac{1}{n} \sum_{i=1}^n |e_i|$$

Peak Signal-to-Noise Ratio (PSNR):

$$PSNR = 20 \log_{10} \frac{L^2}{\frac{1}{MN} \sum_{i=1}^n \sum_{j=1}^n (I_r(i,j) - I_s(i,j))^2}$$

STANDARD DEVIATION (SD):

$$\sigma = \sqrt{\sum_{i=0}^L (i - \bar{I})^2 h_i f(i)}$$

Where $\bar{I} = \sum_{i=0}^L I * h_i f(i)$

4.1. Scene 1

In this case a cat image is taken (Figures 7-13; Table 1). Here one original image (Reference Image) and two source images are taken and are applied to all four techniques and output image i.e fused image is sometimes compared with the reference image for performance metric calculation. Finally a table is drawn which gives all the information regarding the techniques performance and image quality.

4.2. Scene 2

The above said operation is repeated here also and finally a table is drawn to compare all four image fusion techniques (Figures 14-20; Table 2). The performance of the image fusion algorithms could be estimated precisely when the ground truth (without reference) image is not available. The metrics showed in the table 1, table 2 bolded font are better among others.

5. CONCLUSION

This paper has demonstrated the potential of image fusion technique as a tool for improving the quality of the sensed images. All techniques try to reduce the data size without affecting the important content in the sensed images also gives high quality information regarding the objects present in the images. Here mainly four image fusion techniques have been simulated and compared i.e. image fusion using DWT, CWT, PCA and Laplacian Pyramid. These techniques are simulated with and without reference image. The results show that the performance by the Laplacian pyramid is worst in all the cases and the performance of PCA is very good for most of the cases, some other times DWT performance hold good. CWT's performance was better then compare to DWT, PCA and Laplacian Pyramid if decomposition

Table 2

Performance evaluation metrics to evaluate image fusion algorithm

	Laplacian	PCA	DWT	CWT	Referred original image
RMSE	44.72	40.88	77.48	73.375	Yes
SNR	10.84	5.96	22.33	22.826	Yes
MAE	1.016	3.47	6.67	6.423	Yes
PSNR	38.74	67.824	56.59	57.581	Yes
PFE	2.047	3.954	2.564	2.41	Yes
SD	52.36	54.662	56.59	56.96	No
Image quality	Average	BETTER	GOOD	GOOD	

level is increased. The results of wavelets depend upon the decomposition levels. The results will be much better if one goes for higher level decomposition then just going for single level decomposition but these things are not required in PCA.

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