Cluster Based Evaluation of Image Fusion Algorithms

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Abstract

The general requirements of an image fusion process are that it should preserve all valid and useful pattern information from the source images, while at the same time not introducing any artifacts. However it is not possible for the fusion algorithms to combine images that may contain all information from the source images without introducing some form of artifacts. As the image fusion technologies have been developing in many applications such as remote sensing, medical imaging, machine vision, military applications in recent years, the methods that can assess or evaluate the performance of fusion algorithms are of very important. Since the various image fusion algorithms combine images at different levels, they may result in some form of artifacts in the fused image. Hence more number of methods or quality metrics is required to evaluate the quality of fused image. This paper described twelve image quality metrics which are used to evaluate the quality of an image. Using these metrics, some of the image fusion algorithms are evaluated and are clustered into three groups (good, average and worst) using Fuzzy-C-Means (FCM) clustering technique by considering the cumulative metric value as an objective criterion.

Keywords: Image Fusion, Quality Metrics, Pyramid, FCM.

1. Introduction

Image fusion is a sub-field of image processing in which more than one image are fused to create a single image which is more informative and accurate than any of the source images. The process of image fusion is performed for multi-focus, multi-sensor, multi-temporal, multi-modality images. In multi-focus images, the objects in the scene which are closer to the camera are in focus and the farther objects get blurred. When the farther objects are focused, the closer objects get blurred. To achieve an image where all the objects are in focus, the image fusion is used. In remote sensing applications, most remote sensing sensors [20], such as Landsat 7, SPOT, Ikokos, QuickBird, GeoEye-1, and WorldView-2, simultaneously collect low resolution MS and high resolution Pan Images. To effectively fuse the low resolution MS and high resolution Pan images efficient fusion algorithms are required. Satellites, such as QuickBird, IKNOS, IRS, bundle 1:4 ratio of a high resolution (HR) panchromatic (PAN) band and low resolution (LR) Multispectral (MS) bands in order to support both spectral and spatial resolutions [11]. Image Fusion algorithms are used to combine the spatial information present in the PAN image and spectral information present in the LR MS images into an single image. Whereas in Medical applications, multi-modality images of the same scene are captured by different modalities (IR, MRI, PET, and EMRI) results in an image containing different pattern information. Multi-temporal images of the same scene are captured by same camera but at different times. In all these cases, to obtain an image that contains all details, image fusion is used.
Image fusion is generally performed at three different levels of information representation that is pixel level, feature level and decision level [10,7,12]. In pixel level image fusion, simple mathematical operations are applied on the pixel or intensity values the source images. However these methods usually smoothens the sharp edges or leave the blurring effects in the fused image. In feature level image fusion, the source images are segmented into different regions (features) and the values are calculated for the segmented regions. Using any of the fusion rules, the features are selected and combined to get a fused image. In decision level image fusion, the objects in the source images are detected first and then fused using any of the fusion algorithms.

A number of image fusion algorithms have been presented in the literature [13,11]. This paper considers Simple Fusion Methods, PCA and Pyramid Fusion Methods based on pixel level. A brief description about these methods and also its pseudo-code was presented in the conference [10].

Evaluation of Image Fusion algorithms are of very important, since quality of a fused image is required. Some of the reference image quality metrics was presented in the conference and fusion algorithms was quantitatively evaluated using those metrics [10]. This paper includes some more reference and non-reference metrics and based on that fusion algorithms are evaluated and classified using clustering technique. The data has been organized into an efficient representation that characterizes the population. Clustering [9], is a process in which observed data or entities are grouped together to form a number of clusters in such a way that the entities within a cluster are more similar to each other than those in other clusters.

2. Fusion Methods

a. **Simple Fusion Methods**

Simple fusion methods [10] such as simple average, weighted average, maximum selection, minimum selection perform some simple mathematical calculations on the raw pixel values of source images to get a fused image.

b. **Principal Component Analysis (PCA)**

Principal component analysis is a mathematical procedure that transforms a number of potentially correlated variables into a smaller number of uncorrelated variables called principal components. PCA also called as Hotelling Transform [13]. A common way to find the principal components of a data set is by calculating the eigenvectors of the data covariance matrix. The projections of the data on the eigenvectors are the principal components. The corresponding eigenvalues give an indication of the amount of information that the respective principal components represent. Principal components corresponding to large eigenvalues represent a large amount of information in the data set and that component is considered for fused image.

c. **Pyramid Methods**

Image pyramid is a data structure designed to support multi-resolution image analysis through reduced image representation [1]. An image pyramid can be described as a collection of low-pass or band-pass copies of an original image in which both sample density and resolution are decreased in regular steps. The basic strategy of image fusion based on pyramid is to construct a fused pyramid representation from the pyramid representations of the original images. The fused image is obtained by taking the inverse pyramid transform. There are several pyramid-based fusion schemes available and some of them are given below.

Laplacian Pyramid of an image is a set of band-pass images, 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 [5]. In Laplacian fusion approach the Laplacian pyramids for input images are used. A strength measure is used to decide form which source what pixels contribute at each specific sample location. For example local area sum can be used as a measure of strength.

Filter-Subtract-Decimate Pyramid is very similar to Laplacian pyramid and only the difference is in obtaining the difference images in creating the pyramids. In Laplacian pyramid, the difference image at level k is obtained by subtracting an image unsampled and then low-pass filtered at level k+1 from the Gaussian image at level k. Whereas in FSD pyramid [2, 5], this difference image is obtained directly from the Gaussian image at level k subtracted by the low-pass filtered image of Gaussian image. FSD pyramid fusion method is computationally more efficient than the Laplacian pyramid by skipping an unsampling step.

Gradient Pyramid is obtained by applying as set of 4 directional gradient filters (horizontal, vertical and 2 diagonal) to the Gaussian pyramid at each level. At each level, these 4 directional gradient pyramids are combined together to obtain a combined gradient pyramid [6] that is similar to a Laplacian pyramid. Therefore Gradient pyramid fusion is same as the Laplacian pyramid fusion except the Laplacian pyramid is replaced with the combined gradient pyramid.

Ratio of Low-Pass pyramid is constructed by taking the ratio of two successive levels of the Gaussian pyramid. Ratio of low-pass pyramid [13] is very similar to Laplacian pyramid fusion except replacing the Laplacian pyramid by the ratio of low-pass pyramid.

Morphological Pyramid is obtained by applying the morphological filters [12,15] to the Gaussian pyramid instead of low-pass or band-pass filters at each level and taking the difference between two neighboring levels. A morphological filter is used for noise removal and image smoothing. It is similar to low-pass filter, but it does not change shapes and locations of objects in the image. It composed of a number of elementary transformations like closing and opening transformations. The opening operator consists of other two operators, erosion followed by dilation. The morphological pyramid fusion is similar to Laplacian pyramid fusion except replacing the Laplacian pyramid by the morphological pyramid.

Contrast Pyramid construction is similar to ratio of low-pass pyramid. Contrast is defined as the ratio of the difference between luminance at a certain location in the image plane and background luminance to the local background luminance. Contrast pyramid fusion [13] is performed as follows: First, a ROLP pyramid is constructed for each of the source images. Next, a Ratio of Laplace pyramid is constructed for fused image by selecting values from corresponding nodes of the component pyramids.

3. Image Quality Evaluation

Image quality assessment plays an important role in all image processing applications. Image quality metrics are used to benchmark different image fusion algorithms by comparing the objective metrics. The objective metrics quantify the difference in the fused image. Image fusion quality metrics can be divided into two categories: reference and non-reference [13] quality metrics. The reference quality metric evaluates against the reference image. These image fusion quality metrics may be either qualitative or quantitative. In practical applications, neither qualitative nor quantitative evaluation alone will satisfy the needs perfectly [14]. So mostly, both qualitative and quantitative assessments are used. By considering A and B as input images, F as Fused image and R as reference image, the quality metrics are defined as follows.

Non-reference Quality Metrics

The non-reference metrics [7,3,10] does not require an ideal image as a reference to calculate the metric values. The value is calculated either only by using a fused image or using both input images and fused image. These matrices are very useful when the reference image is not available.

a. Entropy (E)

Entropy is defined as amount of information contained in a signal. The entropy of the fused image can be evaluated as

$$E = -\sum_{i=0}^{L-1} p_i \log_2 p_i \tag{1}$$

Where L is the number of pixel levels in the fused image. P_i is probability of occurrence of a particular gray level i. Entropy can directly reflect the average information content of an image. If entropy of fused image is high, it indicates that the fused image contains more information.

b. Root Mean Square Error (RMSE)

RMSE between the input images and the fused image is defined as follows

$$E1 = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A(i,j) - F(i,j))^2} \tag{2}$$

$$E2 = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(B(i,j) - F(i,j))^2} \tag{3}$$

Then,

$$RMSE = (E1 + E2)/2 \tag{4}$$

Lesser value represents the fused image is good in quality.

c. Spatial Frequency (SF)

Spatial frequency is used to measure the overall activity of a fused image and is defined as

$$SF = \sqrt{SF^2 + CF^2} \tag{5}$$

Where RF and CF is row frequency and column frequency

$$RF = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=2}^{n}(F(i,j) - F(i,j-1))^2} \tag{6}$$

$$CF = \sqrt{\frac{1}{mn}\sum_{j=1}^{n}\sum_{i=2}^{m}(F(i,j) - F(i-1,j))^2} \tag{7}$$

A large value of special frequency describes the large information level in the image.

Reference Quality Metrics

The reference quality metrics [4,19] require an ideal image as a reference to calculate the metric values. The value is calculated using both input images and fused image.

d. Standard Deviation (SD)

The standard deviation represents the difference of an image

$$\sigma = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(R(i,j) - \overline{Z}))^2} \tag{8}$$

Where Z is the mean value of fused image. The bigger value of standard deviation means more different of two images.

e. Root Mean Square Error (RMSE)

RMSE between the reference image and the fused image is defined as follows.

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(R(i,j) - F(i,j))^2} \tag{9}$$

Higher the value represents the fused image is lower in quality.

f. Peak Signal to Noise Ratio (PSNR)

The PSNR between the reference image and the fused image is defined as follows.

$$PSNR = 10X \log_{10}\left(Peak^2 / MSE\right) \tag{10}$$

Higher the value represents the fused image is greater in quality.

g. Average Difference (AD)

The AD between the reference image and the fused image is defined as follows.

$$AD = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left|A_{ij} - B_{ij}\right| \tag{11}$$

Higher the value represents the fused image is more deviated from the reference image.

h. Structural Content (SC)

The Structural Content between the reference image R and the fused image F is defined as

$$SC = \sum_{i=1}^{m}\sum_{j=}^{n}\left(R_{ij}\right)^2 \Big/ \sum_{i=1}^{m}\sum_{j=1}^{n}\left(F_{ij}\right)^2 \tag{12}$$

It indicates the ratio between the contents of fused image and the reference. If this value is nearly equivalent to 1.0 both these images have same content.

i. Normalized Cross Correlation (NCC)

The Normalized Cross Correlation between the reference image R and the fused image F is defined as

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n} R_{ij} * F_{ij} \Big/ \sum_{i=1}^{m}\sum_{j=1}^{n}\left(R_{ij}\right)^2 \tag{13}$$

Higher the value represents the fused image is closer to the reference image.

j. Image Quality Index (IQI)

Image quality index measures the similarity between two images.

$$IQI = \frac{m_{ab}}{m_a m_b} \cdot \frac{2xy}{x^2 + y^2} \cdot \frac{2m_a m_b}{m_a^2 + m_b^2} \tag{14}$$

Its value ranges from -1 to +1. IQI is equal to 1 if both images are identical.

k. Cross Entropy (CE)

Cross entropy represents the difference of two images and defined as

$$CE = \sum_{i=0}^{L-1} p_i \log_2 \frac{p_i}{q_i} \tag{15}$$

The smaller value of entropy of intersection means the fusion acquires more information from the original image.

l. Normalized Absolute Error (NAE)

The Normalized Absolute Error between the reference image R and the fused image F is defined as

$$NAE = \sum_{i=1}^{m}\sum_{j=1}^{n} | R_{ij} - F_{ij} | \Big/ \sum_{i=1}^{m}\sum_{j=1}^{n} R_{ij} \tag{16}$$

Higher the value represents, the fused image is lower in quality.

4. Clustering Techniques

Clustering is a technology that is being used in many technologies [9] that are emerging today. Clustering means grouping of objects into different groups based upon some common characteristics.

The members of a cluster can't be defined very precisely as there are many ways to represent a cluster. The members are formed only based upon the way the cluster is defined. For example, at times the cluster might be defined very distinctively so that every member falls into a specific group. At other times the cluster may be overlapping with each cluster, thus making one member to fall in more than one group.

The most commonly used clustering techniques in many of the applications [17,18] are

1. K-Means Clustering
2. Fuzzy C-Means Clustering

In this paper, Fuzzy C-Means clustering is adapted to classify the fusion algorithms into various clusters [Good, Average & Worst] based on the cumulative value of quality metrics.

Fuzzy C-Means Clustering

Fuzzy clustering is a method to get "natural groups" in the fusion algorithms using an assumption of a fuzzy subset on clusters. The fuzzy set theory allows an element of the data to belong to a cluster with a degree of membership that has a value in the interval [0, 1]. The most known method of fuzzy clustering is the Fuzzy C-Means (FCM) method [8].

The membership grades of an entity decide the degree of the entity to which it belongs in a cluster in fuzzy set theory. Fuzzy C-Means tries to imitate K-means in minimizing the objective function

$$J = \sum_{i=1}^{c}\sum_{j=1}^{c1} \left(u_{ij}\right)^{m} \left\| x_{ij} - v_j \right\|^2 \tag{17}$$

Where u_{ij} is the membership degree of data x_i to the cluster v_j. The parameter m is called the fuzzifier factor and determines the level of cluster fuzziness. The objective of the Fuzzy C-Means algorithm is the minimization of the intra-cluster variability.

Each point is assigned a degree of belonging to a cluster in Fuzzy clustering. This degree determines the belonging of a point to multiple clusters rather than one cluster completely. The summation of the degrees of a point in all clusters is defined as 1. In Fuzzy C-Means the mean of degree of all points weighted against belonging to a cluster forms the centroid. The distance of the cluster is inversely proportional to the degree of belongings. Then the real parameter m>1 is used to conventionalize and fuzzify so that the sum equals 1.

The methodology used to for implementing the Fuzzy C-Means clustering is described as follows.

i. Fuse the input images using various fusion algorithms and obtain the fused image.

ii. Calculate the various metric values using the above mentioned equations for each fused image.

iii. Obtain the summative value of all metric values for each of the image.

iv. Define the number of clusters 'n'.

v. Call the built-in function 'fcm' by passing number of clusters and an array containing the summative metric value.

vi. Get the clustered plot and store it

5. Experiments and Results

The above mentioned fusion algorithms are tested with various multi-focus, multi-modality and multi-sensor images. For all data set, metric values are calculated and fusion algorithms are clustered using Fuzzy-C-Means clustering technique based on summative metric values (PSNR, SF, NAE an AD) as objective function. Since these metric values has predominant role in image fusion.

$$F = (PSNR + SF + NAE - AD) \tag{18}$$

Data Set1:

To allow helicopter pilots navigate under poor visibility conditions (such as fog or heavy rain) helicopters are equipped with several imaging sensors, which can be viewed by the pilot in a helmet mounted display. A typical sensor suite includes both a low-light-television (LLTV) sensor and a thermal imaging forward-looking-infrared (FLIR) sensor. In the current configuration, the pilot can choose on of the two sensors to watch in his display. A possible improvement is to combine both imaging sources into a single fused image which contains the relevant image information of both imaging devices. In Fig.1 a1 shows the LLTV sensor image. It has clear information about the trees, buildings etc. But the runway is not clear here. Fig.1 a2 is FLIR sensor image which has clear information about runway. Fig.1 a3 is an ideal image which is used as the reference image for calculating the quality metric values. The output images of various fusion algorithms are shown in Fig.1. Also, the clustering of the various fusion algorithms using Fuzzy C-Means clustering technique is shown in Fig. 2.

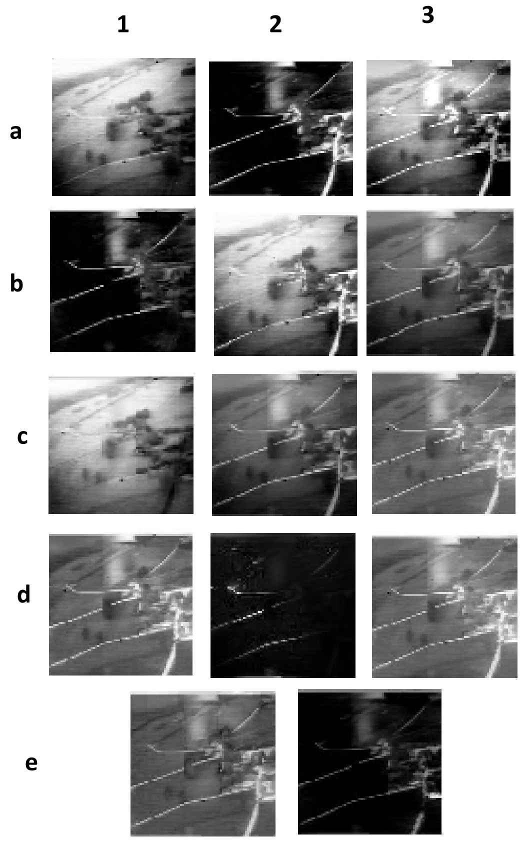

Fig. 1 Input, Reference and Output Images of Pilot Data Set

a1) LLTV Sensor **a2)** FLIR sensor **a3)** Reference Image
b1) Average **b2)** Max. Selection **b3)** Min. Selection
c1) Weighted Average **c2)** PCA Method **c3)** FSD Method
d1) Laplacian **d2)** Ratio of low-pass pyramid **d3)** Gradient
e1) Morphological Pyramid **e2)** Contrast Pyramid

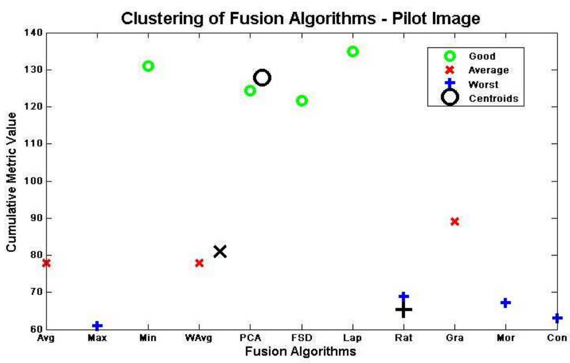

Fig. 2 Clustering of Image Fusion Algorithms for Pilot Image using Fuzzy C-Means Algorithm

Data Set2:

All the above mentioned image fusion algorithms are tested with UN Camp data set (visible image and infrared image). In Fig.3 a1 shows the visible image which contains the information that can be seen through a naked eye. In Fig.3 a2 shows the infrared image that has the information which cannot be seen visibly. The man standing behind the bushes can be seen in the infrared image which is not available in visible image. The fusion algorithms combine both these images into a single image that contains all the details. In Fig. 3 a3 is an ideal image that contains both the pattern information available in visible image and as well as in infrared image. The output images of various fusion algorithms are shown in Fig. 3 and the clustering of various fusion algorithms for an UN Camp is also given in Fig. 4.

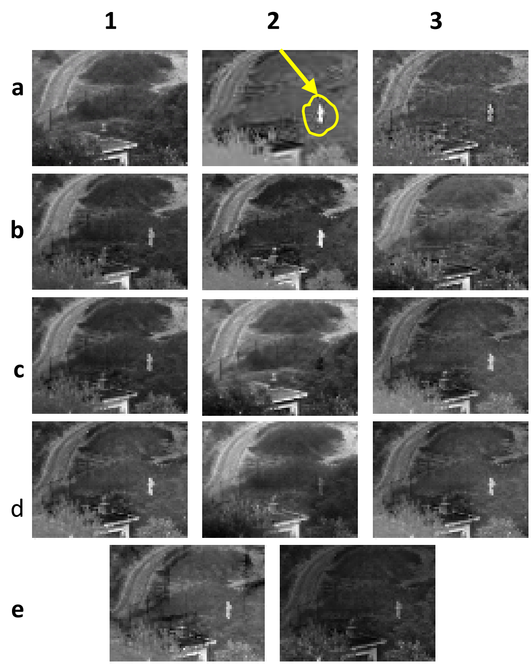

Fig. 3 Input, Reference and Output Images of UN Camp Data Set

a1) Visible Image **a2)** IR Image **a3)** Reference Image
b1) Average **b2)** Max. Selection **b3)** Min. Selection
c1) Weighted Average **c2)** PCA Method **c3)** FSD Method
d1) Laplacian **d2)** Ratio of low-pass pyramid **d3)** Gradient
e1) Morphological Pyramid **e2)** Contrast Pyramid

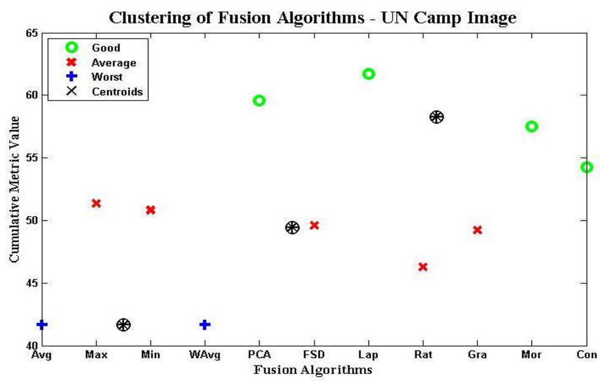

Fig. 4 Clustering of Image Fusion Algorithms for UN Camp Image using Fuzzy C-Means Algorithm

Data Set3:

Fig.5 shows the multi-focused input images, an ideal image and the output of all fused algorithms. In Fig.5, a1 is right-focused, a2 is left-focused and a3 is an ideal image which is both left and right focused. The clustering of these fusion algorithms for multi-focused image is shown in Fig.6.

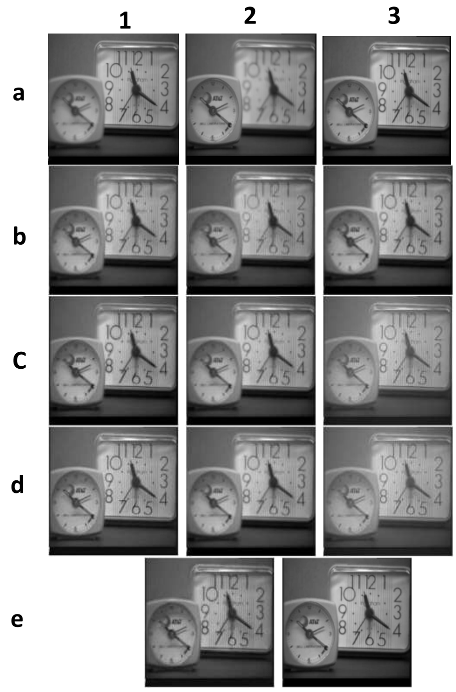

Fig. 5 Input, Reference and Output Images of Multi-focused Clock Data Set

a1) Left Focused **a2)** Right Focused **a3)** Reference Image
b1) Average **b2)** Max. Selection **b3)** Min. Selection
c1) Weighted Average **c2)** PCA Method **c3)** FSD Method
d1) Laplacian **d2)** Ratio of low-pass pyramid **d3)** Gradient
e1) Morphological Pyramid **e2)** Contrast Pyramid

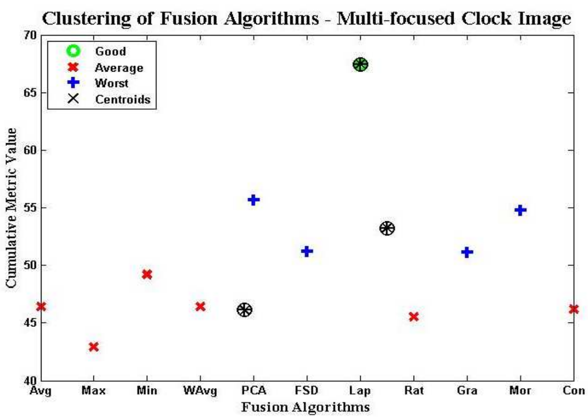

Fig. 6 Clustering of Image Fusion Algorithms for multi-focused Clock Image using Fuzzy C-Means Algorithm

6. Discussions

In the figure 2, the 'Good' cluster contains minimum selection, PCA, FSD and Laplacian Pyramid methods. Among all those methods, Laplacian has the highest cumulative value. In the figure 4, the FCM classifies PCA, Laplacian, Morphological and Contrast as 'Good' cluster. Figure 6 shows that Laplacian method only is in 'Good' cluster. From these clusters and also from the output images it is once again [10] proved that the Laplacian method results a better performance.

7. Conclusion

The quality of an image is very important and even more crucial in most of the applications such as Medical Analysis and Diagnosis, Remote Sensing, Defense Applications and Computer Vision. A single metric is not enough to determine the quality of a fused image. Hence more number of metrics (both reference and non reference) is required to evaluate them. In this paper, 12 image quality metrics are discussed and successfully tested for various data sets and found that Laplacian method results in good performance.

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