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Enhancing the Lifetime of Wireless Multimedia Sensor Network Through Image Fusion

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Abstract

The advances in camera technology and wireless sensor network (WSN) have encouraged the development of wireless multimedia sensor network (WMSN), which can collect multimedia data from its surrounding environment. Multimedia data such as video, image and audio is larger in volume than scalar data such as temperature, pressure and humidity. Larger size of multimedia data makes it a challenging issue in battery-limited sensor network. Thus to transmit multimedia data, more energy is required which reduces the lifetime of the network. Image fusion technique is applied to reduce the amount of data to be transmitted for WMSN. In this paper, we apply the energy efficient multimedia image fusion technique for WMSN. Multimedia image fusion eliminates the redundant data, improves the quality of multimedia data and enhances the lifetime of WMNS.

***Keywords**: Wireless multimedia sensor network, image fusion, PCA, lifetime, Energy consumption.*

1. Introduction

Recent developments in wireless communication, sensor technology, imaging techniques and embedded system have made possible the wireless sensor network to transmit multimedia information. Wireless multimedia sensor network (WMSN) consists of a large number of nodes with limited sensing, computation and communication facilities [1, 2]. Sensor nodes are resource constrained nodes, large amount of energy is consumed in data transmission. Hence to increase the lifetime of the network it is essential to reduce the number of bits transmitted [21]. Image fusion is a promising technique that can be used in WMSN to reduce the volume of multimedia data transmission. Image fusion is used in real world applications such as medical diagnose with multi modal image, person or weapon detection in defense system, classification of objects, e.g. roads, rivers, mountains and towns, etc.

Wireless multimedia sensor networks (WMSNs) consist of sensor nodes that have multiple sensing units which collect scalar information (e.g., temperature, pressure, humidity, etc.) as well as multimedia information (e.g. image, audio and video). The sensor nodes of WMSN are expected to perform more function as compared to conventional nodes. WMSNs can acquire and process complex like capture an image, record audio or video as well as simple information such as temperature, pressure and flow rate. Large amount of information acquired from the environment, which is more plentiful and prominent than in traditional WSN [22].

WMSNs are deployed in non-accessible area and hostile environment, so it is difficult to replace the batteries of sensor nodes [3]. Large numbers of sensor nodes are deployed to monitor its surrounding environment. In WMSN, similar data is observed by

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neighboring sensors and transmit such data to the sink [23]. During transmission of data to sink, a large amount of energy is consumed. To reduce the energy consumption and prolong the network lifetime, we can apply image fusion techniques to reduce the redundant data because more energy is consumed in data transmission as compared to data processing at sensor node [4].

Image fusion is a process of combining number of images, captured by different sensors of different field of view (FoV), to form a single but more informative image. The fused image is formed to improve image content and to make it easier for the user to detect, recognize, and identify targets and increase situational awareness [5]. Image fusion process integrates set of images which are captured from different FoV into a single image with best possible quality. The quality of image depends on thedemands of the specific application, which is usually related to its importance.

Figure 1 shows the steps involved in image fusion. Set of images are captured from different sensor nodes and transmitted to the cluster head. Cluster head performs the image fusion by applying different steps and then generates a fused image which is then transmitted to the sink.

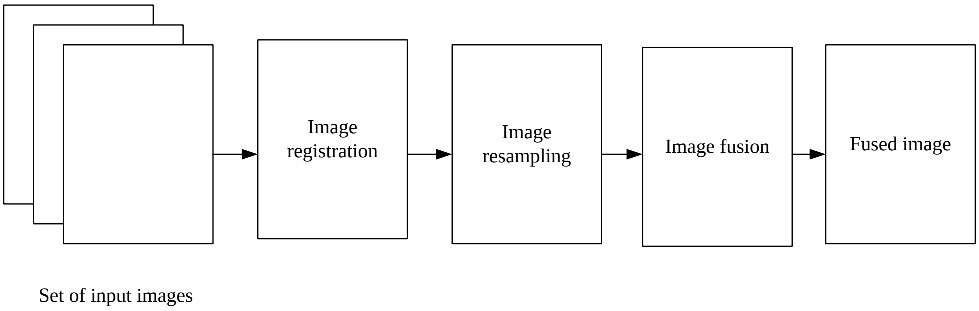

Figure 1. Preprocessing of Image Fusion

Image registration is the process of transforming different input images into one coordinate system. Image resampling is a process of manipulating the images. Resampling consists of processes that involve size, sharpness, efficiency and smoothness of the image. Image fusion aims at the integration of various complementary images data into a single, best possible quality image [24].

The rest of the paper is organized as follows. Section 2 reviews the related work. Image fusion techniques have been presented in Section 3. Section 4 describes the image quality metrics for image fusion technique. In Section 5 we present the results of performance evaluation of the method and Section 6 concludes the paper.

2. Related Work

K. Amolins et al. has suggested wavelet image fusion technique [6]. Wavelet transform methods produce better results than standard methods. Wavelet transforms are applied using non-decimated algorithms, the results are visually and spatially better than when the transforms are applied using decimated algorithms.

C. Pohl et al. has given a general introduction to multi-sensor data fusion [7]. This paper describes and explains mainly pixel based image fusion of Earth observation satellite data as a contribution to multisensory integration oriented data processing. This paper explained the concepts, methods and applications of image fusion as a contribution to multi-sensor integration oriented data processing. Since then, image fusion has received increasing attention.

The Laplacian Pyramid was first introduced for binocular fusion in human stereo vision [8]. The implementation used a Laplacian Pyramid and a maximum selection rule at each point of the pyramid transform. Due to similarity in the Laplacian operation set of band-pass copies of image is referred as the Laplacian Pyramid. Laplacian Pyramid is constructed by applying four basic steps (1) Blurring (low-pass filtering) (2) Sub-sampling (reduce the size) (3) Interpolation (expand) and (4) Differencing (subtract two images pixel by pixel). The lowest level of Laplacian Pyramid is constructed from the original image.

Liqiang Guo et al. suggested multi focus color image fusion technique using Quaternion Curvelet Transform (QCT) [9]. Each color input image is described by set of quaternion values coefficients. Different set of image fusion rules are applied and fine level of coefficient is constructed, which are responsible for construction of quaternion based multi resolution representation. The fused color image is obtained by the inverse quaternion curvelet transform.

Y.H. Yan et al. proposed Dual-Tree Complex Wavelet Transform – Principal Component Analysis (DTCWT-PCA) technique [10]. The proposed image fusion method combines two methodologies (1) Dual-Tree Complex Wavelet Transformation and (2) Principal Component Analysis. The contributions of these two techniques include the following aspects (1) Principal Component Analysis is successfully applied to image fusion by using dual-tree complex wavelet transform domain component (2) the dual-tree complex wavelet transform is used to represent the whole image in a computable dimensional space.

These techniques are implemented for image processing and numbers of quality assessment methods are used to measure the quality of image. By applying these techniques in wireless multimedia sensor network, we can enhance the lifetime of the network and reduce the energy consumption of sensor nodes.

3. Image Fusion Techniques

The main purpose of image fusion is to improve the quality of multimedia data. Image fusion process collects beneficial information from set of images and together to form the fused image, whose quality is generally better than the input images quality. Image fusion process can be classified in two groups; (1) Spatial domain fusion method, and (2) Transformation domain fusion methods [11]. Spatial domain fusion method directly deals with the pixels whereas transformation domain fusion images are transformed to frequency domain and then perform all the fusion operations and perform inverse transformation to get the resultant image. Various image fusion techniques are available in literature and are described below:

3.1 Simple Average Method

In this method, simple average of image pixels is calculated. The regions of image comprise of higher pixel intensity [11]. This algorithm is a simple way to obtain an output image with all regions in focus.

The value of the pixel P(i, j) of each image is taken and added. This sum is then divided by n to obtain the average. The average value assigned to the corresponding pixel of the output image is

$$\mathrm{Avg}(i, j) = \frac{P_1(i, j)+P_2(i, j)+ \ldots + P_n(i, j)}{n} \tag{1}$$

Where $P_k(i, j)$ is the pixel value of kth image and n is the set of input images. Figure 2 shows the simple average function performed on two input images.

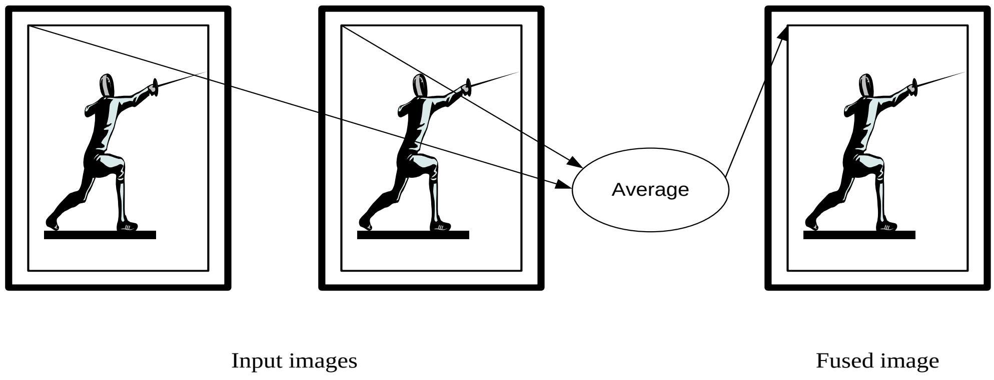

Figure 2. Pixel Intensities at Every Position (i, j) are Averaged to Obtain the (i, j) Pixel of the Fused Image

3.2 Simple Maximum Method

In this method select maximum value of pixel from set of corresponding image pixels. The quality of image is higher in this method because highest pixel values are chosen from the set of corresponding pixel values. The greater the pixel values, the more in focus the image. So, this method results highly focused fused image [12].

The value of the pixel P(i, j) of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel

$$\mathrm{Max}(i, j) = \max \left\{P_1(i, j), P_2(i, j), \ldots, P_n(i, j)\right\} \quad (2)$$

Figure 3 shows this operation.

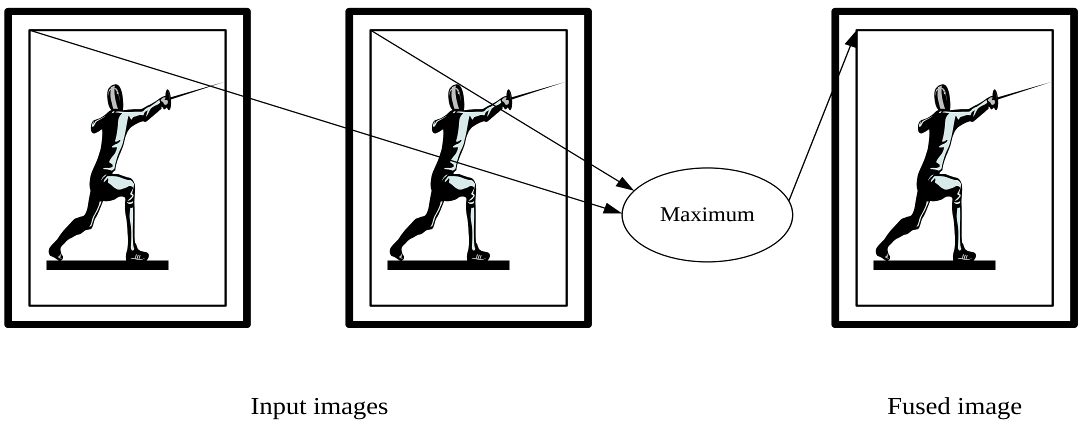

Figure 3. The Maximum of the Pixel Intensities at Position (i, j) is Selected as the (i, j) Pixel of the Fused Image

3.3 Principal Component Analysis (PCA)

Principal component analysis (PCA) is a classic technique in statistical data analysis, data compression and image processing. PCA technique is used to transform a number of correlated variables into smaller number of variable called principal components. The number of principal components is less than or equal to the number of original variables [13]. It transforms the original data in such a manner that first principal component has largest variance. Second principal component has smaller value than the first principal component. These two principal components are orthogonal to each other [14].

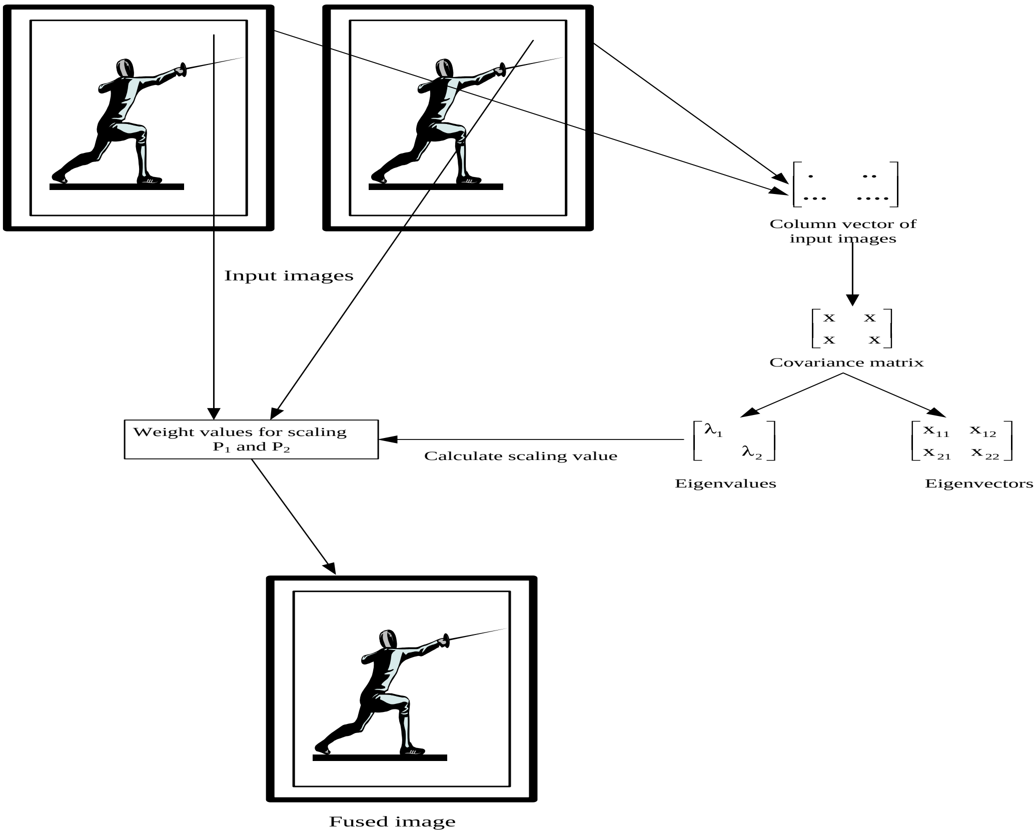

Figure 4. The Input Image Pixels at Positions (i, j) being Scaled using PCA to Get Fused Image

PCA reduces the multidimensional data set to lower data dimensions. Largest eigenvalue increases the variance and reduces covariance by projecting data from original space to eigenspace. PCA helps to reduce redundant information and highlights the components with biggest influence so as to increase the signal-to-noise ratio [15].

PCA is suitable for those applications in which huge amount of data are to be analyzed. PCA is widely used in data compression and pattern matching by expressing the data in a way to highlight the similarities and differences without much loss of information [16].

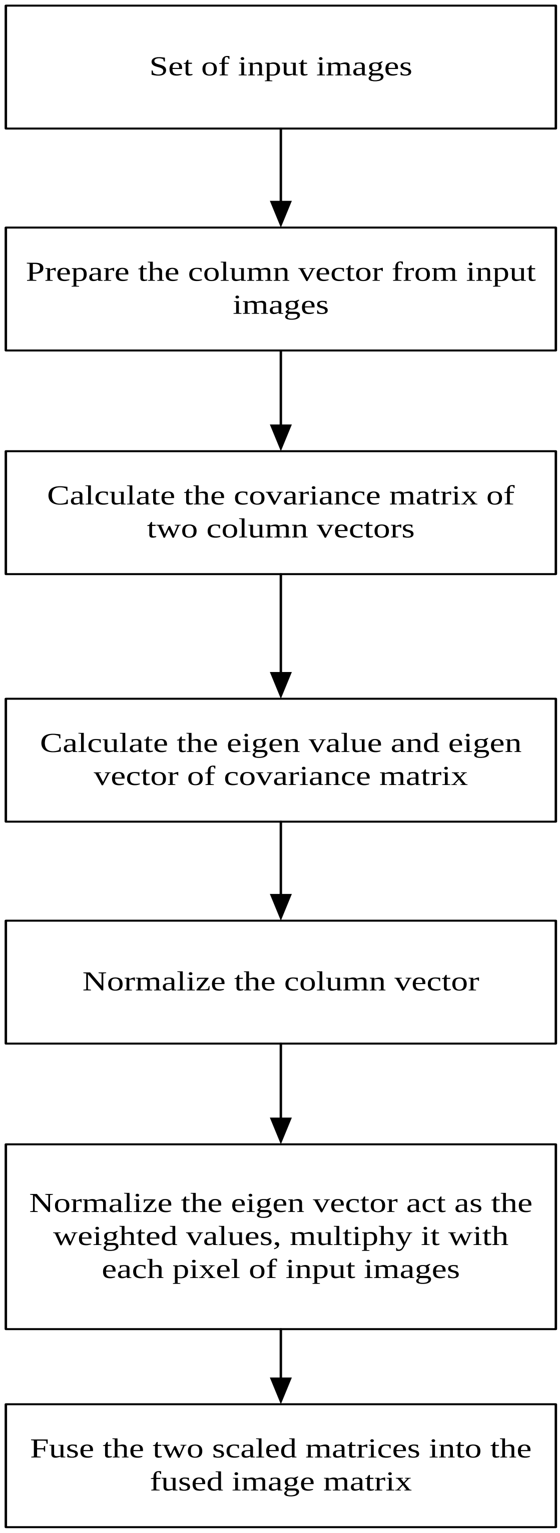

Figure 5. Image Fusion by PCA

Figure 4 shows the PCA technique to convert input images into fused image.

Let images P1(i, j), P2(i, j) be two images of size $m \times n$ matrix, the steps for PCA are:

1. Generate the column vectors, from the input image matrices.

2. Calculate the covariance matrix of the two column vectors formed in 1.
3. Calculate the eigenvalues (V) and the eigenvectors (λ) of the covariance matrix.
4. Normalize the column vector corresponding to the largest eigenvalue by dividing each element with mean of the eigenvector (λ).
5. Normalized eigenvector value act as the weight values which are respectively multiplied with each pixel of the input images.
6. Sum of the two scaled matrices calculated in 5 will be the fused image matrix.

The information flow diagram of principal component analysis based image fusion algorithm is shown in Figure 5.

4. Image Quality Metrics

Distortions in the quality of images occurred during acquisition, processing, compression, storage, transmission and reproduction may result in a degradation of visual quality. Image quality assessment methods is classified into these categories (1) Full Reference Method (2) No Reference Method and (3) Reduced Reference Method [11, 17]. In full reference method, an image quality depends upon the compression with the reference image, which is assumed to be perfect in quality. In many applications reference image is not applicable so we use the no reference method. In reduced reference method, the reference image is partially available.

4.1 Mean Square Error (MSE)

Mean square error (MSE) of an estimator is to calculate the difference between estimated value and the true value of the quantity being estimated. MSE is a measurement of image quality difference. Quality of image is inversely proportional to the mean square error i.e. larger the value of mean square error then the quality of image is poor. Mean square error between the reference image and the fused image is [17]

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}-B_{ij}\right)^2 \qquad (3)$$

Where $m \times n$ is the size of two images. A_{ij} is the pixel density values of the reference image and B_{ij} is the pixel density values of the fused image.

4.2 Peak Signal to Noise Ratio

Peak signal to noise ratio (PSNR) is defined as the ratio between maximum possible power of the signal to the power of the corrupting noise that creates distortion of image [18]. The PSNR can be represented as

$$PSNR = 10 \times \log_{10}\left(\frac{peak^2}{MSE}\right) \qquad (4)$$

$$peak^2 = 255\sqrt{3mn} \qquad (5)$$

Where $m \times n$ is the size of two images. 255 is the true color used in image.

4.3 Normalized Cross Correlation

Normalized cross correlation (NCC) is used to find the similarity between fused image and registered image. Normalized cross correlation is defined as the ratio between net sum of the correlated of the expected and obtained data and the expected data. Here a cross correlation is performed between the expected data and the obtained data and normalized with respect to the expected data [11]. The NCC value would ideally be 1 if the fused and the reference images are identical.

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} \times B_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2} \tag{6}$$

Where $m \times n$ is the size of two images. A_{ij} is the pixel density values of the reference image and B_{ij} is the pixel density values of the fused image.

4.4 Average Difference

Average difference (AD) is calculated as the average value of the difference between the fused image and the registered image. The corresponding pixel values of the perfect Image A and the fused image B is considered. The difference of the corresponding pixel density values is averaged to obtain the metric. This metric helps in providing the overall average difference between the corresponding pixels of the two images that specifies, how much different is the fused image from the perfect image [11].

$$AD = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(|A_{ij} - B_{ij}|\right) \tag{7}$$

Where $m \times n$ is the size of two images. A_{ij} is the pixel density values of the reference image and B_{ij} is the pixel density values of the fused image.

4.5 Structural Content

Structural content (SC) is defined as the ratio between the content of the both the reference image and the fused image. Practically, it is the ratio between the net sum of the square of the reference image and the net sum of square of the fused image [19]. Structural content metric value would be 1, but SC being 1 does not mean that the fused and perfect images are identical.

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}\right)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(B_{ij}\right)^2} \tag{8}$$

Where $m \times n$ is the size of two images. A_{ij} is the pixel density values of the reference image and B_{ij} is the pixel density values of the fused image.

4.6 Normalized Absolute Error

Normalized absolute error (NAE) is defined as the error value normalized with respect to the reference image or the perfect image. The net sum of the error value which is the difference between the reference image values and the actual obtained image values is divided by the net sum of the reference image values [20]. The NAE will be zero if both the fused and the perfect images are identical.

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(|A_{ij} - B_{ij}|\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n}A_{ij}} \tag{9}$$

Where $m \times n$ is the size of two images. A_{ij} is the pixel density values of the reference image and B_{ij} is the pixel density values of the fused image.

4.7 Entropy

Entropy of image calculates the quantity which is used to described the image i.e. amount of information which must be achieved after fusion techniques. Entropy of an image is directly proportional to the information content of the image i.e. an image having higher information will have higher entropy [16]. An image that is perfectly flat will have entropy of zero.

$$\text{Entropy} = -\sum_{i} P_i \log_{10} P_i \tag{10}$$

Where P_i is the probability that the difference between two adjacent pixels is equal to i.

Table 1 shows the metric ideal values and error values in case of fused image and the input image. In case, the fused image is not perfect, the Table 1 specifies the range of the value the metric will span between.

Table 1. Quality Assessment Metric, Ideal Values and Error Values

Metric	Ideal Value	Error Value
Mean Square Error	0	>0
Peak Signal Noise Ratio	NA	>1
Average Difference	0	>0
Structural Content	1	>0 and <1
Normalized Cross Correlation	0	>0 and <1
Normalized Absolute Error	0	>0 and <1

5. Performance Evolution

Sensor node within the cluster captures almost same information from different field of view (FoV). This multimedia information is transmitted to the CH by its members and then CH performs different steps like image registration, image resampling, etc. before applying image fusion technique. Image fusion techniques improve the quality of image.Here we have fused set of images by applying different fusion techniques and compared the quality of fused image. We have compared the results of simple average, select maximum and PCA technique for image fusion. The efficiency of quality of image depends upon the performance metrics, which includes mean square error (MSE), peak signal to noise ratio (PSNR), normalized cross correlation (NCC), average difference (AD), normalized absolute error (NAE) and structural content (SC).

Example 1. Fusion of gray scale images.

(a) (b)

Figure 6. Set of Input Gray Scale Images

Figure 6 shows the set of gray scale input images and Figure 7 shows the fused image after applying PCA technique.

Figure 7. Fused Gray Scale Image after Applying PCA Technique

Table 2. Comparison of Different Fusion Techniques for Gray Scale Images

Technique	MSE	PSNR	NCC	AD	SC	NAE
Simple Average	11275.5	7.609	0.5402	98.110	3.355	0.4524
Select Maximum	239.70	24.34	1.009	-4.1725	0.9763	0.205
PCA	3555.05	12.622	0.9896	-5.693	0.9544	0.1351

We have compared the result for gray scaled images by applying different image fusion techniques. Table 2 compares quality of images by calculating different quality assessment metrics for different technique and it is observed that the PCA technique is better than the simple average and select maximum technique.

Example 2. Fusion of colored images.

(a) (b)

Figure 8. Set of Input Colored Images

Figure 8 shows the set of input colored images and Figure 9 shows the fused image after applying PCA technique. It is found that PCA technique is better than the other techniques.

Figure 9. Fused Colored Image after Applying PCA Technique

Table 3. Comparison of Different Fusion Techniques for Colored Images

Technique	MSE	PSNR	NCC	AD	SC	NAE
Simple Average	2707.85	13.9043	0.7262	36.4691	1.8356	1.6392
Select Maximum	957.31	20.9734	1.0775	16.81	0.851	0.1228
PCA	493.906	21.3968	0.9803	1.93135	1.0383	0.1074

In order to study the effect of image fusion in WMSN, we have performed experiments to compare the clustering technique (having no fusion) with the fusion technique. Network lifetime has been taken as performance metric.

Network lifetime

Network lifetime of wireless multimedia sensor network is the time spam from deployment to the instant the network ceases to achieve objective of its deployment. The definition of network lifetime is application specific. In Figure 10 we observe that the network lifetime increases as the number of nodes increases because the sensing field area is constant and there is increase in the number of nodes. So each node has to sense the small area and less energy is consumed by the nodes so there is increase in the network lifetime.

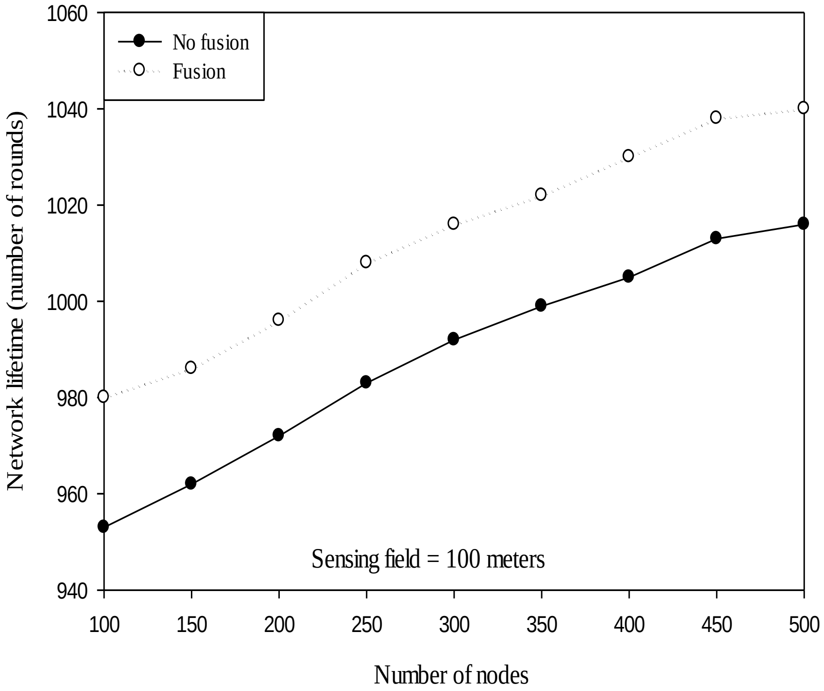

Figure 10. Effect of Number of Nodes on Network Lifetime

Figure 11 shows the effect of sensing field on the network lifetime for constant number of nodes. We have observed that network lifetime goes on decreasing as the sensing field area is increasing. There is increase in the sensing field but number of nodes is constant. As the area goes on increasing the node has to consume more energy for sensing the area so large amount of energy is consumed by sensing units.

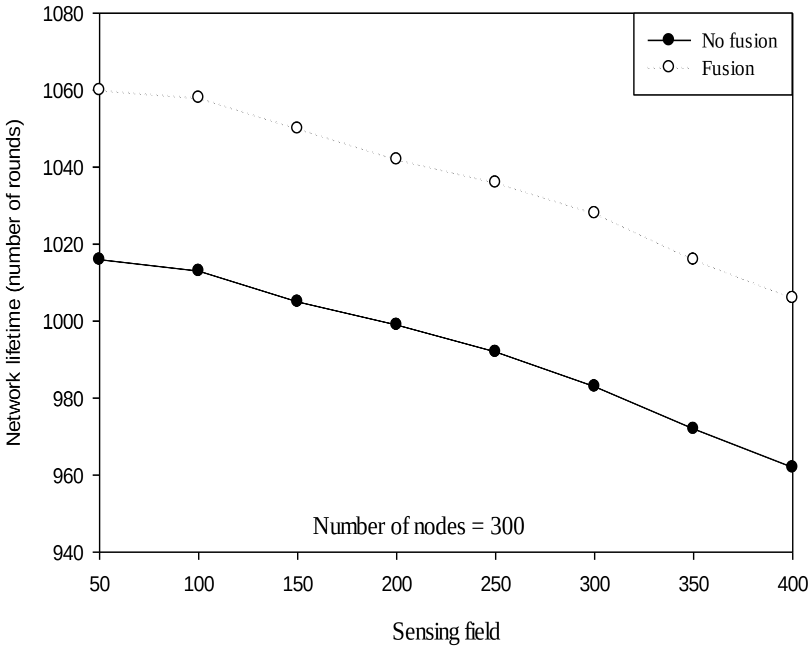

Figure 11. Effect of Sensing Field on Network Lifetime

Energy Consumption

Energy consumption is the total energy consumed for sending and receiving the packets, and the energy for processing the multimedia information. In WMSN both communication and processing energies are considered because multimedia information is large in volume. Energy consumption per round is the total energy consumed within the sensor network for sensing the multimedia information and transmitting the sensed information to the sink. Figure 12 and Figure 13 shows the simulation results for variation in energy consumption per round for clustering, data compression and PCAIF (without compression). In Figure 12 we have observed that energy consumption per round increases as the number of nodes increases. Increase in number of nodes leads to increase in the total sensing energy, total aggregation and total communication energy. The simulation result shows that PCAIF technique (Fusion) is better than data compression and clustering technique (No fusion).

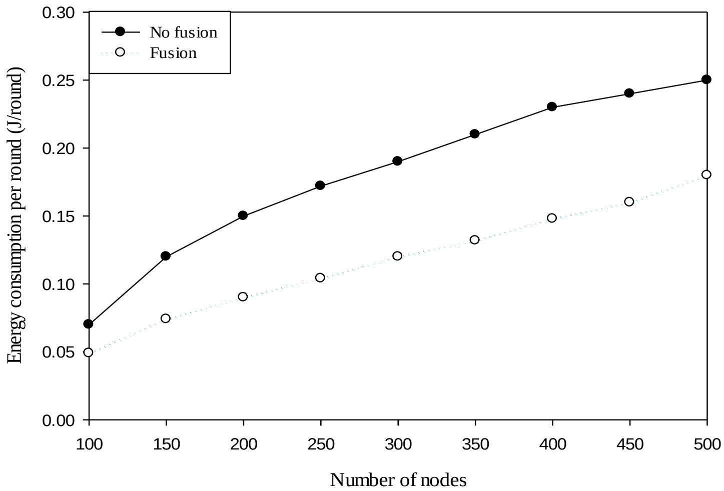

Figure 122. Effect of Number of Node on Energy Consumption

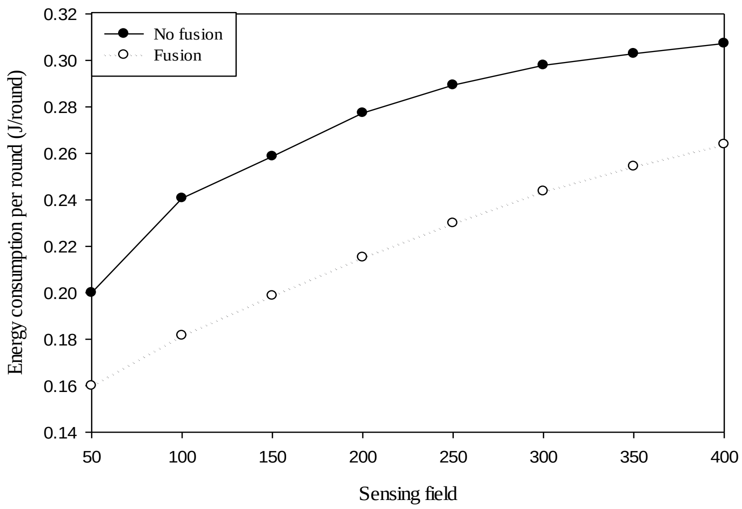

Figure 133. Effect of Sensing Field on Energy Consumption

Figure 13 shows the simulation result for effect of variation in sensing field side length from 50 to 400 meters, keeping the node deployment fixed at 400 nodes. It is observed that energy consumption increases with the increase in the sensing field, because the distance between sink and sensing node increases which also increases the data transmission energy.

6. Conclusion

In this paper, we have applied principal component analysis based fusion technique for wireless multimedia sensor network. The cluster head collects different FoV set of images from its members and applies PCA fusion technique on different images then transmits the fused image to the sink. The simulation results show that the applied method efficiently improves the quality of fused image with lesser mean square error. It reduces the energy consumption of sensor nodes and thus increases the lifetime of the network.

References

[1] I. F. Akyildiz, W. I. Su, Y. Sankarasubramaniam and E. Cayirci, “A Survey on Sensor Networks”, IEEE Communication Magazine, vol. 40, no. 8, **(2002)**, pp. 102-114.
[2] L. Mottola and G. P. Picco, “Programing Wireless Sensor Networks: Fundamental Concepts and State of the Art”, ACM Computing Surveys, vol. 43, no. 3, **(2011)**, pp. 1-51.
[3] I. F. Akyildiz, T. Melodia and K. R. Chowdhury, “A Survey on Wireless Multimedia Sensor Networks”, Computer Networks, vol. 51, no. 4, **(2007)**, pp. 921-960.
[4] Y. Xiao, W. Li, M. Siekkinen, P. Savolainen, A. Y. Jaaski and P. Hui, “Power Management for Wireless Data Transmission Using Complex Event Processing”, IEEE Transection, vol. 61, no. 2, **(2012)**, pp. 1765-1777.
[5] F. Sadjadi, “Comparative Image Fusion Analysis”, IEEE Computer Society Conference on Computer Vision and Pattern Recognition -Workshops (CVPR), **(2005)**, pp.160-168.
[6] K. Amolins, Y. Zhang and P. Dare, “Wavelet Based Image Fusion Techniques – An Introduction, Review and Comparison”, ISPRS Journal of Photogrammetry and Remote Sensing, vol. 62, no. 4, **(2007)**, pp. 249-263.
[7] C. Pohl and J. L. Van Genderen, “Multisensor image fusion in remote sensing: concepts, methods and applications”, International Journal of Remote Sensors, vol. 19, no. 5, **(1998)**, pp.823-854.
[8] P. J. Burt and E. Adelson, “The Laplacian Pyramid as a Compact Image Code”, IEEE Transaction on Communication, vol. 31, no. 4, **(1993)**, pp. 532-540.
[9] L. Guo, M. Dai and M. Zhu, “Multifocus Color Image Fusion Based on Quaternion Curvelet Transformation”, Optical Express, vol. 20, no. 17, **(2012)**, pp. 18846-18860,.
[10] Y. H. Yan, L. Li, Fubo and Y. Z. Yang, “Image Fusion Based on Principal Component Analysis in Dual Tree Complex Wavelet Transform Domain”, International Conference on Wavelet Active Media Technology and Information Processing (ICWAMTIP), **(2012)**.
[11] D. K. Sahu and M. P. Parsai, “Different Image Fusion Techniques – A Critical Review”, International journal of Modern Engineering research (IJMER), vol. 2, no. 5, **(2005),** pp. 4298-4301.
[12] M. Chandana, S. Amutha and N. Kumar, “A Hybrid Multi-focus Medical Image Fusion Based on Wavelet Transform”, International Journal of Research and Reviews in Computer Science (IJRRCS), vol. 2, no. 4, **(2011)**.
[13] Principal Component Analysis Wikipedia http://en.wikipedia.org/wiki/Principal_component_analysis.
[14] D. Kumar, C. S. Rai and S. Kumar, “Principal Component Analysis for Data compression and Face Recognition”, INFOCOMP Journal of Computer Science, vol. 7, no. 4, **(2008)**, pp. 48-59.
[15] Sharanabasavaraj, S. Guruprasad, M. Z. Kurian and H. N. Suma, “Multi-Modality Image Fusion of PET/CT by Integrating Methods, DWT-PCA”, International Journal of Advanced Computer Engineering and Communication Technology (IJACECT), vol. 2, no. 2, **(2013)**, pp. 49-53.
[16] T. Singh, M. Kaur and A. Kaur, “A Detailed Comparative Study of Various Image Fusion Techniques used in Digital Images”, International Journal of Advanced Engineering Technology, vol. 4, no. 3, **(2013)**, pp. 50-52.
[17] A. Mishra and S. Rakshit, “Fusion of Noisy Multi Sensor Imagerys”, Defense Science Journal, vol. 58, no. 1, **(2008)**, pp. 136-146.
[18] J. B. Martens and Meesters, “Image Dissimilarity”, Signal Processing, vol. 70, no. 5, (**1998)**, pp. 155-176.
[19] K. Silpa and S. Aruna Mastani, “Comparison of Image Quality Metrics”, International Journal of Engineering Research and Technology (IJERT), vol. 1, no. 4, **(2012)**.
[20] V. S. Roshni and K. Revathy, “Using Mutual Information and Cross Correlation as Metrics for Registration of Images”, vol. 2, no. 4, **(2006)**, pp. 474-481.

[21] A. S. Poornima and B. B. Ambedkar, "SEEDA: Secure End-to-End Data Aggregation in Wireless Sensor Networks", 7th International Conference on Wireless and Optical Communications Networks, **(2010)**.
[22] C. Chen, "Data Aggregation Techniques for Wireless Multimedia Sensor Networks: A Survey", IEEE International Conference on Vehicular Electronics and Safety, **(2010)**.
[23] P. Kumar and Narottam Chand, "Clustering in Wireless Multimedia Sensor Networks Using Spectral Graph Partitioning", International Journal of Communication, Networks and System Sciences (IJCNS), vol. 6, no. 3, **(2013)** pp. 126-132.
[24] J. G. Denipote and M. S. V. Paiva, "A Fourier Transformation-based Approach to Fusion High Spatial Resolution Remote Sensing Images", 6th Indian Conference on Computer Vision, Graphics & Image, **(2008)**.

