A Spatial Correlation Based Power Aware Event Driven Image Stitching In Wireless Multimedia Sensor Network

Chethan L S, Manjunatha P

Abstract: Wireless multimedia sensor network(WMSN) is an image sensor which is attached to sensor node to capture information within the field of view (FOV). Due random deployment of multimedia sensor nodes there exist overlapped FOV between multimedia sensor nodes. Overlapped FOV causes redundant data transmission which leads to increased power consumption and reduced life time of a node. Another factor which may reduce the energy consumption is to capture image continuously. To escalate these issues we have designed event driven spatial correlation based image stitching algorithm. There are two modules in this scheme, first event detection module capture the image only when event is detected and second module perform image stitching when the cameras capture information. Experimental results shows there is a considerable improvements in terms of reduction in data processed.

Keyword: WMSN, FOV, ECC.

I INTRODUCTION

Wireless multimedia sensor network [1] is a wireless sensor node which is capable of capturing visual information and processing. As increased processing of visual information in WMSN lead to increased energy consumption and bandwidth utilization. Numerous camera nodes are located in given surveillance area exhibit spatial correlation when cameras have overlapped FOV [2]. This overlapped information lead to redundant data transmission in the network which leads to reduction in network lifetime.SPIHT based lifting wavelet based compression algorithm [3] uses adaptive compression algorithm which is best suitable for power hungry network. A hybrid SVD-DWT-DCT [4] based compression algorithm uses clustering approach where computation is distributed among the nodes. The advantages of this technique are to maintain low complexity with considerable image quality and greater compression ratio. To preserve energy in WMSN, the fast DCT zonal approach is proposed [5] which combine DCT with cardiac and DCT with zones. The DCT with cardiac [6] is a multiplier less and by applying algorithm 8X8 DCT matrix is generated. In block based compression schemes [7] , sorting based on descending values of their entropy. Power consumption is reduced by compressing the blocks which has less entropy. All the above technique greatly reduces the image size, transmission power but the quality of the image diminishes when we compress the image and these techniques are suitable only for the single multimedia sensor node. When multiple cameras connected there will be redundant information due to overlapped FOV.Another way to compress image is to Image stitching where redundant information are eliminated using feature matching between two images. Slepian wolf (SW)[8] or Wyner-Ziv (WZ) [9] proposed a distributed coding which uses motion compensation to generate side information. Using motion compensation the reconstruction is possible at decoder side. The setback of this technique is that it leads substantial difference between theoretical and practical approach. A technique of SPIHT and EZW coding [10] we can reduce amount of data transmission in WMSN. This technique is used to eliminate the redundant information to enhance the network lifetime. The above discussed methods will eliminate the redundant information but the elimination of redundant information will be done continuously this because the image sensor will capture the information continuously. This will further lead to increased energy consumption. To tackle this we are proposed power aware event driven image stitching algorithm, here sensor will capture the information only when event is detected and another advantage over conventional methods is that it will eliminate complete redundant information and produce image which has less in memory.

II SYSTEM DESIGN

In our technique we use raspberry pi module to design event based image capture and homography technique to eliminate redundancy and to generate stitched image.

A. EVENT BASED IMAGE CAPTURE:

Event detection module consists of Raspberry pi [11] board, camera module and PIR sensor. Raspberry pi is development board which has ARM processor which is more suitable for power aware systems. The camera module and PIR sensor is attached the board is as shown in figure.1. Here camera captures the image only when there is an event detected by sensor. When there is no event detected, camera will be in power off condition. Instead of capturing information or an image continuously this module capture only when there is valid event occurs.

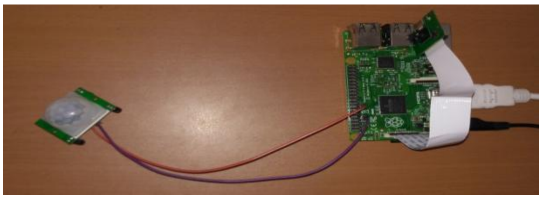


Figure.1. Event detection module setup

Figure.2 shows the working flow of event detection module. The camera module is attached to the raspberry pi board has limited FOV[12]. Image captures the information within the FOV so we need place PIR sensor within the FOV. System is designed in such a way that camera will be in power off mode until there is a detection of valid event. When event occurs within the FOV then PIR sensor will send the information back to raspberry pi board to power on the camera to capture an image.

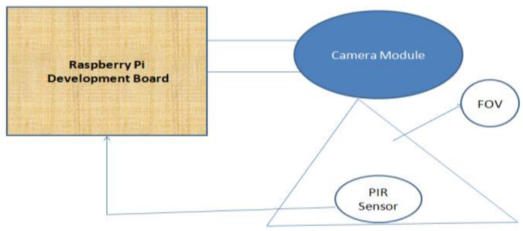


Figure.2. Working Of Event Detection And Capturing Module

B. SPATIAL CORRELATION BASED IMAGE STITCHING:

In this section, first entropy [13] and joint entropy [14] measures are discussed, second section describes calculation of entropy correlation coefficient and finally image stitching model us discussed. Algorithm of complete model is shown below.

Algorithm for complete model:
1. Mutual information, Entropy and joint entropy are applied between images.
    a) To estimate entropy, Shannon's entropy model is used.
    b) Using individual image entropy the mutual information is calculated.
2. Identify entropy correlation coefficient.
3. Implement image stitching based on SIFT algorithm
    a) Extract local features between two images.
    b) Compare and extract similar features between images.
    c) Using homography matrix image stitching is performed.

Entropy Estimation:

Spatial correlation is mainly depends on entropy function which is given by the equation

$$H(X) = -\sum P_i \log P_i \quad (1)$$

where P_i represents a probability of the system.

To calculate image entropy, we need to consider grey level histogram of an image. Now we can write image entropy as

$$H = -\sum_{k=1}^{L} P(r_k)\log\big(P(r_k)\big) \quad (2)$$

Where L represents all grey levels of an image and probability of k^{th} grey level is obtained by $P(r_k)$.

Mutual Information:

Mutual information is a measure of common information between two entities. The mutual information between two entities A and B can be measured with entropy and joint entropy. Mutual information which is related to joint entropy can be written as:

$$I(A;B) = H(A) + H(B) - H(A,B) \quad (3)$$

Where $H(A)$ and $H(B)$ are Shannon entropy and the joint entropy is denoted as$H(A,B)$.

To get mutual information joint histogram is measured which is 2D histogram for a pair of image. Joint histogram of an image pair is given by:

$$P(a,b) = \frac{h(a,b)}{\sum_{a,b} h(a,b)} \quad (4)$$

$P(a,b)$ is the joint mass probability function and two separate probabilities are written as

$$P(a) = \sum_b P(a,b) \quad (5)$$

$$P(b) = \sum_a P(a,b) \quad (6)$$

Now we can find joint entropy as function of mutual information and individual image entropy is given by

$$H(A,B) = H(A) + H(B) - I(A;B) \quad (7)$$

Where, individual image entropy is represented by $H(A)$ and $H(B)$ and $I(A;B)$ is a mutual information.

Entropy correlation coefficient (ECC):

Mutual information varies depending on the amount of overlapped information between the images. The samples we get from mutual information are reduced when the area of overlapped FOV is reduced. To reduce mutual information sensitivity, NMI (normalized mutual information) is used. NMI is written as

$$NMI(A,B) = \frac{H(A)+H(B)}{H(A;B)} \quad (8)$$

Another form of NMI is to define equation for ECC

$$ECC = \frac{2I(A;B)}{H(A)+H(B)} \quad (9)$$

The relationship between ECC and NMI is given by equation,

$$ECC = 2 - \frac{2}{NMI} \quad (10)$$

SIFT (Scale Invariant Feature Transform):

SIFT is a feature detection algorithm used to find similar features between images. In our work we are utilizing this algorithm to find common points between images to eliminate redundancy introduced by overlapped FOV. Algorithm to implement SIFT is explained below.

Algoritm

1. Two input images with overlapped area between images.
2. Image local features are identified using SIFT algorithm.
3. Count the features of individual images.
4. Compare identical features between overlapped images.
5. Count identical feature points between two images.

Homography using RANSAC algorithm:

Let f(x,y) is a original image which is transformed version of g(x,y) under the transform obtained by homography matrix H :

$$H = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & 1 \end{bmatrix} \qquad (11)$$

Where homography parameters are denoted by $(h_1 \ldots . h_8)$ and the relationship between source and reference image is

$$f(x,y) = g(x,y) \qquad (12)$$

$$\begin{cases} X = \frac{h_1x+h_2y+h_3}{h_7x+h_8y+1} \\ Y = \frac{h_4x+h_5y+h_6}{h_7x+h_8y+1} \end{cases} \qquad (13)$$

To calculate the homography elements of a matrix H and error Err(h) is expressed as

$$Err(h) = \sum_{(x,y)\in\Omega}[f(X,Y) - g(x,y)]^2 \qquad (14)$$

$$Err(h) = \sum_{k=1}^{|\Omega|} \in_k^2 (H) \qquad (15)$$

Where total number of pixels In overlapped region is given by $|\Omega|$.

F Finding homogeneous coordinate points:

To perform image stitching we need to consider the geometric transformation related to image stitching. Image 2D points are represented as (x, y, w) and the Cartesian coordinates are $({}^{x}/_{w}, {}^{y}/_{w})$. Geometric transformation in homogeneous coordinates are represented as

$$u = H.x \qquad (16)$$

$$\begin{bmatrix} u' \\ v' \\ w' \end{bmatrix} = \mathrm{H.}\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad (17)$$

Where,$u = {}^{u'}/_{w'}$,$v = {}^{v'}/_{w'}$, $w' \neq 0$.

To translate coordinates homography matrix is represented in equation (18) Where translation along x axis and y axis is given by t_x and t_y.

$$H_{translation} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \qquad (18)$$

Rotation angle between two unregistered images are measured as, image registration method is used to calculate θ value. The homography rotation matrix is:

$$H_{rotation} = \begin{bmatrix} cos\theta & -sin\theta & 0 \\ sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad (19)$$

By multiplying rotation and translation matrix we will get final homography H, the matrix is shown in equation (20).

$$H = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} cos\theta & -sin\theta & 0 \\ sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ m_6 & m_7 & m_8 \end{bmatrix} \qquad (20)$$

Final stitched image size using the homography matrix is

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ m_6 & m_7 & m_8 \end{bmatrix} * \begin{bmatrix} x \\ y \\ z \end{bmatrix} \qquad (21)$$

Algorithm for RANSAC

1. Get n points (number of features matched between two images)
2. Set threshold inlier, iteration and number of points.
3. Using random point compute best fit
4. Count inlier and refit
5. Coefficient is chosen with most inlier

III RESULTS AND DISCUSSION

In our work first step is to identify entropy of individual image and using that we need to find joint entropy and entropy correlation coefficient which is essential to calculate mutual information. Figure.3. shows images captured with overlapped FOV. In figure there is a similarity between two images. Table.1. shows the corresponding value of entropy, joint entropy and mutual information.

(a) Image A

(b) Image B

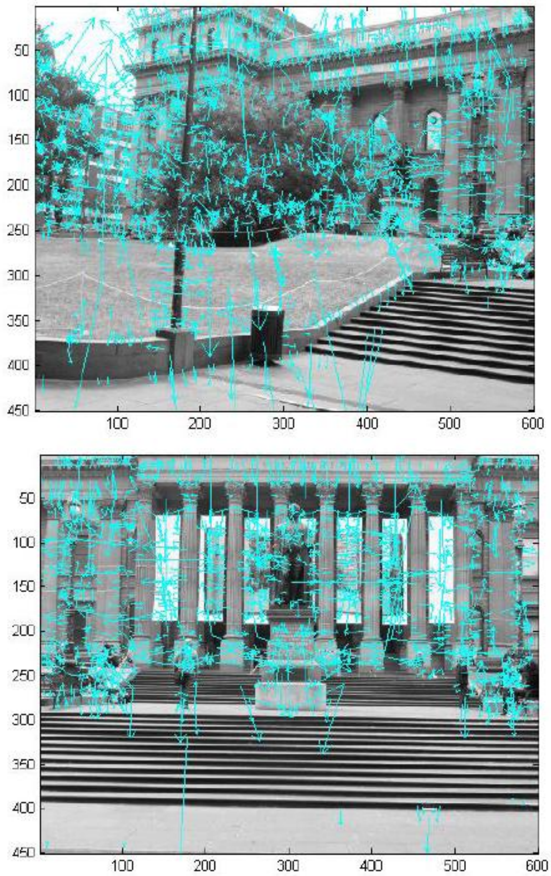
Figure.3. images with overlapped region

Table.1 Joint entropy and entropy correlation matrix

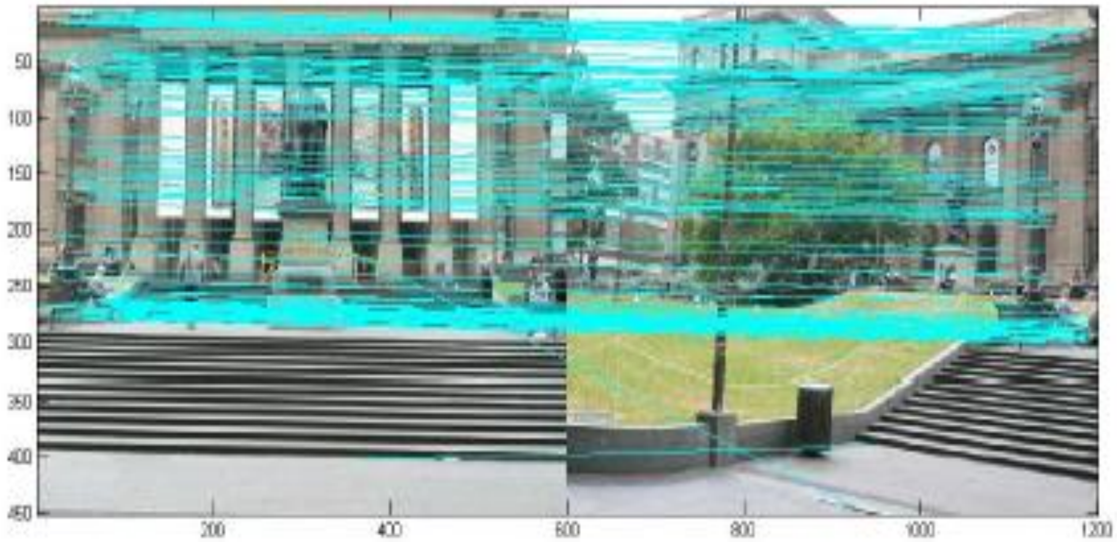
Image	Simulation values from the result
Entropy H(A)	7.5607
Entropy H(B)	7.7227
Mutual information between A and B I(A,B)	0.2002
Mutual information between B and A I(B,A)	0.2002
Joint Entropy, H(A,B)	$JE = \begin{bmatrix} 7.5607 & 15.0832 \\ 15.0832 & 7.7227 \end{bmatrix}$
ECC	$ECC = \begin{bmatrix} 1 & 0.0262 \\ 0.0262 & 1 \end{bmatrix}$

Feature matching is an essential component in image stitching to identify similar features between images captured with a camera having overlapped FOV which is shown in Figure.4.

(a) Image (b) Image B



(c) Detected feature of A (d) Detected feature of B

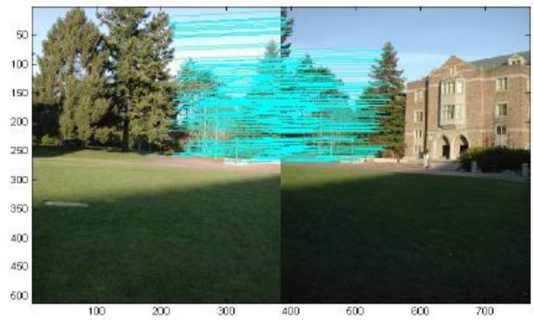


(e) Matched features between two images

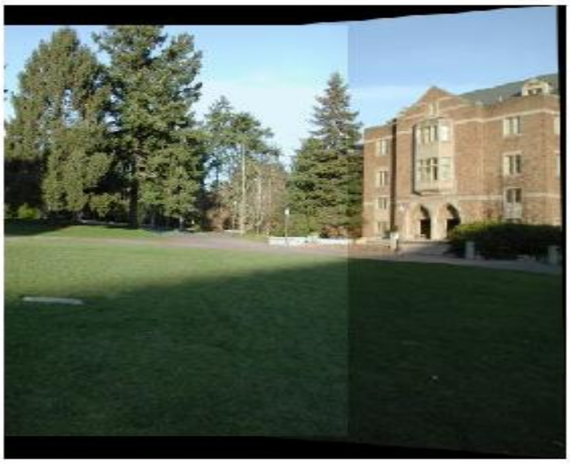
Figure.4. Mapping Of Similar Features Between Images

Finally, the image stitching is performed using homography matrix and the transformed image is as shown in Figure.5, and required parameters are shown in table.2. The memory requirement to store images are compared with SPIHT-EZW are shown in table.3.

(a) Image A **(b) Image B**



(c) Matched features (d) Transformed image A



(e) Final stitched image

Figure.5. Final Stitched Image Using Matched Feature Points Between Two Images

Table.2. Matched feature points using homography matrix estimation

Evaluated feature Parameters	Results
Identified key points of Image A	1400
Identified key points of Image B	995
Similar key points between A and B	259
Homography matrix	$H = \begin{pmatrix} 0.8789 & 0.0212 & 203.6123 \\ -0.0865 & 0.9713 & 10.3302 \\ -0.0003 & 0.0000 & 1.0000 \end{pmatrix}$

Table.3. Required Memory To Transfer The Image

Image	Size using proposed method	Using SPIHT coding with EZW tree structure
Image A	500kb	500kb
Image B	600kb	600kb
Stitched Image	550kb	895.7kb

IV CONCLUSION

WMSN consume huge amount of energy when it is capturing visual information continuously and transfer it to destination. An effective power management and power saving strategy is required to enhance the network lifetime. Hence we proposed spatial correlation based power aware event driven image stitching in WMSN that can reduce the energy consumption as well as memory requirement of an image. Experimental results shows that the memory requirement is better compared to SPIHT-EZW technique.

REFERENCE

1. J. Yick, B. Mukherjee and D.Ghosal, "Wireless sensor network survey," Computer Network, Elsevier, vol.52, pp. 2292–2330, 2008.
2. Mohammad Alaei and Jose M. Barcelo-Ordinas, "Node Clustering Based on Overlapping FoVs for Wireless Multimedia Sensor Networks," IEEE Wireless Communication and Networking Conference, 2010.
3. Fu Xiao,et.al, "Research on Image Compression and Transmission Mechanism for Wireless Multimedia Sensor Networks," IEEE, pp.788-791, 2011.
4. Nirali Patel and Jayesh Chaudhary, "Enhancing Multimedia Compression and Transmission Technique to Aid Energy Efficient Wireless Multimedia Sensor Network", ICACCT,pp.378-383,2018.
5. Lecuire, Vincent & Makkaoui, Leila & Moureaux, J.-M. "Fast zonal DCT for energy conservation in wireless image sensor networks.," Electronics Letters. 48. Pp.125-127. 2012.
6. B. Heyne, C. Sun and J. Goetze, "A computationally efficient high quality cordic based DCT," IEEE 14th European Signal Processing Conference, pp. 1 – 5, 2015.
7. A. Mittal, C. Kundu, R. Bose and R. Shevgaonkar, "Entropy based image segmentatio with wavelete compression for energy efficient LTE systems," IEEE 23 International Conference on Telecommunications (ICT), pp. 1-6,2016.
8. Arvind Yedla,et.al, "Universality for the noisy Slepian-Wolf problem via spatial coupling," IEEE International Symposium on Information Theory Proceedings, 2011.
9. Shirin Jalali,et.al, "A Universal Scheme for Wyner–Ziv Coding of Discrete Sources," IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 56, NO. 4, pp.1737-1750,2010.
10. Wai Chong Chia,et.al, "Multiview Image Compression for Wireless Multimedia Sensor Network using Image Stitching and SPIHT Coding with EZW Tree Structure," International Conference on Intelligent Human-Machine Systems and Cybernetics,pp.298-301,2009.
11. Fatma Salih and S.A. Mysoon Omer, "Raspberry pi as a Video Server," (ICCCEEE), 2018.
12. Edward Shen and Richard Hornsey," Local image quality metric for a distributed smart camera network with overlapping FOVs," Fifth ACM/IEEE International Conference on Distributed Smart Cameras, 2011.
13. David Minnen,et,al.," Image-Dependent Local Entropy Models for Learned Image Compression," ICIP, 2018.
14. G. Hong,et,al,." Joint entropy and multiband prediction for lossless image compression," Fifth International Conference on Image Processing and its Applications, 1995.