ENTROPY CORRELATION COEFFICIENT TECHNIQUE FOR VISUAL DATA IN MULTIMEDIA SENSOR NETWORK

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ABSTRACT:.-.**The nodes are interconnected in Wireless multimedia sensor networks (WMSNs) in the form of wireless mode. These interconnected devices transmit their locally processed data to the sink. With the availability of low cost CMOS cameras, WMSN's consists of camera at the sensor node in visual information application. These camera sensor devices capture their observations limited by the Field of View (FoV) as an image. The observed image is then sent to the sink. Large numbers of cameras are deployed in WMSN in order to cover the whole scene of the WMSN field. Part of the area in WMSN field is defined as the area of interest which may be required by any example application. Depending on the application required, the cameras covering that area are selected to send their observations to the sink. Since the WMSN field consists of cameras densely deployed, there exists correlation among their observed images.**

Keywords—source image entropy, mutual Information, joint entropy, ECC, SIFT.

I. INTRODUCTION

An emerging trend for the retrieval of video streams, still images and sensing information from the surrounding environment is the WMSN. A WMSN has wide range of applications such as video surveillance, environmental monitoring, and industrial process control. Compared to the scalar data from wireless sensor networks, the multimedia sensor network should transmit their data with certain quality of service. The energy consumption, bandwidth and limited processing capabilities existing with sensor nodes are important parameters to be considered. Thus WMSN requires more complex data compression method for reducing the consumption of energy and bandwidth by the sensor node. Among the WMSN data, visual information is the most dominating part. Camera provides image which is related directly to the field of view that is limited by sensing direction. A video analyzing method based on correlation is proposed in [4], but this is used for two sensors which do not differ little. Also this method limits the number of sensors to two. Thus the processing of more than two sensors in WMSN for visual information is the problem. In this context, the dissertation presents the implementation of correlation characteristics of images covered by the cameras. Based on the correlation characteristics of images the image mosaicing process is carried out to remove the redundant data among the images and also provide image compression.

Single camera deployed in a field is able to cover only a limited observation which is dependent on its view. In the field if the required application wants the area to be observed and to the sink greater than that of single camera FoV, then there exists a loss of information in the transmission. As the entire field is of large when compared to the single camera field of view, Multiple cameras are incorporated in the WMSN field for visual information retrieval. Hence the Wireless Multimedia Sensor Network comprises of large number cameras, deployed in a field is as shown in Figure 2.1. It can be seen that there are few selected area which are application dependent. With the defined area of interest cameras covering the area are selected to send their observations to the sink.

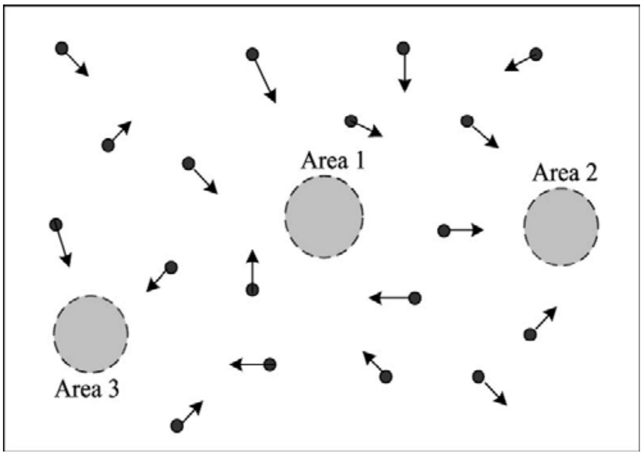


Fig: WMSN with cameras and areas of interest

Camera sensor node observations are dependent on their field of view. The Field of View is represented as a sector. Figure 1.2(a) shows the camera FoV in which camera point is denoted as P. The sensing radius is represented as V. α is the offset angle between the sensing direction and a radius of the sector. Cameras can make its observation within its Field of View only.

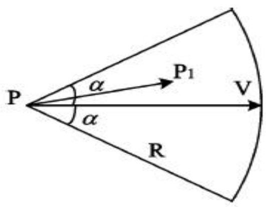


Fig: (a) camera Field of View

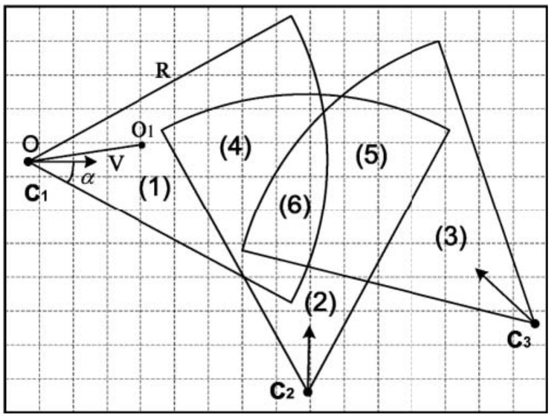


Fig: (b) Overlapped Field of View

In the field even with area specified and selecting only the cameras which cover that area, correlation between camera exists. This is because the adjacent camera nodes usually exhibits high levels of correlation. This results in data redundancy in the visual information gained by the network. Camera senses a 3-D scene and projects it as 2-D image. The overlapped FoV for three cameras is as shown in Figure 1.2(b). It can be observed that all the three cameras are correlated to each other. The the observations made by cameras with overlapped FoV results an overlapped image. This infers that there exists correlation between the images covered by the cameras with overlapped FoV's. This correlation between images represents the amount of redundancy between the observed images from the camera.

Thus in order to eliminate the redundancy in image SIFT based image mosaic process is applied. When the number of images are two this method can be applied in an ease way. Difficulty arises when number of images to be merged are more than two. Also the case with the sequence known SIFT can be repeatedly applied to merge the images. But when the sequence is unknown and this becomes difficult. Hence to select which images to be used for merging process is obtained from the Entropy Correlation Coefficient Model. Thus the out come of the project provides the solution for redundancy removal for the case of multiple images, obtained from a WMSN camera observations.

II. RELATED WORK

Cameras used in the WMSN for visual Information provide their observations in the form of a 2-D image. The processing at the cluster head for the removal of redundancy in the images is performed. As the process is carried out on mages the basics of image processing has to be dealt. The combination of the sensor network and image processing field is implemented in this dissertation. In this direction in the first phase of the dissertation a vast review of literatures available in the area of Wireless Multimedia Sensor Network and image processing applied to the medical images has been conducted.

Pu wang et al. [2] have proposed an information theoretic image compression model with an objective to maximize the overall compression of the visual data collected in a WMSN. The work consists an entropy-based divergence measure (EDM) scheme to estimate the efficiency of compression for the joint coding on the images collected by spatially correlated cameras. This scheme consider only the camera deployment as inputs without requiring properties of real images. The considerations are highly related to the broadband laboratory oriented implementation. Hence the theoretical concepts from this work on the spatial correlation of cameras were adopted for the study on correlation characteristics of cameras.

Rui Dai et al.[1] have proposed a theory of spatial correlation model for visual data in WMSNs. With the help of camera sensing method and its implementation, a spatial correlation function is obtained to describe the correlation characteristics of visual data observed by cameras with overlapped field of views. In this paper the Joint effect of multiple correlated cameras and an entropy-based framework to measure the amount of visual data provided by multiple cameras in the network is developed according to the correlation model the camera selection algorithm is also designed.

Devarajan et al.[5] have proposed distributed algorithm for camera calibration with the automatic, external,metric calibration of a network of cameras with no centralized processor. With interest in calculation of correlation based on cameras,estimation of each cameras focal length, location and sensing direction in a network is a must. Hence the study on the internal and external parameter is extracted from this paper.

Wu et al.[?] have proposed a collaborative image coding and transmission scheme to minimize the effort for data transmission. In this paper Size matching method to coarsely register images for finding maximum overlap to exploit the spatial correlation between images acquired from nearby sensors is presented. A lightweight and efficient background subtraction method is employed to detect targets in this proposal. Only the regions of target and their spatial locations are transmitted to the monitoring center.

From this paper study on Spatial and temporal correlation is performed.

Wiegand et al.[6] have proposed a an overview of the technical characters of H.264/AVC, Based on study of video coding technology is done based on this paper.

Wu et.al [7] have proposed a method for efficient compression and transmission of images in a resource-constrained multinodes wireless network. This can be achieved by distributing the workload of compressing an image over multiple adjacent sensor devices. By doing so, these solutions do not explore the correlation of the observed images among adjacent sensors. This paper provides study on the adjacent nodes and multihop communication in WMSN’s.

Wang et.al [8] have used structural similarity as an alternative motivating method for the design of image quality measures. In this paper the traditional approach for image quality assessment based on sensitivity of error was implemented to show its limitations. Basic concepts on image quality measure was studied from this paper.

Puri et al.[9] have proposed the principles of lossy distributed compression from multiuser information theory for PRISM which is a video coding. PRISM enables transfer of the computationally expensive video encoder motion-search module to the video decoder. In this scheme distributed video coding was proposed to exploit the adjacent frame correlation. But the accuracy was not obtain for correlation method among subsequent video frames, it leads to limited encoding efficiency of distributed video coding. The concept of frame adjacent was studied to compare it with the camera node adjacency.

Pluim et al.[10] have proposed a a description of entropy and mutual information for the application in medical field. The paper presents the history of Entropy,Joint Histogram and mutual information. With the history presented, the paper describes the application of these basics for image registration based mutual information for medical images. The concept of mutual information, Entropy and joint Entropy applied for image is used to for the implementation of individual source Entropy,Mutual information and Joint Entropy of camera images.

Studholme et al.[11] have developed automated 3D multi-modality medical image alignment. This method is purely depend on entropy. In this application where misalignment can be large with respect to the imaged field of view, invariance to overlap statistics is an important consideration. Current entropy measures are reviewed and a normalized measure is proposed which is simply the ratio of the sum of the marginal entropies and the joint entropy. This paper provides the information about the normalized correlation coefficient termed also as Entropy Correlation Coefficient. This Entropy Correlation Coefficient forms the root work of this dissertation.

Manjunath et al.[?] have proposed the use of Gabor wavelet features for texture analysis and provide a comprehensive experimental evaluation. Comparisons with other multi-resolution texture characters using the Brodatz texture database indicate that the Gabor characters provide the best pattern retrieval accuracy. This paper mainly deals on the image processing methodology and in particular using texture information for browsing and retrieval of big image data. The idea for implementation of feature based detection for the project is extracted from this paper.

Jain [12] has proposed a different algorithms for clustering. Hierarchical clustering described in this paper as min-linkage or full-linkage or average-linkage is studied. The correlation coefficient between one group and another group can be obtained. The hierarchical clustering scheme shows the merged images as a representation the clustering form. In the project to obtain the correlation between on image and the other hierarchical clustering is performed.

A.Annis Fathimaa et al.[13] have proposed a modified form of SIFT algorithm for image stitching. This method is implemented using constant moments combined with SIFT charecteristics is presented to reduce the time and computational complexity. It is observed that only a small part of the adjacent view images are overlapped. Hence, It aims in detecting overlapping part for extracting matching points. The overlapping regions are determined using gradient based dominant edge extraction and invariant moments. In the deduced region, the SIFT (Shift Invariant Feature Transform) characters are extracted to determine the matching features. The registration is carried on with RANSAC (Random Sample Consensus) algorithm and final output mosaic is obtained by warping the images. The proposed approach results in reduced time and computational when compared to existing methods. From this paper the SIFT based image mosaic is extracted to implement for the project.

Based on the above review of literatures, this dissertation aims to study and implement ECC model in WMSN for visual information. The implementation of Entropy, Mutual information and Joint Entropy is obtained from method proposed in [10].Implementation of correlation coefficient using the obtained entropy and mutual information is as given by [11]. Depending on the ECC value two image merging process has to take place. This implementation uses SIFT feature extraction method as given from [13]. The combined work upto this stage is presented in the algorithm from [1]. The camera selection based on the correlation coefficient is performed as given by the algorithm in [1].

III. METHODOLOGY

This section deals about the significance of Joint Entropy and ECC in WMSN for Visual information. If Xi is the covered image transmitted to the sink by a camera sensor Si, then the amount of information gained at the sink is H (Yi). If there is a group of sensor S = S1; S2; ; SN and their transmitted images are Y1;Y2; ;YN to the sink, then the amount of information gained at the sink will be the joint entropy H(Y1;Y2; ;YN). Thus the joint entropy of the images has to be estimated.

A. Joint Entropy for two images

Consider that two camera sensors A and B cover the required area of interest in WMSN. Let each camera captures one image of it field of view, denoted as image A and image B. The measure in the amount of information obtained when a single source is considered (image A from camera A or image B from camera B) in the form of individual entropy will be less when compared to the joint entropy of both the images A and B (both camera observations considered). If the complete seen covered by both the cameras have to be sent to the sink then the joint Entropy of the two images is sent rather than individual entropies. Hence, the joint entropy is more likely to be transmitted instead of single source. For the estimation of joint entropy between two images A and B in WMSN (2.14) is used.

B. Entropy correlation coefficient (ECC)

The entropy correlation coefficient (ECC) provides the correlation degree between two images A and B. The value of ECC ranges from zero to unit. When the source A and B are different the value is zero and when the ECC value is unit it indicates that source are same. The increase in the ECC value implies that the two sources are more correlated. The amount of information obtained together by the two images i.e., the Joint Entropy of two images depends on the ECC. If the correlation degree is more between the two images A and B, the joint entropy gained from the two images A and B is less.

C. Implementation

(a) Image A

(b) Image B

Table 2.1: Simulation results for two overlapped input images

Figure	Result from the simulation
Individual source Entropy for Image A, H(A)	7.5607
Individual source Entropy for Image B, H(B)	7.7227
Mutual information between image A and image B, I(A,B)	0.2002
Mutual information between image B and image A, I(B,A)	0.2002
Joint entropy matrix, H(A,B)	$JE = \begin{bmatrix} 7.5607 & 15.0832 \\ 15.0832 & 7.7227 \end{bmatrix}$
Entropy correlation co-efficient (ECC) matrix	$ECC = \begin{bmatrix} 1 & 0.0262 \\ 0.0262 & 1 \end{bmatrix}$

D. Image feature detection

SIFT ALGORITHM

SIFT feature detection consists of four main stages.

Stage 1: Scale-space extrema detection

This stage computes all scales and image locations. By using Difference of- Gaussian function it can be implemented efficiently. which identifies the potential interest points that are invariant to orientation and scale.

Stage 2:. Keypoint Identification

At each estimated location , a detailed model is fit to determine scale and location. Keypoints are selected on basis of measures of their stability.

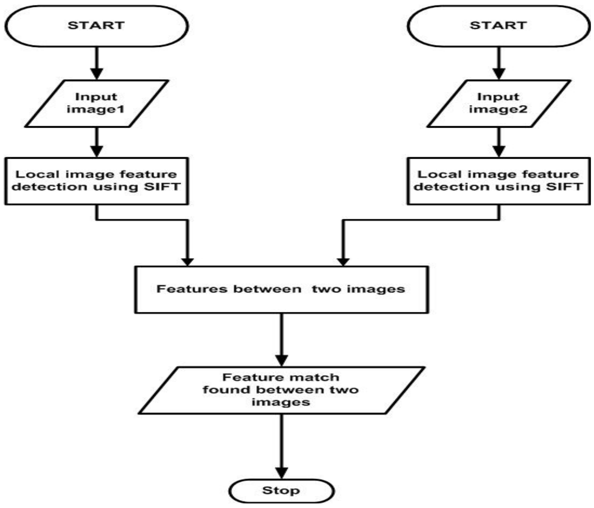
Stage 3: Orientation assignment

Based on local image gradient directions multiple orientations are allocated to each keypoints.. All further operations are performed on image information that has been transformed relative to the assigned scale, orientation, and location for each characters, thereby providing constant values to these transformations.

Stage 4: keypoint descriptors development

After identification of keypoints, based on scale and orientation, image gradients are measured. These gradients are transformed into a representation which admits significant levels of local change in illumination and shape distortion.

Flowchart for SIFT based match between two images



E. Homography using RANSAC algorithm

RANSAC stands for "RANdom SAmple Consensus". RANSAC is a robust method to estimate parameters of a mathematical model from a set of observed data which contains outliers by an repetitive process. This method generates a reasonable result only with a certain probability. With this probability the repetition increase is allowed. The algorithm was first developed by Fischler and Bolles at SRI international in 1981. Even though the method is old its robustness has made it useful in many applications. The algorithm is performed for a set of points detected or pre-computed. In our implementation RANSAC is applied for the points set for the image which are obtained using SIFT feature detection algorithm.

The steps for the RANSAC estimation is as follows:

1.Obtain n points (in this case this value is from the matched features from two images).

2.Initialize the number of points, iterations, threshold inlier.

3. Compute for best fit using random points (fit using 2 random points)

4. Count the inliers, if more than threshold Inlier, refit else iterate

5. choose the coefficient with the most inliers

IV. RESULT ANALYSIS

Figure 4(a) and 4(b) are the two overlapped input images. The number keypoints for Figure 4(a) is found to be 313 and for Figure 4(b) is 249.

Fig 4.1: (a) Image A (b) Image B

The transformation is obtained for image B with respect to the image A. This transformation of image is as shown in Figure 4.3(a). The transformation obtained is based on the homography matrix which is as given in Table 4.1. The wrapped image with redundancy removed using the implementation method described so far is as shown in Figure 4.3(b). The similar features found between Figure 4.1(a)and Figure 4.1(b) is 55. The SIFT match between two images is as shown in Figure 4.2. In this example image set, the two images are of different orientation. The SIFT features are efficiently matched even with this condition of orientation change.

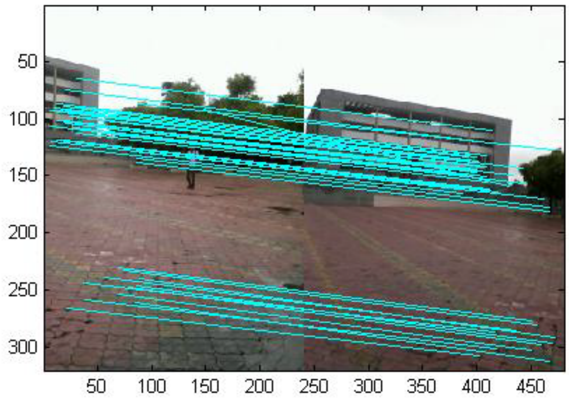


Fig 4.2:SIFT feature matched between two images

Table 4.1: Simulation results for two overlapped input images.

Figure	Result from the simulation
Keypoints for image A	313
Keypoints for image B	249
Matched keypoints between two images	55
Homography matrix estimation between two images, H	$H=\begin{pmatrix} 1.4242 & 0.0183 & -205.119 \\ 0.1973 & 1.4004 & -101.8926 \\ 0.0016 & 0.0003 & 1.0000 \end{pmatrix}$

(a) Image A transformed with respect to Image B

(b) Mosaiced output image

Fig 4.3: Transformation and Mosaic output.

VI. CONCLUSION

Correlation coefficient: The correlation coefficient measures the amount of overlapped regions between all the N images. Results provide a [NXN] correlation matrix for N images. From the matrix of the simulated results it can be observed that the correlation value has the range from 0 to 1. Joint Entropy of multiple images Joint Entropy is used to calculate the amount of matter obtained when two images are joined. Joint entropy of multiple images is obtained from the correlation matrix. Merging of two overlapped images indicated by the correlation coefficient For the merging process in the case of multiple images, SIFT based image mosaic technique is implemented.

VII. REFERENCES

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