

# High Resolution Image Reconstruction with Smart Camera Network

R.Nikitha<sup>1</sup>, C.K.Sankavi<sup>2</sup>, H.Mehnaz<sup>3</sup>, N.Rajalakshmi<sup>4</sup>, Christo Ananth<sup>5</sup>

U.G.Scholars, Department of ECE, Francis Xavier Engineering College, Tirunelveli<sup>1,2,3,4</sup>

Associate Professor, Department of ECE, Francis Xavier Engineering College, Tirunelveli<sup>5</sup>

**Abstract—** In this work, a framework of feature distribution scheme is proposed for object matching. In this approach, information is distributed in such a way that each individual node maintains only a small amount of information about the objects seen by the network. Nevertheless, this amount is sufficient to efficiently route queries through the network without any degradation of the matching performance. Digital image processing approaches have been investigated to reconstruct a high resolution image from aliased low resolution images. The accurate registrations between low resolution images are very important to the reconstruction of a high resolution image. The proposed feature distribution scheme results in far lower network traffic load. To achieve the maximum performance as with the full distribution of feature vectors, a set of requirements regarding abstraction, storage space, similarity metric and convergence has been proposed to implement this work in C++ and QT.

**Index Terms—**Computer vision, Object Reconstruction, Visual Sensor Networks

## I. INTRODUCTION

A Visual Sensor Network is a network of spatially distributed smart camera devices capable of processing and fusing images of a scene from a variety of viewpoints into some form more useful than the individual images. A visual sensor network may be a type of wireless sensor network, and much of the theory and application of the latter applies to the former. The network generally consists of the cameras themselves, which have some local image processing, communication and storage capabilities, and possibly one or more central computers, where image data from multiple cameras is further processed and fused.

Local processing of the image data reduces the total amount of data that needs to be communicated through the network. Local processing can involve simple image processing algorithms (such as background subtraction for motion/object detection, and edge detection) as well as more complex image/vision processing algorithms (such as feature extraction, object classification, scene reasoning). Thus, depending on the application, the camera nodes may provide different levels of intelligence, as determined by the complexity of the processing algorithms they use. The cameras can collaborate by exchanging the detected object features, enabling further processing to collectively reason

about the object's appearance or behavior. At this point the visual sensor network becomes a user-independent, intelligent system of distributed cameras that provides only relevant information about the monitored phenomena. Therefore, the increased complexity of vision processing algorithms results in highly intelligent camera systems that are oftentimes called smart camera networks.

The issue of ensuring and preserving coverage of an area with controlled redundancy using WSNs has been widely investigated, and efficient algorithms have been proposed.

The main goals of coverage optimization algorithms are to preserve coverage in case of sensor failure and to save energy by putting redundant sensor nodes to sleep. Choosing which nodes to put in sleeping or active mode should be done carefully to prolong the network lifetime, preserve coverage and connectivity, and perform the task at hand. However, when camera sensors are involved, three-dimensional coverage of space is required, which increases the complexity of the coverage issue. Coverage of networked cameras can be simplified by assuming that the cameras have a fixed focal length lens, are mounted on the same plane, and are monitoring a parallel plane.

Visual data collected by camera nodes should be processed and all or relevant data streamed to the BS. It is largely agreed that streaming all the data is impractical due to the severe energy and bandwidth constraints of WSNs. And since processing costs are significantly lower than communication costs, it makes sense to reduce the size of data before sending it to the BS. However, visual data processing can be computationally expensive. Reliable data transmission is an issue that is more crucial for VSNs than for conventional scalar sensor networks. While scalar sensor networks can rely on redundant sensor readings through spatial redundancy in the deployment of sensor nodes to compensate for occasional losses of sensor measurements, this solution is impractical for VSNs, which are characterized by higher cost and larger data traffic. Moreover, most reliable transmission protocols proposed for conventional scalar data WSNs are based on link layer acknowledgment messages and retransmissions. They are therefore not suitable for visual data transmission due to their stringent bandwidth and delay requirements. The initial phase of visual data processing usually involves object detection. Object detection may trigger a camera's processing activity and data communication. Object



detection is mostly based on light-weight background subtraction algorithms and presents the first step toward collective reasoning by the camera nodes about the objects that occupy the monitored space.

Since detection of objects on the scene is usually the first step in image analysis, it is important to minimize the chances of objects' fault detection. Thus, reliability and light-weight operations will continue to be the main concerns of image processing algorithms for object detection and occupancy reasoning.

The main objective of [1] is to provide reconstruction theory and techniques for image reconstruction and creating enhanced resolution images from irregularly sampled data. The relationship between the aperture function, the measurement sampling, and the reconstruction has been examined in this paper. The methodology used in this paper is image reconstruction and resolution enhancement algorithm. This algorithm provides improved resolution images by taking advantage of oversampling and the response characteristics of the aperture function to reconstruct the underlying surface function sampled by the sensor. This algorithm can generate images from the observations at a resolution better than the mainlobe aperture resolution of the sensor.

The algebraic reconstruction technique (ART) and scatterometer image reconstruction (SIR) algorithms can be termed resolution enhancement algorithms because of their ability to fully reconstruct attenuated signal components. SIR is more robust than Multiplicative ART and Additive ART in the presence of noise. Both AART and MART produce slightly different results based on the different regularizations. The results show that the image reconstruction and resolution enhancement algorithms such as AART, MART, and SIR provide an effective way to increase the effective resolution of remotely sensed imagery. The advantage of this paper is that the sampling and aperture function considerations in the design of the sensor system provide better resolution and the high-pass nature of the reconstruction filter increases the noise power. The main drawback of this paper is that it will limit the number of iterations before noise overtakes the reconstruction.

The main objective of [2] is to develop a new algorithm for density estimation using the EM algorithm with a ME constraint. The proposed Maximum-Entropy Expectation-Maximization (MEEM) algorithm provides a recursive method to compute a smooth estimate of the maximum likelihood estimate. The MEEM algorithm is particularly suitable for tasks that require the estimation of a smooth function from limited or partial data, such as image reconstruction and sensor field estimation. The methodology used in this paper is Maximum-Entropy Expectation – Maximization algorithm. The MEEM algorithm is used to provide the optimal estimates of the weight, mean, covariance for kernel density estimation. The basic EM algorithm estimates a complete set from partial data sets and therefore we propose to use the EM and MEEM algorithms in these image reconstruction and sensor network

applications. The EM algorithm relies on a simple extension of the lower-bound maximization method to prove that our algorithm converges to a local maximum on the local generated by the Cauchy-Schwartz inequality, which serves as a lower bound on the augmented likelihood function.

The results indicate that, in most cases the results under maximum entropy show better results than the conventional EM algorithm. When we use a small number of centers, the result of minimum entropy penalty shows better results than the results of the conventional EM algorithm and maximum entropy penalty. This is due to the characteristics of maximum and minimum entropy. The advantages of this paper are that the maximum entropy solution provides smooth solution and the minimum entropy solution provides the least smooth distribution. It provides a very high performance than various other methods.

The objective of [3] is to develop a theory of phase singularities (PSs) for image representation. PSs are calculated by the Laguerre-Gauss filters which contain important information of an image and provide an efficient and effective tool for image analysis and presentation. PSs are invariant to translation and rotation and the positions of PSs contain nearly complete information for reconstructing the original image up to a scale. To examine the usefulness of PSs, we develop two applications: object tracking and image matching. In object tracking, the iterative closest point (ICP) algorithm is used to determine the correspondences of PSs between two adjacent frames. The use of PSs allows us to precisely determine the motions of tracked objects. In image matching, we combine PSs and scale-invariant feature transform (SIFT) descriptor to deal with the variations between two images and examine the proposed method on a benchmark database. The ICP algorithm is used for aligning two groups of points based on geometrical information. The ICP starts with a rough initial estimation on the transformation between the two groups of points, and then iteratively refines the transformation by identifying the matching points and minimizing an error metric.

The result shows that PSs are generally stable to real noise and image deformation and the proposed method is used to find a large number of matching points for each pair, which distribute over the whole images. The advantage of this paper is that this method is more robust and we can find correct matching pairs.

The main objective of [4] is to collect considerably less data than conventional systems, and display only what is relevant for the task at hand. The proposed method is not an alternative when the perfect reconstruction of arbitrary images is required, but nevertheless operates within the same framework by extracting information from compressive measurements. Compressed sensing holds the promise for radically novel sensors that can perfectly reconstruct images using comparatively simple hardware and considerably fewer samples of data. In surveillance applications vast regions of the image may not contain object of interest, and may therefore not be of significance to the operator.

Reconstruction Algorithms is the methodology used in this paper. In this algorithm reconstruction using compressed sensing will always require more samples than if it were possible to directly measure projections on an underlying basis in which the object is sparse. This paper is not concerned with perfect reconstruction of the full image from a relatively few samples, but with the reconstructions of specific objects that are present in the image. The results of simulation shown that the proposed approach can be realized assuming different basis sets to represent the object and irrespective of the choice of basis set, the weighting process always yields a better result. The advantage of the paper is to achieve the greatest possible compression and reconstruction fidelity and the weights can be optimized to emphasize greater discrimination between the objects and background which should lead to enhanced visualization of interested objects in the image.

The objective of [5] is to present a novel approach for the study of signal reconstruction from randomly scattered sensors in a multidimensional space. The random sampling using constant-mean point processes yields an unbiased estimate of the signal. Iterative reconstruction scheme is the methodology used in this paper. The classical iterative reconstruction forms a sequence of unbiased estimates of band-limited signals, which converges to the true function in the mean-square sense. The use of an ideal band-limited operator in the iterative reconstruction method improves the reconstruction substantially and removes many of the artifacts. The iterative estimation method performs efficiently even when the sensors are sparse. The performance of the iterative estimation method for 2-D image reconstruction and field estimation from Poisson and uniformly distributed sensors are also demonstrated in this method. The field estimation problem is formulated as signal reconstruction from scattered sensors. This approach is an extension of the problem of image reconstruction from limited samples. The solution to these problems is based on classical methods for function estimation from irregular samples. When the samples are distributed according to a homogeneous Poisson process in the plane, the point process is constant mean and corresponds to the density of the process in the limit as the number of samples approaches infinity.

The simulation results rely on a finite number of Poisson distributed random samples on a bounded region. We interpret these random samples as an extraction of a bounded region from an unbounded plane with an infinite number of Poisson samples. The advantage of this paper is that the energy is confined within a certain bandwidth and improves the reconstruction of images.

## II. EXISTING SYSTEM

Computer Vision Algorithm is used in this existing system. By using this algorithm large amount of digitized visual data is processed. High end hardware is required for

processing. It leads to the formation of star network structure, a powerful processing unit. In this system, only one sensor node is used, so the processing of large amount of digitized data is difficult. The advantage of this method is that it allows simplicity of routing. A conceptual problem of this centralized approach is that it is not scalable, i.e., it does not scale with the number of sensors used. When additional nodes are added to such a configuration, the central processor becomes a major bottleneck. In some cases, the number of visual sensors may go into the hundreds. It is obvious that the requirements for transmitting and processing the data in such a large system are correspondingly large.

## III. PROPOSED SYSTEM

In this project, a framework of feature distribution scheme is proposed for object matching. Each individual node maintains only a small amount of information about the objects seen by the network. Nevertheless, this amount is sufficient to efficiently route queries through the network without any degradation of the matching performance. Efficient processing has to be done on the images received from nodes to reconstruct the image and respond to user query. The proposed feature distribution scheme results in far lower network traffic load. To achieve the maximum performance as with the full distribution of feature vectors, a set of requirements regarding abstraction, storage space, similarity metric and convergence has to be proposed to implement this work in C++.

The SQL database package is used for database connectivity. The SQL database performs functions such as insert, delete and update. The insert function is used to insert the data into the database. The delete function is used to delete the entire row in a database. The update function updates all the data in the database.

## IV. RESULTS AND DISCUSSION

In this the user first sets the path of the folder where the background images are present. After selecting the path click the start button to process the filename of the background image and find out the node number of that background and stored it in the database. Click close to exit from the window. Fig.1. shows the storage of background images in the database.



Fig.1. Receive background image



#### A. RECEIVE FOREGROUND OBJECT

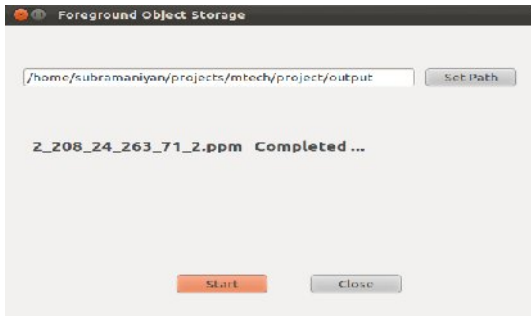


Fig.2. Receive foreground object

In this the user first sets the path of the folder where the foreground objects are present. After selecting the path click the start button to process the filename of the foreground object and find out the node number and frame number of that foreground and stored it in the database. Click close to exit from the window. Fig.2. shows the storage of processed foreground object in the database.

#### C. IMAGE STITCHING



Fig.3. Image Stitching

In image stitching the node number, frame number and the co-ordinates of the foreground objects in the background image have to be found in the database. The objects which are not stitched with the background in the database are taken first and then find out the corresponding node number of that object. Then the node's corresponding background image is taken and stitches it with the foreground object and is stored in the database. After stitching the process gets completed and this message will be shown to the user. Click close to exit from the window. Fig.3. shows the process of image stitching.

#### D. USER QUERY PROCESSING

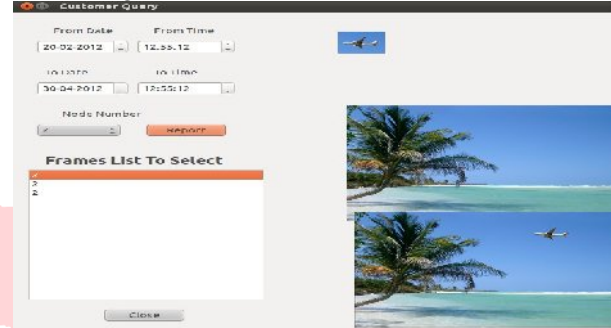


Fig.4. Object Reconstruction

When a user wants to know about the foreground objects that is present during a time, then the user enters the starting date that is from date and to date and also he enters the node number that is from which node, the user wants the foreground object to be seen. The server retrieves the correct background and foreground objects from the database and displays it to the user. Fig.4. shows the reconstructed object.

#### V. CONCLUSION

In this work, a framework of feature distribution scheme is proposed for object matching. In this approach, information is distributed in such a way that each individual node maintains only a small amount of information about the objects seen by the network. Nevertheless, this amount is sufficient to efficiently route queries through the network without any degradation of the matching performance. Digital image processing approaches have been investigated to reconstruct a high resolution image from aliased low resolution images. The accurate registrations between low resolution images are very important to the reconstruction of a high resolution image. The proposed feature distribution scheme results in far lower network traffic load. To achieve the maximum performance as with the full distribution of feature vectors, a set of requirements regarding abstraction, storage space, similarity metric and convergence has been proposed to implement this work in C++ and QT.

#### REFERENCES

- [1] Foroosh, Zerubia, and Berthod, "Extension of phase correlation to subpixel registration," IEEE Trans. Image Process., vol. 11, no. 3, pp. 188-200, Mar. 2002.
- [2] Huang, Burnett, and Deczky, "The importance of phase in image processing filters," IEEE Trans. Acoust., Speech, Signal Process., vol. ASSP-23, no. 6, pp. 529-542, Jun. 1975.
- [3] Khan and M. Shah. Consistent labeling of tracked objects in pattern cameras with overlapping fields of view. IEEE Transactions on Pattern Analysis and Machine Intelligence, 25(10):1355-1360, October 2003.
- [4] Khan and Shah, "Tracking multiple occluding people by localizing on multiple scene planes," IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 3, pp. 505-519, Mar. 2009.
- [5] Lee, Romano, and Stein, "Monitoring activities from multiple video streams: establishing a common coordinate frame," IEEE Trans. Pattern Anal. Mach. Intel. vol. 22, no. 8, pp. 758-767, 2000.
- [6] Long, Hardin, and Whiting, "Resolution enhancement of spaceborne scatterometer data," IEEE Trans. Geosci. Remote Sensing, vol. 31, pp. 700-715, May 1993.



[7] Lowe, D.G. 2001. Local feature view clustering for 3D object recognition. IEEE Conference on Computer Vision and Pattern Recognition, Kauai, Hawaii, pp. 682-688.

