Chapter 4
Fast Progressive Image Transmission

4.1 Introduction
Progressive image transmission provides a convenient User Interface when images are transmitted slowly. We present a progressive image reconstruction scheme based on the multiscale edge representation of images. In the multiscale edge representation, an image is decomposed into Most Significant Points (MSP) which represent the strong edges and Insignificant Points (ISP) which represent weak edges. Image reconstruction is done based on the approximation of image regarded as a function, by a linear spline over adapted Delaunay triangulation. The proposed method progressively improves the quality of the reconstructed image till the desired quality is obtained.

With the emergence of the World Wide Web, images have become an important means of communicating information in the formerly textonly Internet. When people view an image through a low speed connection, for example, via a telephone line or via wireless networks, it will take much time to transmit the whole image. Even with increased bandwidth, transmitting large images such as pictures captured by digital cameras is still relatively slow. The desire to let mobile users participate in the Internet leads to the need to cope with even narrower bandwidth and smaller client displays. If the delay is too long user will feel irritated and will give up. In order to re-duce the bandwidth required for transmitting a given image in a given time, image compression techniques are commonly used to encode images. The encoded results, instead of the original images, are transmitted over
the Internet. After decoding, we can obtain the decoded images, which are similar to the original ones.

Rohit Verma and Siddavatam Rajesh [22],[23],[24] have developed a fast image reconstruction algorithms using second generation wavelets and splines. Image Compression and Reconstruction algorithms have been developed by many researchers.

Siddavatam Rajesh [25] has developed a fast progressive image sampling using B-splines. Carlos Vazquez et al, [28] has proposed interactive algorithm to reconstruct an image from non-uniform samples obtained as a result of geometric transformation using filters Delaunay triangulation [34],[37] has been extensively used for generation of image from Irregular data points. The image is reconstructed either by linear or cubic splines over Delaunay Triangulations of adaptively chosen set of significant points[26]. This paper concerns with progressive triangulation of an image using standard gradient edge detection techniques and reconstruction using bivariate splines from adapted Delaunay triangulation until the desired quality of the reconstructed image is not obtained.

Although image compression provides an efficient and effective method to reduce the amount of data needed to represent an image, it oftentimes requires receivers to wait for the completely encoded results before reconstructing the image. If the decoded image is not the expected one, then receivers must transmit another image again. Progressive Image Transmission (PIT) techniques have been proposed to alleviate this problem by first sending a coarse version of the original image and
then resending it progressively. Progressive image transmission can help reducing the latency when transmitting raster images over low bandwidth links[27]. Often, a rough approximation (preview) of an image is sufficient for the user to decide whether or not it should be transmitted in greater detail[29],[31-33]. This allows the user to decide whether to wait for a more detailed reconstruction, or to abort the transmission. Progressive image transmission has been widely applied for many applications, such as teleconferencing, remote image database access and so on.

Existing approaches for PIT have adopted, explicitly or implicitly, the minimal distortion principle to decide the importance. For example, in the SPIHT algorithm [38], the coefficients with larger magnitude are considered more significant for they will cause larger distortion. The algorithm will therefore sort the coefficients by their magnitudes before transmission.

Some PIT techniques have adopted HVS (human visual system) weighting in spectral domain to improve the perceptual quality of the transmitted image [39],[40]. However, they did not consider the attention change in spatial domain. Popular image standards such as JPEG and JPEG2000 do support ROI coding, but they do not provide any mechanism for automatic ROI definition.

The thesis describes the significant sample point selection and the modeling of the 2D images using the Linear Bivariate splines is elaborated. We also describe the reconstruction algorithm and its complexity. The significant measures for reconstruction have been discussed. Experimental results along with comparison of
the proposed method with APEL are discussed in the end.

4.2 Progressive Significant Sample Point Selection
All the progressive sampling methods take the coarse-to-fine approach—some kind of uniform sampling is applied again and again in different resolutions. The concept is adding one sample point at a time, with the key question being where the next sample should be placed. If our goal is a good reconstruction, the next sample location should be the one that minimizes the expected overall reconstruction error. This section provides a generic introduction to the basic features and concepts of novel Progressive Sample Point Selection algorithm.

4.3 Proposed Algorithm
Let M be a mXn matrix representing a grayscale image. The algorithm involves the following steps:

1) Initialization: initialization of variables.
2) Edge Detection: Edge detection using sobel and canny filters.
3) Filtering: Passing the images/matrices through range filter.
4) First Phase Transmission: Transmission of strong edges resulting in a coarse image.
5) Second Phase Transmission: Transmission of weak edges resulting in a fine image.
6) Third Phase Transmission: Detailed information for improving the reconstructed image.
7) Subsequent Phase Transmission: detailed transmission is continued till
desired resolution is achieved.

4.3.1 Initialisation

\[
\begin{align*}
X_I &= 0; X_2 = 0; X_3 = 0 & x \in X_1, X_2, X_3 \\
Y_I &= 0; Y_2 = 0; Y_3 = 0 & y \in Y_1, Y_2, Y_3 \\
Z_I &= 0; Z_2 = 0; Z_3 = 0 & z \in Z_1, Z_2, Z_3
\end{align*}
\]

\(X, Y, Z\) are matrices for representing \(x, y, z\) pixel co-ordinates.

\(H\) is the starting level for third phase retransmission.

\(M\) is the increment level for third phase retransmission. The values of \(H\) and \(M\) represent the network bandwidth used for image transmission.

\(\text{Count1}=0; \text{Count2}=0; \text{Count3}=0;\) are integers representing the number of points obtained for triangulation at successive phases of transmission.

\(Xs\) is Data Set for Sobel Filter and \(Xc\) is Data Set for Canny Filter.

4.3.2 Edge Detection

An edge detector like sobel or canny takes a grayscale image as its input and returns a binary image of the same size, with 1's where the function finds edges in the original image and 0's elsewhere.
Figure 4.1: Edge Detection (Sobel)[22]

The Sobel method finds edges using the Sobel approximation to the derivative. It returns edges at those points where the gradient of I is maximum. In this method all the edges that are not stronger than a default threshold value are ignored. We can also specify our own threshold value. So this method does not identify weak edges which can be seen clearly in the Figure 4.1. This method was giving too less points to get the required triangulation.

The Canny method finds edges by looking for local maxima of the gradient of image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore more likely to detect true weak edges. The result is the following image. But again this resulted in too many points for the required triangulation.
4.3.3 Filtering

After identifying the edges, the resulting image is passed through a filter so that the edges become prominent and we get more points near the edges. In order to obtain good triangulations most significant points are chosen. Range filter filters an image with respect to its local range. It returns an array, where each output pixel contains the range value (maximum value - minimum value) of the 3-by-3 neighborhood around the corresponding pixel in the input image.

4.3.4 First Phase Transmission

Input: Original Lena Image \( I(x,y) \);

Step 1: for \( k=1, 3, 5, 7 \ldots \ldots \ldots \ldots 2n-1 \)

Step 2: Locate a point \( P(x,y) \) such that \( P(x,y) \subseteq X_s \)

Step 3: Add \( P(x,y) \) to matrices \( X_1, Y_1, Z_1 \)

Step 4: \( \text{count} = \text{count} + 1 \)

Step 5: end
Output:  \( l(X_1, Y_1, Z_1) \in X_s \)

### 4.3.5 Second Phase Transmission

Input:  \( X=0; Y=0; \) count=0;  \( Z=0; l(X, Y) \)

Step 1: for k= 1, 4,7,11,.................3n-2

Step 2: Locate a point \( P(x, y) \) such that

Step 3: \( P(x, y) \in X_c \) and \( P(x, y) \in X_s \)

Step 4: Add \( P(x, y) \) to matrices to \( X_2, Y_2 \) and \( Z_2 \)

Step 5: count = count+1

Step 6: end

Output: \( l(X_2, Y_2, Z_2) \in X_c \cup X_s \)

### 4.3.6 Delaunay Triangulation

Delaunay triangulation [35, 36, 37] is also popular due to its following properties:

1) It gives a unique set of triangles \( T \), provided that no four points in \( S \) are co-circular,

2) It guarantees optimal triangulation according to the min-max angle criterion, i.e. the smallest angle is maximal.

3) It gives the smoothest piecewise linear approximation for a given data set.

In the Delaunay triangulation method [37], the location of the global nodes defining the triangle vertices and then produce the elements by mapping global nodes to
element nodes. Element definition from a given global set can be done by the method of Delaunay Triangulation. The discretization domain is divided into polygons, subject to the condition that each polygon contains only on global node, and the distance of an arbitrary point inside a polygon from the native global node is smaller than the distance from any other node. The sides of the polygon thus produced are perpendicular bisectors of the straight segments connecting pairs of nodes.

4.3.7 Third Phase Transmission

To further improve the triangulations, in every triangle a point is inserted at the centroid of the triangle and triangles are formed including that point. This algorithm is useful for even those images having low gradient at the edges or weak edges.

Input: TRI(X1+X2, Y1+Y2)

Step 1: T=Dataset (TRI)
Step 2: for threshold=H to 0 step M
Step 3: for m=1, 2, 3, 4,5,6,7......................N
Step 4: If Area > Threshold
Step 5: C(x,y)=Centroid of Triangle TN
Step 6: add C(x,y) to data set (X3,Y3,Z3)
Step 7: count = count+1
Step 8: end
Step 9: end
Step 10: \( \text{TRI} = \text{delaunay}(X,Y) \)

Output: \( I(X3, Y3, Z3) \in Xc \cup Xs \)

4.3.8 Subsequent Phase Transmission

Depending upon the requirement of resolution the image fine detail information can be generated further by centroid of triangles and passed in subsequent phases till required resolution is obtained.

4.4 Image Reconstruction Using Linear Bivariate Splines

The transmitted image as a result of the three phases of transmission is reconstructed at the receiver's end. The reconstruction is carried out based on the approximation of image regarded as a function, by a linear bivariate spline over adapted Delaunay triangulation.

The Linear Bivariate Splines are used very recently by Laurent Demaret et al [9]. The image is viewed as a sum of linear bivariate splines over the Delaunay triangulation of a small recursively chosen non uniform set of significant samples \( S_k \) from a total set of samples in an image denoted as \( S_n \). The linear spline is bivariate and continuous function which can be evaluated at any point in the rectangular image domain in particular for non uniform set of significant samples denoted as \( S_k \) from a total set of samples in an image denoted as \( S_n \).

If we denote \( \Omega \) as the space of linear bivariate polynomials, for the above set
the linear spline space \( \Omega_L \), containing all continuous functions over the convex hull of \( S_k \) denoted as \([S_k]\).

**Definition:** If for any triangle \( \Delta \in T(S_k^k) \) where \( T(S_k^k) \) is the delaunay triangulation of \( S_k^k \) in \( \Omega \) defined as
\[
\Omega_L = \{ x : x \in [S_k^k] \} \forall \Delta \in T(S_k^k) \}
\]
then any element in \( \Omega_L \) is referred to as a linear spline over \( T(S_k) \). For given luminance values at the points of \( S \), \{\( I(y) \): \( y \in S \)\} there is a unique linear spline interpolant \( L(S, I) \) which gives

\[
L(S, I)(y) = I(y) \forall \ y \in S
\]

where \( I(y) \) denotes the image \( I \) with \( y \) samples that belong to \( S \). Using the above bivariate splines and the concept of Significant Sample point selection algorithm discussed above the original image can be approximated and the reconstruction of the image can be done as per the algorithm given below.

### 4.5 Reconstruction Algorithm

The following steps are used to reconstruct the original image from set of regular points comprising of significant \( (S_K) \) and insignificant points \( (I_K) \):

**INPUT:**

1. Let \( S^N = \text{data set} \ S \in S^K \quad U \ I^K \)
2. \( Z^0 \): luminance
3. $S^0$: set of regular data for initial triangulation

Step 1. Use Delaunay triangulation and Linear Bivariate Splines to produce unique set of triangles and image.

Step 2. Use Progressive Significant sample point selection algorithm to find a set of new significant points (SP).

Step 3. Get $S^K = S^{K-1} + \text{SP}$

Step 4. Repeat steps 1 to 3 to get the Image $I_R(y)$

Step 5. Return $S^K$ and $I_R(y)$

OUTPUT:

Most Significant Sample Set ($S^K$) and Reconstructed Image $I_R(y)$

4.6 Algorithm Complexity

In general, the complexity of the non-symmetric filter is proportional to the dimension of the filter $n^2$, where $n \times n$ is the size of the convolution kernel. In canny edge detection, the filter is Gaussian which is symmetric and separable. For such cases the complexity is given by $n+1$ [41]. All gradient based algorithms like Sobel do have complexity of $O(n)$. The complexity of well known Delaunay algorithm in worst case is $O(n^{\text{ceil}(d/2)})$ and for well distributed point set is $\sim O(n)$. $N$ is number of points and $d$ is the dimension. So in 2D, Delaunay complexity is $O(N)$ is any case.

Step 1: Sobel Edge Detector: $O(n)$

Step 2: Canny Edge Detector: $O(n)$

Step 3: Filtering (rangefilt): $O(n)$
Step 4: First Phase Transmission: $O(2n-1)=O(n)$
Step 5: Second Phase Transmission: $O(3n-2)=O(n)$
Step 6: Third Phase Transmission: $O(n)$
Step 7: Image Reconstruction: $O(n)$

Hence the total complexity of the proposed algorithm is $O(n)$ which is quite fast and optimal.

4.7 Experimental Setup

The algorithm has been tested with MATLAB simulation on standard LENA image.

4.8 Measurement Metrics

A well-known quality measure for the evaluation of image reconstruction schemes is the Peak Signal to Noise Ratio (PSNR),

$$PSNR = 20 \times \log_{10} \left( \frac{b}{RMS} \right)$$

where $b$ is the largest possible value of the signal and RMS is the root mean square difference between the original and reconstructed images. PSNR is an equivalent measure to the reciprocal of the mean square error. The PSNR is expressed in dB (decibels). The popularity of PSNR as a measure of image distortion derives partly from the ease with which it may be calculated, and partly from the tractability of linear optimization problems involving squared error metrics.

4.9 Results and Discussions

We have used absolutely addressed Picture Element coding (APEL) [40] to compare
the effectiveness of our proposed method. APEL is a robust, loss-less image coding technique, which transforms binary images into a tessellation of independent black picture elements. As the APEL technique operates on a binary level, the encoding of grey-scale images must employ a Bit Plane Coding (BPC) [39] stage. APEL inter-leaves and sends the larger pixels from each of the bit-planes immediately after the transmission has begun so that a coarse image can be encoded by the recipient. Subsequently, as further pixels arrive, a finer image can be decoded by the recipient. APEL decreases the visual impact of errors by rearranging the addresses of pixels in an ascending order and placing two contiguous pixels a considerable distance apart in the data-stream, the probability of both being destroyed by the same burst is de-creased. Error can be detected and removed by removing the out-of-order addresses and consecutively transmitted non-neighbor pixels.

The proposed method transmits the image pixels as per increasing order of significance. Proposed method sends the pixels corresponding to the strong edges as soon as the transmission begins and enables the recipient to reconstruct a coarse image. In due course, pixels corresponding to weaker edges and other lesser significant pixels (second and third phase transmission) are sent to the recipient which improves the definition of the reconstructed image. In our proposed method we define the reconstruction error as \[ || \text{IO} - \text{IR} || / || \text{IO} || \], where \text{IO} is the original image and \text{IR} is the reconstructed image.

The reconstructed image at various levels of transmission for APEL coding scheme and proposed method are shown in Figure 4.3.
Figure 4.3: Comparison of (b) APEL coding[19] and (a) proposed method at various levels of transmission.

Figure 4.4: (a)-(d) First phase Transmission.
Figure 4.5: (a)-(d) Second phase Transmission

Figure 4.6: (a)-(d) Third phase Transmission

Figure 4.7: (a)-(d) Fourth phase Transmission
Figure 4.8: (a)-(d) Fifth phase Transmission

Table 4.1: PSNR at various stages of transmission

<table>
<thead>
<tr>
<th>S No</th>
<th>Progressive Transmission Phases</th>
<th>Proposed Method dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>First phase – Figure 4.4 (a) – 4.4(d)</td>
<td>13.90</td>
</tr>
<tr>
<td>2</td>
<td>Second phase – Figure 4.5 (a) – 4.5(d)</td>
<td>21.68</td>
</tr>
<tr>
<td>3</td>
<td>Third Phase – Figure 4.6(a) – 4.6(d)</td>
<td>21.97</td>
</tr>
<tr>
<td>4</td>
<td>Fourth Phase – Figure 4.7(a) – 4.7(d)</td>
<td>23.41</td>
</tr>
<tr>
<td>5</td>
<td>Fifth Phase – Figure 4.8(a) – 4.8(d)</td>
<td>27.22</td>
</tr>
</tbody>
</table>

4.10 Conclusions

In this paper, algorithm based on significant point selection is applied for progressive image transmission. Experimental results on the popular image of Lena are presented to show the reconstructed image at various phases of transmission. Set of regular points are selected using Canny and Sobel edge detection and Delaunay triangulation method is applied to create triangulated network. The set of
Increasingly significant sample points are transmitted in each transmission phase. The gray level of each sample point is interpolated from the luminance values of neighbor significant sample point. The original image, sample points, Delaunay triangulation and its reconstruction results along with the error image are shown for LENA image.

The PSNR value goes on increasing towards the latter phases of transmission. Thus we can fairly approximate that the proposed Progressive Transmission technique can transmit the image progressively varying the image quality. This indicated by the range of the PSNR that varies from 13.9 to 27.22 dB.