# AMSI - Semigraph approach for Lossless Image Compression and Image Processing

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## ABSTRACT
Semigraph was defined by Sampathkumar as a generalization of a graph. In this paper a star semigraph is constructed by clustering a monochrome image, called semigraph of segmented image. Adjacency matrix of the semigraph of segmented image, AMSI, is used for storing the image. An algorithm for converting an image into AMSI and conversely an algorithm to retrieve the image from AMSI are given. Ratio of the size of original JPEG image to the size AMSI on an average is 1.6. AMSI gives a lossless image compression technique with compression ratio 1.6 for JPEG images. The same compressed representation of an image can further be used to do various operations on the image. Using AMSI, algorithms to find photographic negative and pseudocoloring of a grey scale image, and colour masking of a colour image are also given.

## General Terms
Semigraph, Image compression, Color masking, Pseudocoloring.

## Keywords
adjacency matrix of semigraph, semigraph of segmented image (SSI), adjacency matrix of semigraph of segmented image (AMSI)

## 1. INTRODUCTION
Image is an object type which records visual perception. Image compression is a process to obtain compact representation of an image, reducing memory requirement for image storage. Basically, there are two types of image compression, namely lossy and lossless. Some examples of lossless image compression are PNG, GIF. The most common example of lossy compression is JPEG. Weinberger et al. suggested an algorithm in lossless image compression using JPEG-LS [16]. Zukoski et al. proposed a compression technique for medical images [19]. Pralhadrao et al. introduced principles of PSR (Pixel Size Reduction) for lossless image compression algorithm [9]. Various compression techniques have been proposed and are in use [1, 3, 8, 15, 17, 18].
Image segmentation is to classify an image into several clusters according to some feature of the image. Interpretation of the clustering is dictated by the domain. In this paper a method to store an image is presented that makes use of adjacency matrix of a semigraph, clustering using the following features- pixel intensity and connectivity.

Semigraph is a generalization of a graph defined by Sampathkumar as follows [12]:

DEFINITION 1.1 Semigraph G is an ordered pair of two sets V and X, where V is a non-empty set whose elements are called vertices of G and X is a set of n-tuples, called edges of G, of distinct vertices, for various n (n at least 2) satisfying the following conditions:

(SG1) - Any two edges have at most one vertex in common.

(SG2) - Two edges $(u_1, u_2, .., u_n)$ and $(v_1, v_2, \dots, v_m)$ are considered to be equal if

(a) m = n and

(b) either $u_i = v_i$ for $i = 1,2, \dots, n$; or $u_i = v_{n+1-i}, for\ i = 1,2, \dots, n$.

Clearly the edge $(u_1, u_2, \dots, u_n)$ is same as $(u_n, \dots, u_2, u_1)$. For the edge e = $(u_1, u_2, \dots, u_n)$, $u_1$ and $u_n$ are called the end vertices of e and $u_2, u_3, \dots, u_{n-1}$ are called the middle vertices of e.

EXAMPLE 1.1 Consider a semigraph G = (V, X) where V = $\{ v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9 \}$ and X = $\{(v_1, v_2, v_3, v_4), (v_4, v_5), (v_1, v_6, v_5), (v_4, v_6, v_7), (v_5, v_7), (v_2, v_6), (v_5, v_9)\}$

In G, vertices $v_1, v_4, v_5, v_7, v_9$ are the pure end vertices, $v_3$ is a pure middle vertex, $v_2$ and $v_6$ are the middle-end vertices and $v_8$ is an isolated vertex.

A semigraph G(V, X) is called a star semigraph if G has exactly one vertex common to all the edges.

In general, for a star semigraph, the vertex which is common can be a pure middle vertex, or a pure end vertex, or can be a middle-end vertex. But for SSI which will be defined in the next section, this common vertex is always a pure end vertex i.e. it is an end vertex of all the edges of a semigraph.

The adjacency matrix of a semigraph is defined as follows [4]:

DEFINITION 1.2 Let G(V, X) be a semigraph with vertex set V = $\{1,2, \dots, n\}$ and edge set X = $\{e_1, e_2, \dots, e_m\}$. Adjacency matrix of G(V, X) is an n × n matrix A(G) = $[a_{ij}]$, which is defined as follows:

1. for every edge $e_i = (i_1, i_2, \dots, i_k)$ of X with $i_1, i_2, \dots, i_k$ being vertices in V, $\forall i_r \in e_i; r = 1,2, \dots, k$

(a) $a_{i_1 i_r} = r - 1$

(b) $a_{i_k i_r} = k - r$

2. All the remaining entries of A(G) are zero.

EXAMPLE 1.2 Let G(V, X) be a semigraph with V = {1, 2, 3, 4, 5, 6} and X = {(1, 2, 5, 6), (5, 4, 3), (1, 4)}.

Then adjacency matrix A(G) is

$$A(G) = \begin{pmatrix} 0 & 1 & 0 & 1 & 2 & 3 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 2 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 1 & 0 & 0 \\ 3 & 2 & 0 & 0 & 1 & 0 \end{pmatrix}$$

In section 2, Algorithm 2.1 generates a semigraph, which is referred to as the semigraph of segmented image (SSI) hence forth. SSI is stored in the form of a matrix, the adjacency matrix of SSI (AMSI), which requires lesser memory than the original image. The original image can be retrieved from AMSI as discussed in algorithm 3.1 given in section 3. Thus, in this paper a new method which compresses the given image with compression ratio 1.6 is proposed. In section 4 the facts obtained from experimental study are discussed. Segmentation and retrieval of colour images are studied in section 5. In section 6 algorithms to find photographic negative, pseudocoloring of a grey scale image and colour masking of a colour image are discussed.

## 2. SEMIGRAPH OF SEGMENTED IMAGE (SSI)

For a pixel (i, j), the set of pixels in the image adjacent to (i, j) i.e. {(i − 1, j), (i −1, j −1), (i−1, j +1), (i, j −1), (i, j +1), (i+1, j −1), (i+1, j), (i+1, j +1)} is called 8-neighbourhood of (i, j). In this paper, two pixels $P_1$, $P_2$ in an image are said to be connected if
there exists a sequence of pixels $P_1$, $Q_1$, $Q_2$, …, $Q_k$, $P_2$ starting and ending with $P_1$, $P_2$ such that each pixel $Q_i$ is adjacent to (in neighbourhood of) the pixels preceding and following it.
First segmentation of a grey scale image is considered.

THEOREM 2.1 A grey scale image can be represented as a union of star semigraphs.

Proof: Let im be a gray scale image with resolution m × n. Thus, intensity matrix of im is an integer matrix of size m × n with entries from 0 to 255. Suppose there are k distinct intensity levels in im, say $int_1$, $int_2$, …, $int_k$. Partition the set of pixels in im into k subsets {$S_1$, $S_2$,…, $S_k$} such that each $S_i$ = {Set of pixels in im with intensity $int_i$}.

Consider the partition set $S_1$. All the pixels in $S_1$ are not necessarily connected. Partition $S_1$ into subsets $C_1$, $C_2$, …, $C_{r1}$ such that all the pixels in $C_j$ , j = 1, …, r1 form a connected component of im. Thus, all the pixels in $C_j$ are connected and have same intensity $int_1$. Construct a star semigraph $G_1$ corresponding to $S_1$ as follows: vertices of $G_1$ are pixels in $S_1$ plus one vertex representing the intensity of $S_1$ i.e. int1. G1 has r1 edges, one each corresponding to $C_1$, $C_2$, …, $C_{r1}$ such that edge corresponding to Cj is ($p_1$, $p_2$, …, $p_{cj}$, $int_1$), where $p_1$, $p_2$,…, $p_{cj}$ are the pixels in Cj written in some order.

Repeat the same process for every Si and form a star semigraph Gi of the pixels in $S_i$ having intensity $int_i$. Thus, im can be represented using a union of star semigraphs. ∎

A semigraph which is the union of star semigraphs obtained as described in the theorem 2.1 above is called Semigraph of Segmented Image (SSI).

EXAMPLE 2.1 In the image given in Figure 1, there are four different intensity levels corresponding to: (a) three circles, (b) two rectangles above diagonal, (c) two rectangles below diagonal and (d) background. Each of these forms a cluster i.e. a star semigraph in SSI. The three circles are three components of the image having same intensities. As they are not connected, there are 3 edges in the star semigraph having a common end vertex representing intensity which is a feature vector of this cluster. Similarly, the two rectangles above diagonal form two edges of a star semigraph having common end vertex as the feature vector of this cluster, and the two rectangles below diagonal form a star semigraph with two edges. The background forms one cluster, which is connected. Hence the corresponding star semigraph contains only one edge.

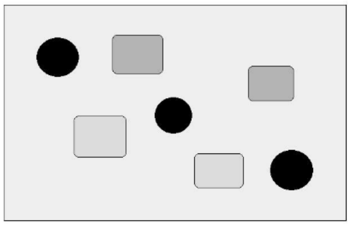

**Fig 1: Image for segmentation**

Following is an algorithm which segments the given image using intensity levels and obtains a semigraph which is a union of star semigraphs as discussed in theorem 2.1. This semigraph is called semigraph of segmented image. Threshold value, $\theta$ , used in the algorithm given below is provided by the user or is decided by application domain expert. In Algorithm 2.1, a pixel from the image under consideration which is added to SSI is be said to be 'visited'. When 8-neighborhood of a pixel is investigated, it is said to be 'explored'.

ALGORITHM 2.1 Algorithm to segment grey scale image

Step 1.Select a pixel P from the given image which is neither visited nor explored.

1. Call it seed S. Initiate a new cluster C and store the intensity of seed S as feature vector of C.
2. Investigate 8-neighbourhood of S: For every pixel P in this neighbourhood, if |intensity(P) − intensity(S)| ≤ $\theta$ , then add P to C and mark it as visited.
3. Investigate the 8-neighbourhood of visited vertex, say Q, in C: For every pixel P in the neighbourhood of visited vertex Q, if |intensity(P)−intensity(S)| ≤ $\theta$ , then add P to C and mark P as visited. Mark Q as explored.
4. Repeat 3 till all the visited pixels in C are explored.

Step 2: Select a pixel P from the given image which is neither visited nor explored. If |intensity(P) – intensity(S)| ≤ θ for some seed S previously identified, then initiate a new cluster with seed S, mark P as visited and go to 3 in step 1. Otherwise repeat 1,2,3 in step 1.

Thus, Algorithm 2.1 segments the given image into intensity levels using threshold value, $\theta$ and each cluster contains pixels with intensity within threshold limit of feature
vector of that cluster. Each connected component of the image having intensity within tolerance limit forms an edge of SSI. All these edges together form a star semigraph with exactly one end vertex as a common vertex. This common end vertex is the feature vector.

EXAMPLE 2.2 Consider an intensity matrix im given below.

$$
\text{im} = \begin{pmatrix} 145 & 5 & 5 & 21 & 21 & 21 \\ 145 & 5 & 190 & 190 & 21 & 21 \\ 145 & 21 & 21 & 21 & 21 & 21 \\ 21 & 190 & 190 & 190 & 21 & 21 \\ 21 & 21 & 21 & 5 & 5 & 145 \\ 21 & 21 & 21 & 145 & 145 & 5 \end{pmatrix}
$$

There are 4 different intensity levels 5, 21, 145, and 190. Thus $S_1$, $S_2$, $S_3$, and $S_4$ are the sets of pixels corresponding to intensities 5, 21, 145, and 190 respectively. $S_1$ ={(1, 2), (1, 3), (2, 2), (5, 4), (5, 5), (6, 6)}, $S_2$ = {(1, 4), (1, 5), (1, 6), (2, 5), (2, 6), (3, 2), (3 , 3), (3, 4), (3, 5), (3, 6), (4, 1), (4, 5), (4, 6), (5, 1), (5, 2), (5, 3), (6, 1), (6, 2), (6, 3)}, $S_3$ = {(1, 1), (2, 1), (3, 1), (5, 6), (6, 4), (6, 5)}, $S_4$ = {(2, 3), (2, 4), (4, 2) , (4, 3), (4, 4)}.

In $S_1$ the pixels {(1, 2), (1, 3), (2, 2)} form one connected component and {(5, 4), (5, 5), (6, 6)} form the other connected component. Hence star semigraph $G_1$ corresponding to $S_1$ has common vertex with intensity 5 and has two edges corresponding to two components. All the pixels with intensity 21 i.e. the pixels in $S_2$ are connected

and $G_2$ has one edge with one end vertex having intensity 21. Similarly there are star semigraphs $G_3$,$G_4$ having one end vertex corresponding to intensities 145, 190 respectively with two edges each.

It can be observed that this method gives us a lossless image representation technique if $\theta = 0$. In fact for any value of $\theta$ which is less than the minimum difference between two successive intensities, AMSI is a lossless image representation.

# 3. ADJACENCY MATRIX OF SEGMENTED IMAGE AND IMAGE RETRIEVAL

In section 2, the semigraph of a segmented image is obtained. To store the image segmented as above, intensity of the feature vectors and (x, y)−coordinates of each pixel is stored. With every pixel is associated a unique integer between 1 to mn which will be called vertex label corresponding to that pixel. In this section matrix representation of the given image in terms of adjacency matrix of SSI, called 'adjacency matrix of semigraph of segmented image' (AMSI), is studied.

Given a gray scale image of resolution $m \times n$, a matrix of size $p \times p$, p = mn+k, is formed where k = Number of distinct intensity levels i.e. number of feature vectors.

For i = 0,…, (m − 1) the vertices in+1, in+2,…, in+n correspond to the pixels (i+1, 1), (i+1, 2),…, (i+1, n) i.e. the first n vertices correspond to the first row of pixels (1, 1), (1, 2),…, (1, n) respectively. The vertices n+1, n+2,…, 2n correspond to the pixels (2, 1), (2, 2),…, (2, n) respectively, etc. In other words a pixel (x, y) corresponds to the vertex (i.e row and column of AMSI) y +(x−1)n, where $1 \le x \le m$, $1 \le y \le n$. The remaining k vertices i.e. the vertices mn + 1,mn + 2,… ,mn + k correspond to the feature vectors.

EXAMPLE 3.1 For the image im given in the example 2.2, number of intensity levels is 4 and resolution is 6 × 6. Hence SSI contains mn + k = 40 vertices. First 36 vertices correspond to the pixels and the vertices 37,38,39, and 40 correspond to the intensities 5, 21, 145, and 190 respectively. Thus the edge sets of the star semigraphs are $E(G_1)$ = {(2, 3, 8, 37), (28, 29, 36, 37)}, $E(G_2)$ = {(4, 5, 6, 11, 12, 18, 17, 24, 23, 16, 15, 14, 19, 25, 26, 27, 33, 32, 31, 38)}, $E(G_3)$ = {(1 ,7, 13, 39), (30, 35, 34, 39)}, $E(G_4)$ = {(9, 10, 40), (20, 21, 22, 40)}. Though AMSI for im is of order 40 × 40, the number of nonzero rows is 11. The number of nonzero rows in AMSI is the number of edges in SSI plus the number of feature vectors.

Note the following facts about AMSI.

- Every edge in SSI has one end vertex as a feature vector and the other end vertex as a pixel.
- . The only nonzero rows in AMSI are the rows which correspond to the end vertices of the edges of SSI. Thus AMSI is a sparse matrix.
- . If any nonzero row amongst first mn rows, say $i^{th}$ row, is considered then it contains a sequence of first $r_i$ integers, 1, 2,…, $r_i$ where $r_i$ is the number of vertices in the corresponding edge. Without loss of generality let these nonzero integers be in the columns $j_1, j_2, \ldots, j_{ri}$ . Observe that $mn < j_{ri} < mn+k$. The pixels corresponding to the vertices i, $j_1$, $j_2$, …, $j_{ri-1}$ have the intensity stored in the feature vector corresponding to the vertex jri . Hence all the pixels with their intensities can be retrieved from the nonzero rows amongst the first mn rows.
- For every row $R_i$, i = mn+1, …, mn+k, corresponding to feature vectors, find the nonzero entries in $R_i$. If these nonzero entries are in the columns $j_1$, $j_2$, …, $j_i$, then corresponding pixels associated with these columns have intensity given by the feature vector. Hence all the pixels with their intensities can be retrieved from the last k rows.

Using the facts mentioned above, theorem 3.1 proves that the original image can be retrieved from AMSI uniquely.

THEOREM 3.1 Original image can be retrieved from AMSI uniquely.

Proof : Given AMSI A of size $p \times p$, to find an image of size $m \times n$ represented by A. The resolution of the given image is $m \times n$ and k = the number of clusters formed, where k = p− mn. Each of the first mn rows (and the corresponding column) of this matrix corresponds to a pixel (x, y) which in turn corresponds to the vertex y + (x − 1)n. If a vertex is a pure middle vertex of SSI, then the corresponding row in AMSI is a zero row. If a row r is nonzero, $r \le mn$, then r is a vertex corresponding to a pixel as one end vertex of an edge of a star semigraph corresponding to intensity, say $int_r$. The other end vertex, s, of this edge is a vertex corresponding to feature vector storing $int_r$. s is a feature vector and is greater than mn. Also, there can not be any other nonzero entry in this row in the column j, j > mn, j ≠s. If row r contains a sequence (0, 1, 2, …, $k_r$) in the columns r, $i_1$, $i_2$, …, $i_{r-1}$, ir = s, then the pixels corresponding the vertices r, $i_1$, $i_2$, …, $i_{r-1}$ have same intensity associated with feature vector $i_r$ = s. In other words, all the columns in $r^{th}$ row with $a_{r,j} \neq 0$, $j \le mn$, the pixel corresponding to column j has intensity given by feature vector s for all j.

As in SSI every star semigraph has feature vector as common vertex and any vertex corresponding to a pixel belongs to exactly one edge, the intensity of every pixel is defined uniquely as given in the original image. Thus, AMSI represents a unique image, and the original image can be retrieved correctly. ■

ALGORITHM 3.1 Algorithm to retrieve image from AMSI

Given an adjacency matrix A of segmented image to extract an image of resolution $m \times n$.

Step 1: From the size of AMSI and m, n find the value of k = number of feature vectors.

Step 2: For i = 1 to mn

{If row i of A is nonzero, then find the column with

largest entry in i, say $j_i$.
Find intensity value, say int, from the feature vector $j_i$.
For pixel corresponding to the vertex i assign the intensity int.
Find the columns with nonzero entries in the row i and for each of these column numbers find the corresponding pixel. For these pixels assign the intensity int.}

EXAMPLE 3.2 In Figure 2 the first is the image considered for segmentation and the second is the image subsequently obtained using algorithm 3.1.

**Fig 2: Example - Image Retrieval**

# 4. EXPERIMENTAL STUDY

The algorithms 2.1, 3.1 are implemented using Matlab. Image under consideration which when converted to AMSI is stored as .csv file. This .csv file is then converted to image. The images tested come from different sources and are of different types. e.g. medical images like Sonography, X-ray, scan, photographs captured by camera like scenery, photo of a person etc.

EXAMPLE 7 Figure 3 is a photograph and Figure 4 is an example of medical image, Xray tested. The first image is the original image and the second is retrieved image.

**Fig 3: Example of Photograph retrieved**

**Fig 4: Example of X-ray image retrieval (Original Image Courtesy Star Imaging and Research Center, Pune.)**

Following are the advantages of this method:

1. For the clusters generated in SSI, we do not have to study the distribution function for generating the original image.
2. The size of .csv file was observed to be smaller than the size of corresponding image. Table 1 gives compression ratio for some images investigated. Average compression ratio for all the images investigated so far is 1.6.
3. The edges are reconstructed clearly.
4. Size of .csv file changes negligibly when the value of $\theta$ changes.

# 5. SEGMENTATION OF A COLOUR IMAGE

In this section colour images stored in RGB format are considered for segmentation. Any colour image can be segmented and then retrieved using algorithm similar to algorithm 2.1. For grey scale images threshold is defined in terms of intensity value. For colour image RGB values are used for defining threshold. The pixels having RGB values within the threshold limit of seed RGB value (i.e. feature vector) belong to the same cluster having RGB of the seed as feature vector of that cluster. Following are the outcomes of the experimental study for segmentation of colour images.

EXAMPLE 5.1 Figures 5 and 6 are the examples of the colour images considered for segmentation.

**Fig 5: Example 1- Color Image Retrieval**

**Fig 6: Example 2 – Color Image Retrieval**

Table 1: Sizes of Original JPEG image and AMSI

| Sr. No. | Image Type(JPEG) | Image Size | AMSI Size | Compression Ratio |
|---|---|---|---|---|
| 1 | Photo Ganga Ghat | 10.6 | 6.4 | 1.656 |
| 2 | Photo Tree | 8.3 | 4.9 | 1.693 |
| 3 | Photo Vivekananda | 11.3 | 6.8 | 1.661 |
| 4 | Sonography Fetus 1 | 60 | 39.1 | 1.5345 |
| 5 | Sonography Fetus 2 | 61.1 | 39.6 | 1.542 |
| 6 | Sonography Pelvic | 62.1 | 40.1 | 1.546 |
| 7 | X-ray fracture 1 | 2.37 | 1.42 | 1.66 |
| 8 | X-ray fracture 2 | 3.03 | 1.87 | 1.62 |
| 9 | X-ray fracture 3 | 3.87 | 2.39 | 1.619 |

# 6. PROCESSING IMAGE USING AMSI

In this section AMSI representation of an image is used for colour masking, to find photographic negative, and for pseudocolring. Algorithms for the same are given here.

## 6.1 Colour Masking

Separating a specific colour(s) is useful for many applications
(i) to display the colour(s) of interest,
(ii) to mask / hide a particular colour(s) for further processing.
Both these objectives are served by colour slicing. To display the colour of interest, first find (r, g, b), the average colour of all shades of the desired colour. Then a hypercube of width w with centre at (r, g, b) is constructed and the colours inside this hypercube are the shades of interest.
Algorithm 6.1 assigns a non-prominent neutral colour or black colour to the image except the shades of desired colour.

ALGORITHM 6.1 For every row corresponding to feature vectors i.e. i = mn+1 to mn+k
Step 1: Find the colour $r_i$, $g_i$, $b_i$ corresponding to row i i.e. corresponding feature vector.
Step 2: If ($|r_i - r| > w/2$) or ($|g_i - g| > w/2$) or ($|b_i - b| > w/2$) then assign a non-prominent neutral colour or black colour to $r_i$, $g_i$, $b_i$.

To mask a specific colour algorithm 6.1 is modified and some neutral colour or black colour is assigned to the colour of interest, while rest of the image remains unchanged.

ALGORITHM 6.2 For every row corresponding to feature vectors i.e. i = mn+1 to mn+k
Step 1: Find the colour $r_i$, $g_i$, $b_i$ corresponding to row i i.e. corresponding feature vector.
Step 2: If ($|r_i - r| < w/2$) and ($|g_i - g| < w/2$) and ($|b_i - b| < w/2$) then assign a non-prominent neutral colour or black colour to $r_i$, $g_i$, $b_i$.

## 6.2 Photographic Negative

Photographic negative of a grey scale image is obtained by reversing the intensity levels of an image.

ALGORITHM 6.2 Algorithm to find Photographic Negative of a grey scale image
Step 1: Find the maximum intensity levels of the image, say M.
Step 2: For every row i corresponding to feature vectors, find the corresponding intensity $int_i$. Assign the intensity $int_i' = M - int_i$ to this row.

In Figure 7 are the photographic negatives of the images given in Figures 2 and 3.

**Fig 7: Example - Photographic Negative Image**

## 6.3 Pseudocoloring of a Grey scale Image

Pseudocoloring of a grey scale image is assigning colours to grey scale values based on some specified criterion [5]. Here using continuous function the grey scale is mapped to a continuous colour space. The R,G,B values are defined as a continuous function of intensity value, for which sine function and some parameters are used.

ALGORITHM 6.3 Pseudocoloring using continuous map
Step 1: Find AMSI of given grey scale image.
Step 2: For an intensity value int, find (R,G,B) values given by $B(int) = \sin(int \times p_1 \times \pi + p_4 \times \pi)$;
$G(int) = \sin(int \times p_2 \times \pi)$;
$R(int) = \sin(int \times p_3 \times \pi)$, where $p_1$, $p_2$, $p_3$, $p_4$ are the parameters chosen suitably.
Step 3: For every row corresponding to feature vectors of AMSI, consider the intensity given by that row, int. Assign the colour (R(int),G(int),B(int)) to the feature vector of the corresponding row in the AMSI of coloured image. The remaining columns of AMSI of grey image are copied to the AMSI of the coloured image.
Step 4: Retrieve the pseudocoloured image from AMSI of coloured image.

EXAMPLE 6.4 Figure 8 exhibits an example of a pseudocoloured image.

**Fig 8: Example – Pseudocoloring of X-ray chest (Original image courtesy Star Imaging and Research Center, Pune.)**

Thus, semigraphs can be effectively used for storing an image and also for its further processing.

# 7. CONCLUSION

This study introduces a novel approach to lossless image compression using the adjacency matrix of a semigraph (AMSI) derived from the semigraph of a segmented image (SSI). The proposed algorithms demonstrate that AMSI not only achieves a consistent compression ratio of approximately 1.6 for JPEG images, but also ensures complete and accurate reconstruction of the original image. AMSI provides a mathematically robust framework that inherently preserves pixel intensity and connectivity, thereby guaranteeing lossless retrieval.
While the present work demonstrates the potential of AMSI as a robust and lossless image compression and processing technique, several directions remain open for future exploration. One promising avenue is the refinement of the algorithm to achieve higher compression ratios without compromising the accuracy of reconstruction. Extending the AMSI framework to video data could enable real-time compression and processing of dynamic sequences, further broadening its practical utility. Another significant scope lies in integrating AMSI with artificial intelligence and deep learning models, particularly for applications in medical imaging, satellite image analysis, and automated pattern recognition.

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## 9. REFERENCES

[1] Ashutosh, N. Subhash Chandra Bose, Ashwini Kumar, A novel Image CompressionTech.: Wavelet-MFOCPN, (2012) 492-495.

[2] Bapat R. B., Graphs and Matrices, First Edition, Hindustan Book Agency, New Delhi, (2012).

[3] Firas Jasmim, Hind E Quasim, Five Modules Method for Image Compression, SIPIJ, (2012) Vol-3, No-5, 19-28.

[4] Gaidhani Y. S., Deshpande C. M., Athawale B. P., Adjacency Matrix of a Semigraph, Electronic Notes in Discrete Mathematics, 63 (2017) 399–406.

[5] Gonzalez Rafael, Richard Woods, Digital Image Processing, Third Edition (2011), Pearson.

[6] Harary F., Graph Theory, Narosa Publishing House, New Delhi, (1988).

[7] Jau -Ji Shen, Hsiu-Chaun Huang, An adoptive Image Compression Method based on Vector Quantization, IEEE, pp-377-381, (2010).

[8] Muthiah R., Neelakantan K., Sharma V., Arora A., Image Compression and Reconstruction using cubic spline interpolation technique, Journal of Comp. Sci., (2019) Vol-5, No-5, 388-391.

[9] Pralhadrao V Shantagiri, K. N. Saravanan, Pixelsize Reduction Lossless Image Compression Algorithm, IJCSIT, Vol-5, (2013).

[10] Rajakumar K., T. Arivoli, Implementation of Multiwavelet transform coding for lossless Image Compression, IEEE, (2013) 634-637.

[11] S. Sahani, M. G. Shayesteh, Bi-level image compression technique using neural networks, IET Image Process, (2012) Vol-16, No-5, 496-506.

[12] Sampathkumar E., Semigraphs and their applications, Report on the Research project, submitted to Department of Science and Technology (DST), India, (May-2000).

[13] Saravan C., R. Ponalagusamy, Lossless Image Compression using Source symbol reduction and Huffman Coding, International Journal of Image Processing, Vol-3, No-5, (2009).

[14] Sharma D. K., Gaur Loveleen, Image Compression and feature extraction using Kohonen's SOM neural network, Journal of Strategic E-commerce, Vol-5, No-1, (2005).

[15] Srikant S., Sukhdev Meher, Compression Efficiency for Combining Different Embedded Image Algorithms, IEEE, pp-816-820, (2013).

[16] Weinberger M. J., Seroussi G., The LOCO-I Lossless Image Compression Algorithm: Principles and Standardization into JPEG-LS, IEEE International Conference on Image Processing, USA, pp-68-72, (1999).

[17] Yei-Fei Tan, Wooi-Nee Tan, Image Compression Technique Utilizing Reference Points Coding with Threshold values, IEEE, IET, pp-74-77, (2012).

[18] Yerva Suresh, Smita Nair, Krishnan Kutty, Lossless Image Compression based on data folding, IEEE, pp-19-28, (2012).

[19] Zukoski, Mathew J., Boult, Terrance, Iyriboz, Tunc, A novel approach to medical Image Compression, International Journal of Bioinformatics Research and Applications, Vol-2, No-1, (2006).