Compression of Compound Images using Fuzzy Clustering Technique

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Abstract
Storage of scanned compound documents is a challenging issue which needs an efficient method to compress the scanned document images. Many techniques are available for compressing the scanned compound images. Most of them have limitation in terms of PSNR value and compression ratio. Hence, a new compression method based on the newly announced coding paradigm called Fuzzy cluster based compression is proposed in this paper that gives high coding efficiency for an extensive variety of image types, by effectively adjusting the input image characteristics. The proposed system utilizes Fuzzy c-mean clustering, Optimization techniques and also a new Tree based compression approach called Enhanced Multidimensional MultiScale Parser (EMMP) which is used to compress the scanned compound document image effectively. Fuzzy clustering results contain a combination of accurate text/graphics and image portions. These results are given into proposed EMMP. In this work, the proposed scheme contains the Binary tree based Compression is used for non-smooth (Text/graphics) image and a quad tree based compression is used for smooth image which is greatly reducing the complexity of segmentation. Finally, pattern matching procedure has been made to match the encoded blocks based on different scale dimensions. The proposed technique provides the best performance in terms of very good PSNR value and high compression ratio.

Keywords: Dictionary Creation, Fuzzy C-means Clustering, Pattern Matching, Scanned Compound Document, R-D Optimization

1. Introduction
In scanned compound image compression, the scanned image is first segmented into different modules before the compression. For this purpose, Layer-based and block-based techniques are the two most important methods which are recurrently used. The majority layer-based approaches use the typical 3-layer Mixed Raster Content (MRC) segmented into the background, foreground and the mask\textsuperscript{1,2}. First segmentation is very complicated since it needs associated mechanism, outline cohesiveness and symbol comparison, on the other hand, the Second approach is Block-based segmentation which is used for scanned images, and this gives less complexity and more spatial resolution\textsuperscript{3}. Another method called Fuzzy c-mean clustering based segmentation technique is used by many researchers on scanned compound images, which gives the flexibility and more accurate segmentation results against pixel classification errors. Fuzzy c-mean clustering technique is used to categorize the image into smooth (picture), text, graphics (multiple color), and image blocks the compression techniques are not only providing high compression ratio, but also encompass low complexity and visually lossless quality. Low complexity is extremely
significant for real-time compression since, cheap image quality reduces the readability of the text.

Block-based approaches are suitable for scanned images. However, scanned images constantly enclose a few quantity of noise and hence a new method is necessary for handling this problem. In this paper, a novel and efficient approach called Fuzzy c-mean clustering algorithm is used. Hence, this approach is used to segment the images into exact text and image blocks.

The use of Fuzzy c-mean clustering algorithm provides significant and accurate segmentation. Many segmentation algorithms are available in the literature for segmenting the medical images. However, the proposed method provides effective compression using segmentation and also it provides a new lossless coding method for text/graphics using Enhanced Multidimensional Multiscale Parser (EMMP). This method compresses the scanned images effectively, since it utilizes the Rate Distortion optimization method (Rate Distortion) to decrease the lagrangian cost. The proposed EMMP uses multiscale estimated block which is attached with an adaptive dictionary. This work reduces the time, complexity and increases the quality of images.

In this approach, the scanned images are separated into smooth (picture) image blocks and non-smooth (text) blocks using Fuzzy c-mean clustering technique to provide a meaningful segmentation. It performs the selection of the most excellent dictionary block using an optimization function and finds the code vector having minimum cost. Moreover, a hierarchy is created which is depending on cost value. Predictive coding is prepared here by using coded sample to build the predictive blocks. It varies from the original and gets residual blocks. Comparing with various predictive models, the proposed method chooses the peak one by applying the dictionary amendment enhancement technique for equivalent encoded blocks. Moreover, EMMP uses a scaled adaptive pattern which includes matching’s along with vectors of varying dimensions. It also includes predictive coding and dictionary adaptation techniques. The predictive coding technique holds the predictable property of generating residue samples with really peaked probability distributions centered on the cost zero that positive discrimination of the arithmetic coder adaptation process of the basics. The enhanced dictionary adaptation results are obtained from the use of prediction error data. Both text and image encoded blocks are matched with the dictionary encoded blocks. In addition, matching blocks which already exist in the dictionary are used in this work and none of matching blocks are stored in the dictionary. Finally, this system concatenation the encoded information which is having minimum cost value with the use of scale and dimension vectors. During the reconstruction process, the reverse process is applied to achieve original image without degrading the quality.

2. Proposed Scheme

In the previous works on scanned compound images, Layer based and block based classification approaches are applied. The main drawback is the occurrence of pixel misclassification error. The existing MMP-Text and MMP- FP methods perform well with respect to horizontal or vertical segmentation. The disadvantages of these existing segmentation algorithms are high complexity and then take more execution time. So, we propose a new technique called as Fuzzy EMMP, which is applied to scanned compound images. In this approach, instead of the layer or block based classification, improved fuzzy, c-mean clustering based, meaningful segmentation is performed to avoid the pixel misclassification errors. Moreover, EMMP is a lossless compression algorithm; it uses the tree based segmentation. It is reducing the execution time. The scanned compound document contains a combination of text/graphics and images. The text blocks or the non-smooth blocks are segmented using the Binary Tree Based Segmentation process where the text blocks are separated recursively in the tree based approach. Finally, the blocks with high costs and the blocks with least costs are divided into separate groups in the tree order. The blocks with higher costs are pruned away to allow only the blocks with small amount of costs and the blocks are subjected to Integer Wavelet Transformations where the pixels from the spatial domain are transformed to the frequency domain and the pixels are transformed into the integer values. Integer values are rounded off by using the quantization process. Finally, the compressed, encoded text blocks are obtained and the encoded blocks are assigned with the code vectors for dictionary matching purposes. Adaptive dictionary for non-smooth side is formed for storing away the obtainable encoded text blocks. The encoded blocks in the dictionary are kept in the tree formation.

Correspondingly, the image blocks or the smooth blocks are segmented using to Quad tree base segmentation process where the image blocks are separated
recursively into four quadrants. This process is maintained at the end of this quad tree segmentation procedure, all the blocks will have the same pixel value. From this, the least cost blocks are chosen by pruning away the high cost blocks. A similar procedure applies where as in the Text. From then, the compressed, encoded image blocks are obtained. The adaptive tree based dictionary for the smooth portion is created for traditional pattern matching methods.

Improvements in these works, by using the Fuzzy EMMP encoding technique are achieved redundancy of data’s are reduced. Hence, this compression is more efficient and the quality of the compressed image is enhanced. The data losses and the complexity are also greatly reduced. The architecture is the proposed system for scanned compound image compression is shown in Figure 1. It consists of major components such as a scanned compound image, preprocessing module, segmentation module, compression module, adaptive dictionary module and decompression module.

![Figure 1](image.png)

**Figure 1.** Block Diagram of Fuzzy EMMP.

### 2.1 Improved Fuzzy-C-Mean Clustering

A fuzzy similarity-based self-constructing feature clustering technique is used in this work for performing incremental feature clustering. It reduces the amount of features used in the text classification approach. The Improved FCM (IFCM) clustering algorithm splits a specified set of data or objects into clusters to form subsets or a group. The division maintains two properties, namely homogeneity within cluster data and heterogeneity among the clustered data, which belongs to dissimilar clusters. Every cluster is recognized by a membership function that uses statistical mean value and deviation. If a pixel is not similar to any existing cluster, a new cluster is formed for this pixel. All the pixels are put into different groups. Finally, many numbers of clusters are created repeatedly. This approach extracts one feature from each and every cluster. The extracted feature equivalent to a cluster is a weighted arrangement of the pixels contained in the cluster. For image segmentation, improved FCM clustering method is designed by including the spatial neighborhood details into the standard FCM clustering technique and also by a priori probability ($p_i$). The prior probability is set to specify the spatial weights of the neighboring pixels on the center pixel in the image. The new fuzzy membership of the current center pixel is again recalculated through this probability obtained value. The method is initialized by a known histogram based FCM algorithm. The steps are the proposed Fuzzy clustering algorithm is as follows.

**Step 1:** Place the cluster centroids $C_i$ value according to the histogram of the image, Fuzzification limitation $f$, the value of $h$ and $k>0$

**Step 2:** Calculate the membership function by using

$$u_{i,g}(a) = \frac{1}{\sum_{j=1}^{c} \left[ \frac{d(g,v_{ij})}{d(g,v_{ij})} \right]^{(y-1)v_{i,g}}}$$

(1)

**Step 3:** Compute the cluster centroids by using

$$v_i(a+1) = \frac{\sum_{g=M_{\text{min}}}^{M_{\text{max}}} (u_{i,g}(a))^{(y)}}{\sum_{g=M_{\text{min}}}^{M_{\text{max}}} (u_{i,g}(a))^{y} \cdot \text{Hist}(g)}, v_i$$

(2)

$$\text{Hist}(g) = \sum_{p=0}^{p-1} \sum_{q=0}^{q-1} \delta(0(p,q) - g)$$

(3)

**Step 4:** Go to step 2 and replicate until convergence

**Step 5:** Calculate the a priori probability, by using

$$p_{it} = \frac{S_i^t}{S_t^i}$$

(4)
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By using the results of membership function and centroids

Step 6: Recalculate the membership function and cluster centroids by using

\[ u_{ix}^{*(a)} = \frac{P_{ti}}{\sum_{j=1}^{c} d_{ij}^{(a)}} / (f-1) \]  
\[ v_{i}^{*(a+1)} = \frac{\sum_{x=1}^{n} (u_{ix}^{(a)})^f x_i}{\sum_{i=1}^{n} (u_{ix}^{(a)})^f} \]  

With the probabilities

Step 7: If the algorithm is convergence, Go to step 8, otherwise go to step 5.

Step 8: Image segmentation after defuzzification using

\[ C_t = \text{arg} \{ \max(u_{i}) \} \quad i = 1, 2, ..., c \]

Where \( P_{ti} \) - Priori probability, \( u_{i} \) is the degree \& membership of \( x_i \) in the \( i^{th} \) cluster, \( C \) No of the cluster, \( f \) - weighting exponent on each fuzzy membership, \( C_i \) - is the prototype of the centroid of the cluster, \( d(x_i, C_i) \) is a distance between object \( x_i \) and cluster \( C_i \) - is a gray level.

The final result of improved fuzzy, c-mean clustering is used to separate the accurate cluster group, which contains separate text/graphics portion and image portion. Afterwards, the proposed EMMP lossless compression algorithm is applied into both text and image pixels. Generally, single compression algorithm is applicable to all type images is very difficult. This proposed algorithm is applicable for both the type of images (Text/graphics and picture).

3. Experimental Results

Experimental analysis is based on two main modules accuracy of segmentation is computed and compression efficiency of the proposed scheme is calculated.

3.1 Metrics to Measure the Segmentation Accuracy

Accuracy Metrics \( A_{comp} \) is used to measure the accuracy of scanned compound images. In our segmentation accuracy, \( A_{comp} \) is calculated using the formula.

\[ A_{comp} = \frac{S_{bg} + S_{fg}}{O_{pixel}} \times 100 \]

Where,
- \( A_{comp} \) = Pixel segmentation accuracy
- \( S_{bg} \) = Segmented pixels in the background compound image.
- \( S_{fg} \) = Segmented pixels in the foreground compound image.
- \( O_{pixel} \) = Overall pixel in the compound image.

Pixel values are present in the foreground and background is,
- \( S_{fg} = \) (high intensity pixel + low intensity pixel) 
- \( S_{bg} = \) only low intensity

Finally,

\[ A_{comp} = \frac{S_{fg} (\text{low intensity pixels}) + S_{fg} (\text{high intensity pixels})}{O_{pixel}} \times 100 \]

Threshold values set for the compound image is to separate the foreground and background.

\[ \begin{cases} \text{if } Th < 10 & \text{background} \\ \text{if } Th > 10 \leq 35 & \text{Foreground} \\ \text{otherwise unsegmented} \end{cases} \]

Compound image contains a combination of Text/graphics and picture portion. Text/graphics portion is present in the foreground and foreground separated based on its assigned threshold values.

The threshold value set for foreground is,

\[ \begin{cases} \text{if } Th > 10 \leq 22.5 & \text{image} \\ \text{if } Th > 22.5 \leq 35 & \text{Text} \\ \text{otherwise unsegmented} \end{cases} \]

Four images, including gray scale and color image are considered in evaluating the quality of the segmentation in our proposed scheme. There are two steps of segmentation is occurring in this work. Based on the Number of pixels in the compound images to calculate accuracy of Acomp and fg. The first step is to calculate the accuracy of text/graphics and picture separation from the foreground. The second step of The above equation is used to compute the accuracy of foreground layer. It consists of low intensity and high intensity pixels. Generally high intensity pixels present in the text portions and low intensity pixels present in the picture portions. accuracy is computed from the foreground and background layer pixels.

\[ A_{fg} = \frac{(S_{fg} (\text{low intensity pixels}) + S_{fg} (\text{high intensity pixels}))}{(S_{fg} (\text{Overall pixels}))} \times 100 \]
Table 1 shows the total number of pixels present in the compound image and after applying segmentation technique to compute the number of pixels is segmented and unsegmented. The proposed scheme overall segmentation accuracy is shown in Table 2.

Table 1. Segments of foreground and background pixels

| Image   | Overall pixels in the image | \( S_{fg} \) Segmented pixels in the background | \( S_{fg} \) Segmented pixels in the foreground | Overall pixels Unsegmented |
|---------|-----------------------------|-----------------------------------------------|-----------------------------------------------|---------------------------|
| Image1  | 103057                      | 49660                                         | 50440                                         | 1192                      |
| Image2  | 83010                       | 39958                                         | 39440                                         | 1600                      |
| Image3  | 84210                       | 43326                                         | 34432                                         | 2210                      |
| Image4  | 86420                       | 42920                                         | 39732                                         | 1834                      |

Table 2. Segmentation accuracy of foreground in %

| Image   | Total image pixels in fg | \( S_{fg} \) Segmented | \( S_{fg} \) Unsegmented | \( S_{fg} \) (low) | \( S_{fg} \) (high) | \( A_{fg} \) (%) |
|---------|--------------------------|------------------------|--------------------------|-------------------|-------------------|------------------|
| Image 1 | 50445                    | 49660                  | 785                      | 22150             | 27510             | 98.44%           |
| Image 2 | 41160                    | 39958                  | 1202                     | 19858             | 20100             | 97.07%           |
| Image 3 | 43652                    | 43326                  | 326                      | 21632             | 21694             | 99.25%           |
| Image 4 | 43960                    | 42960                  | 1006                     | 20100             | 22860             | 97.72%           |

Our proposed scheme is different since it estimates the segmentation more efficiently and meaningfully when compared to a previous segmentation scheme. The percentage of segmentation is comparative with respect to the compound image pixels. The overall segmentation accuracy of 98.03 is obtained from the average value computed from Table 3. Finally, the overall segmentation accuracy graphs are shown in Figure 3 and Figure 4.

Table 3. Segmentation accuracy of scanned compound image in %

| Image   | Foreground | background | Overall pixels in compound image | Overall pixel segmented | Overall pixel Unsegmented | \( A_{comp} \) (%) |
|---------|------------|------------|----------------------------------|-------------------------|--------------------------|------------------|
|         | Total pixel | Segmented pixel | Unsegmented pixel | Total pixel | Segmented pixel | Unsegmented pixel |                      |                      |                      |                 |
| Image1  | 51,420     | 50440      | 980                              | 50445                  | 49660                    | 785              | 103057               | 101865             | 1192               | 98.84%           |
| Image2  | 40250      | 39460      | 790                              | 41160                  | 39958                    | 1202             | 83010               | 81410              | 1600               | 98.07%           |
| Image3  | 35452      | 34432      | 1020                             | 43652                  | 43326                    | 326              | 84210               | 82000              | 1210               | 97.37%           |
| Image4  | 40620      | 39730      | 890                              | 43966                  | 43966                    | 1006             | 86420               | 84586              | 1834               | 97.87%           |

Figure 3. Accuracy of Foreground segmentation.
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4. Conclusions

This paper proposes a new Fuzzy EMMP Scanned compound document encoder based on multi-scale recurring pattern matching. A novel algorithm is utilized here for classification approach, separating the image into smooth and non-smooth blocks using Fuzzy C-Mean clustering technique. A new encoder called EMMP algorithm proposed in this paper using a flexible tree based segmentation that is able to utilize the images’ arrangement in an additional efficient approach. This makes the proposed technique to enhance state-of-the-art IWT based encoders for smooth and non-smooth images. The optimization of EMMP for text, image compression, provides superior rate-distortion performance for a few images and soft gains over supplementary basic encoders of up to 8dB. The experimental results show that the proposed algorithm can be used for scanned document compression. By using Fuzzy EMMP in scanned images, the precision of PSNR value has been improved like 0.30bpp (33.05 dB) in our results.

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