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A NOVEL TECHNIQUE OF IMAGE SEGMENTATION

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ABSTRACT

Segmentation is making the part of image or any object or entity. Pattern recognition and image analysis are the fundamental footsteps of image segmentation. Image segmentation mention to partition of an image into different divisions that is homogeneous or similar and inhomogeneous in some attributes. Image segmentation outcomes have consequence on image analysis. Image segmentation is used to understand images and extract information or objects from them. Unsupervised image segmentation is an incomplete data problem as the number of class labels and model parameters are unknown. There are many algorithms and basic methods available for image segmentation but still there needs to develop an improved method for it. In this paper, we have analyzed EM-HMRF, Gausion mixture model GMM-HMRF and K-GMM-EMM method and compare them on the basis of Time and energy activation graph.

Keywords: Segmentation, EM-HMRF, GMM-HMRF, K-GMM-EM.

1. INTRODUCTION

Images are reviewed as one of the most principal channel of fetching information, in the area of computer vision, by grasping images. In traditional, image noise should be abolished along image processing. Dynamic background is done by utilizing segmentation of video for segmentation we require images. Image segmentation plays major role in segmentation of medical images. Digital image processing is one of the procedures of artificial intelligence and it integrated with fuzzy logic, pattern and machine learning are invaluable in image technique can be grouped following framework-image engineering. Image segmentation is the introductory step and also one of most grinding tasks of image analysis.

The distribution of an image into meaningful structures, image segmentation, is often fundamental step in image analysis, object representation, visualization, and many other image processing tasks. In this paper focus is on how to analyze and represent an object, but we supposed the group of pixels that identified object was known beforehand. We will focus on methods that will identify the particular pixels that make up an entity.

Figure 1: Example of Image Segmentation

A special difference of segmentation techniques has been presented in the past decades, and some categorization is compulsory to introduce the methods properly here. A disseverment grade does not appear to be attainable though, because even two immensely dissimilar segmentations approximates might share properties that flout singular categorization.

2. LITERATURE REVIEW

The image segmentation is a challenging problem that has received an enormous amount of attention by many researchers. For appropriate analysis, different image models have been proposed for taking care of spatial intrinsic characteristics. The popular stochastic model provides the better framework for many complex problems in image segmentation is Markov Random Field (MRF) model.

S.A Barker *et al.* [11] presented an unsupervised image segmentation algorithm based on Markov Random Field for noisy images. The algorithm finds the most likely number of classes, their associated model parameters and generates the corresponding segmentation of the image into these classes. This is done according to MAP criterion.

Yangxing LIU et al. [12] proposed an MRF Model Based Algorithm of Triangular Shape Object Detection in Color Images in 2006 and in 2007 provides an algorithm for detecting multiple rectangular shape objects called Markov Random Field (MRF) [13]. Firstly, for obtaining accurate edge pixel gradient information they use an elaborate edge detection algorithm. Then from the edge map line segments are extracted and some neighboring parallel segments are merged into a single line segment. Finally with MRF Model built on line segments is used for labeling all segments lying on the boundary of unknown triangular objects.

Zhang *et al.* proposed Hidden Markov Random Field (HMRF) model to achieve brain MR image segmentation in unsupervised framework [14]. The segmentation obtained by Zhang's approach greatly depends upon the proper choice of initial model parameters. Quan Wang [7] implements Hidden Markov Random Field Model and its Expectation-Maximization Algorithm. Firstly, Binary edge map information is obtained by performing canny edge detection on original image and gray-level intensities of pixels are obtained by performing Gaussian blur on the original image.

Then K-means clustering is applied on gray-level intensities of pixels. The initial labels obtained from K-means are not smooth and have morphological holes and therefore HMRF-EM is applied to refine the labels.

III.   IMPLEMENTATION OF ALGORITHMS

A. EXPECTATION MAXIMIZATION-HMRF

Firstly, Load the Image then Apply Canny operator after that Perform Blurring and Perform K means Segmentation and Find out the Initial Label of Image then Apply EM Model after that Apply HMRF Model and Find out the Final Label of Image .At the end Save the Image.

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                    ┌──────────────────────┐
                    │   Apply canny operator │
                    └──────────────────────┘
                               │
                    ┌──────────────────────┐
                    │    Perform the Blur    │
                    └──────────────────────┘
                               │
                    ┌──────────────────────────────┐
                    │  Perform K means Segmentation  │
                    └──────────────────────────────┘
                               │
                    ┌──────────────────────────────┐
                    │ Find out the Initial Label of Image │
                    └──────────────────────────────┘
                               │
                    ┌──────────────────────┐
                    │     Apply EM Model     │
                    └──────────────────────┘
                               │
                    ┌──────────────────────┐
                    │    Apply HMRF Model    │
                    └──────────────────────┘
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                    ┌──────────────────────────────┐
                    │ Find out the Final Label of Image │
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                          │  Stop   │
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```
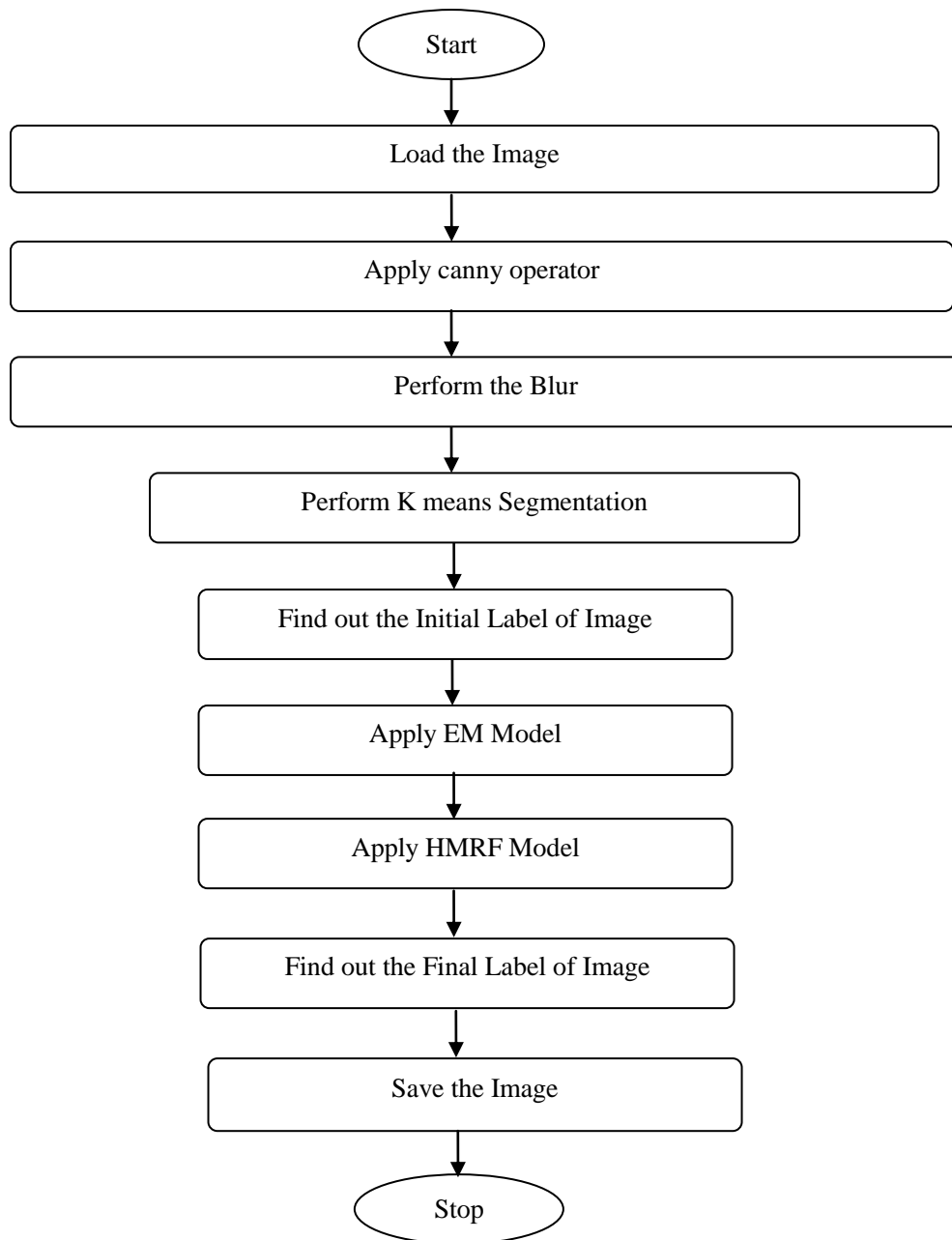
Figure 2: Flowchart of EM HMRF

B. GAUSSIAN MIXTURE MODEL- HMRF

Intensity distribution of each region to be segmented follows a Gaussian distribution with parameters $\theta_{xi} = (\mu_{xi}; \sigma_{xi})$. However, this is a very strong hypothesis which is insufficient to model the complexity of the intensity distribution of real-life objects, especially for objects with multimodal distributions.

Gaussian mixture model (GMM), in contrast, is much more powerful for modeling the complex distributions than one single Gaussian distribution. A Gaussian mixture model with g components can be represented by parameters:

$$\theta_l = (\mu_{l,1} , \sigma_{l,1} , \omega_{l,1})\ldots\ldots\ldots\ldots\ldots\ldots\ (\mu_{l,g} , \sigma_{l,g} , \omega_{l,g})$$

The GMM now has a weighted probability

$$G_{mix}(z;\theta_l) = \sum_{c=1}^{g} w_{l,c} G(z;\mu_{l,c},\sigma_{l,c})$$

Now, the M-step of the EM-algorithm changes to a Gaussian mixture model fitting problem. The GMM fitting problem itself can be also solved using an EM-algorithm. In the E-step, we determine which data should belong to which Gaussian component; in the M-step, we recomputed the GMM parameters.
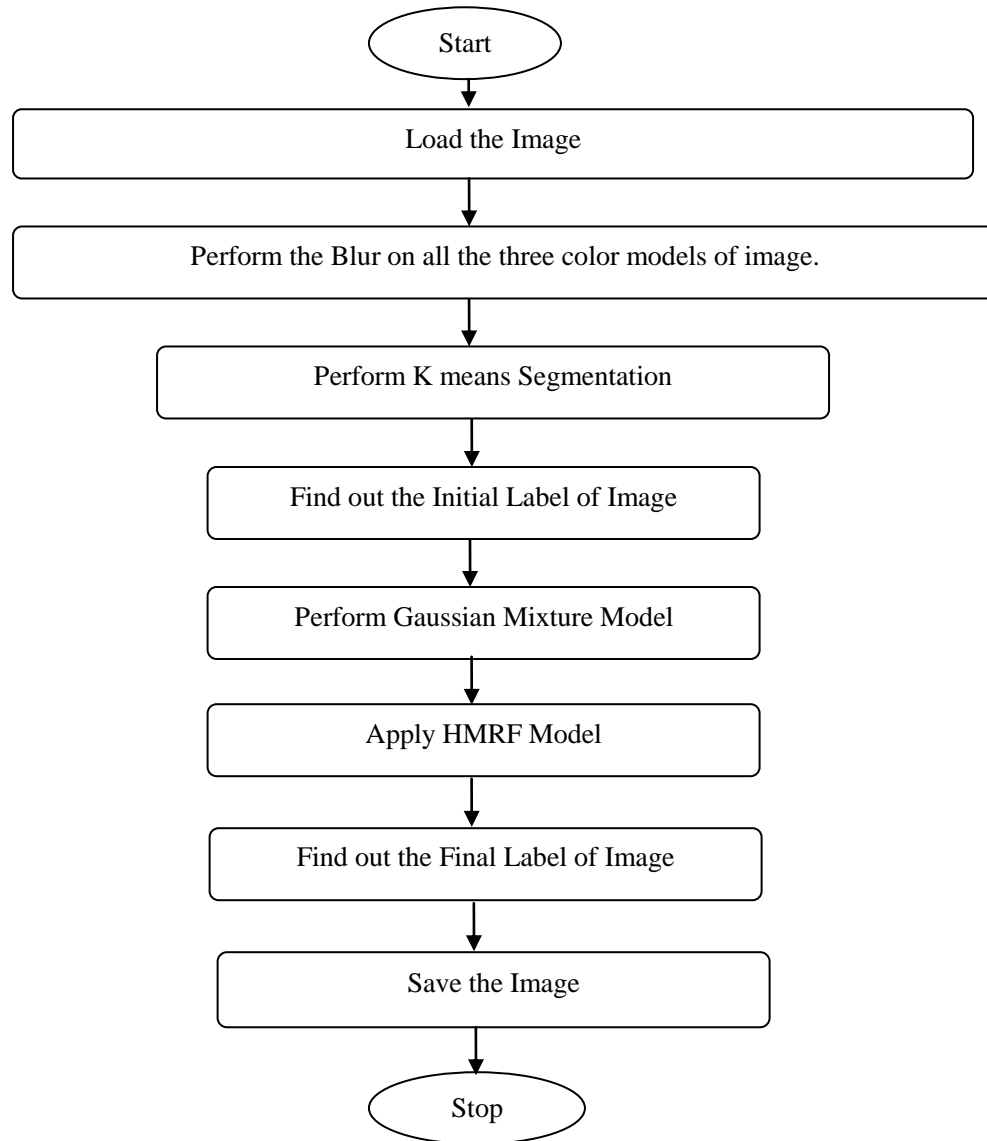
```
        Start
          |
    Load the Image
          |
Perform the Blur on all the three color models of image.
          |
  Perform K means Segmentation
          |
  Find out the Initial Label of Image
          |
  Perform Gaussian Mixture Model
          |
     Apply HMRF Model
          |
  Find out the Final Label of Image
          |
     Save the Image
          |
        Stop
```

Figure 3: Flowchart of GMM HMRF

C. K MEANS GAUSSIAN EM MODEL

In K-means gaussion EM Model firstly Load the Image and Apply Canny operator .Then Perform Blurring after that Perform K means Segmentation and Find out the Initial Label of Image. Apply EM Model and Find out the Final Label of Image. At end Save the Image.
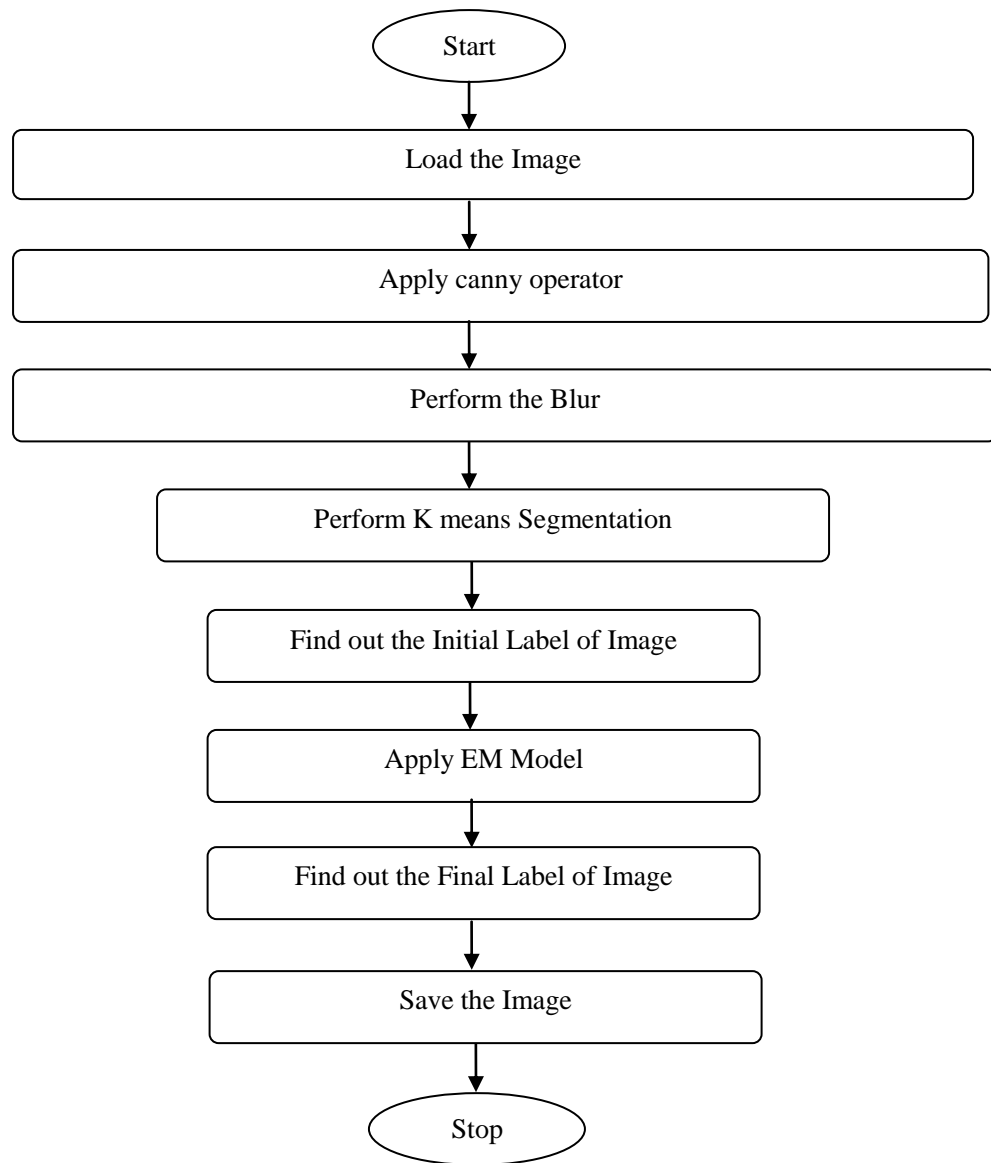
```
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              ┌──────────────────────────────┐
              │        Load the Image         │
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              ┌──────────────────────────────┐
              │       Apply canny operator    │
              └──────────────┬───────────────┘
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              ┌──────────────────────────────┐
              │        Perform the Blur       │
              └──────────────┬───────────────┘
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              │   Perform K means Segmentation │
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              │ Find out the Initial Label of Image │
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              │        Apply EM Model         │
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              │ Find out the Final Label of Image │
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              │        Save the Image         │
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                        │  Stop   │
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```

Figure 4: Flowchart of K MEANS GMM HMRF

D. PROPOSED TECHNIQUE

In Proposed Technique Firstly Load the Image then Perform the Blur on all the three color models of image and Perform K Means Segmentation .Then finds out the Initial Label of Image and Perform Gaussian Mixture Model and Apply EM Model and HMRF Model. Then Save the Final Label of Image and Save the Image as shown as
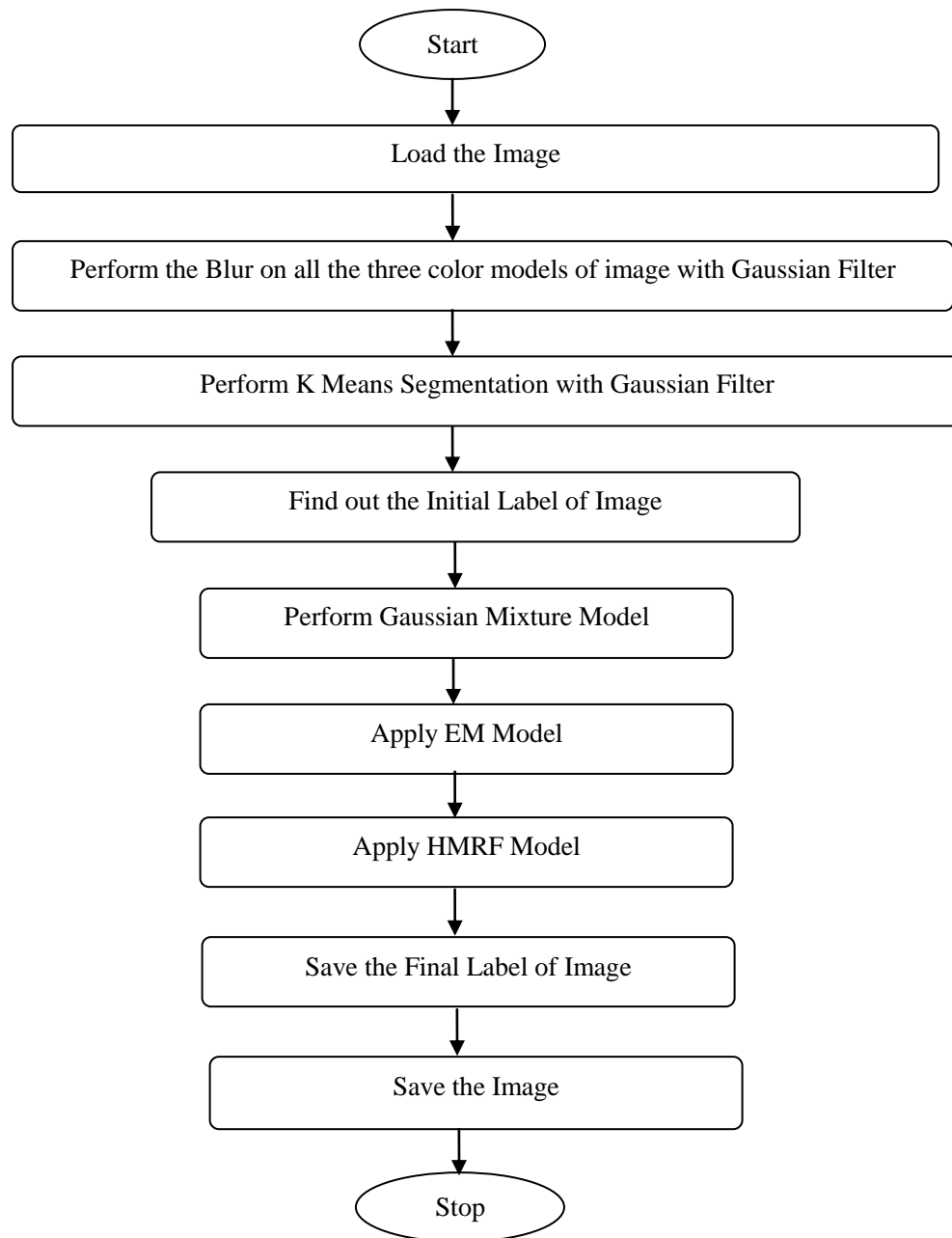
Figure 5: Flowchart of Proposed Technique

IV.   **RESULTS**

This section shows **Implementation Results of Image Segmentation Techniques,** the results of different approaches and compares the energy values and time of segmented images. Following are the results of segmentation algorithms for the techniques discussed in previously.
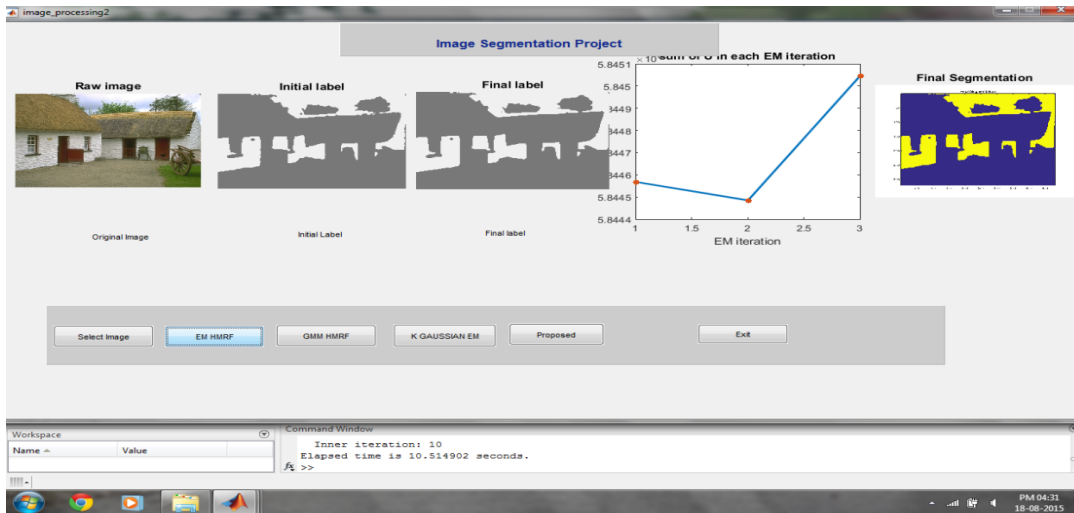
A. Results of EM-HMRF Technique

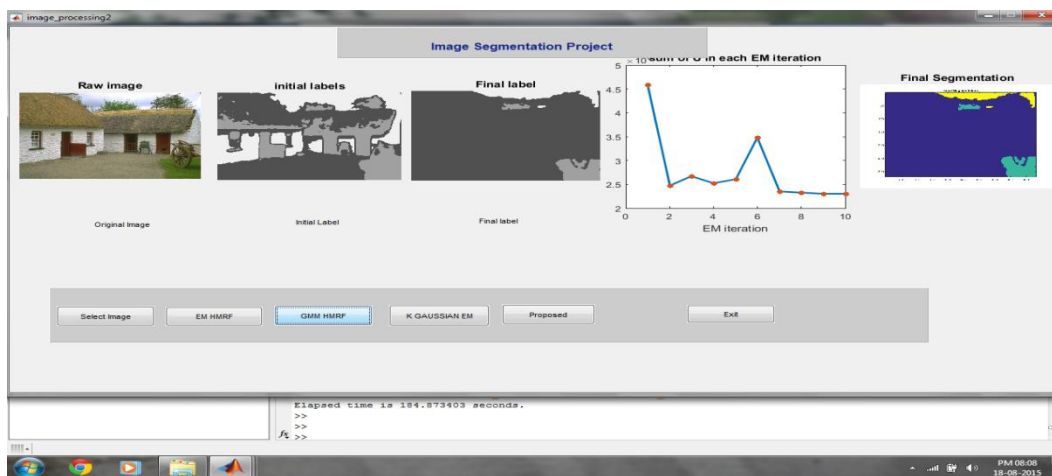**Figure 6: Implementation of EM-HMRF Technique**

B. Results of GMM-HMRF Technique

Figure 7: Implementation of GMM-HMRF Technique

C. Results of K-GMM-EM Technique
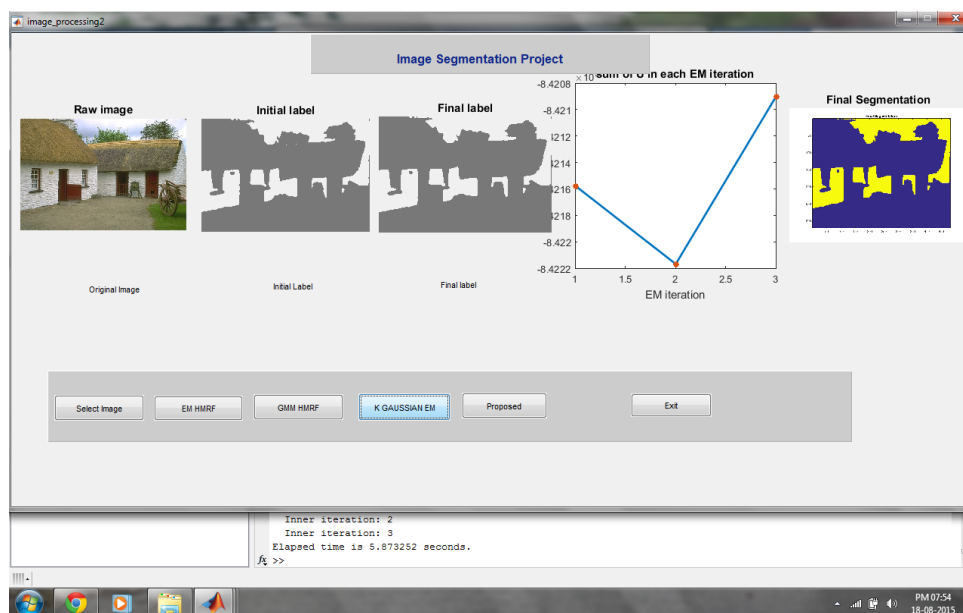
Figure 8: Implementation of K-GMM-EMM Technique

D. Results of PROPOSED Technique
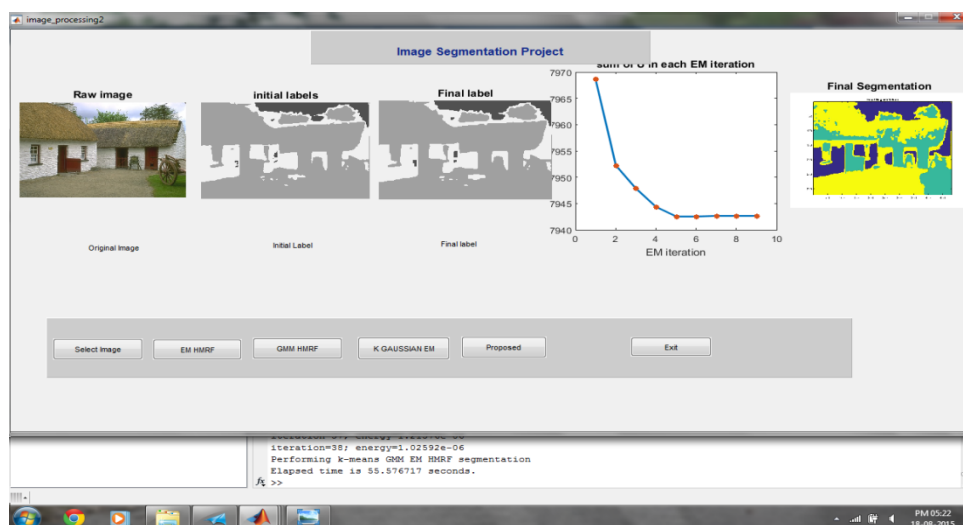
Figure 9: Implementation of PROPOSED Technique

TABLE 1: COMPARISON OF RESULTS

TECHNIQUE NAME	TIME TAKEN	ENERGY AT END
EM-HMRF	10.51 Sec	5.85×10^6
GMM-HMRF	184.87 Sec	2.51×10^6
K-GMM-EMM	5.87 Sec	8.421×10^5
PROPOSED	55.57 Sec	7943

V.   CONCLUSION

The results show that energy graph is minimum for new proposed technique. While the EM-HMRF technique first dips to minimum energy level and then shoots out to the peak energy level. In case of K Mean Gaussian EM model the energy graph becomes flat after some peaks. The GMM-HMRF performs better than EM-HMRF and K Mean Gaussian EM model. The proposed technique is better in terms of energy store in the final image so that segmentation becomes more stable. In future work the proposed algorithm can be further refined in terms of energy and in execution cycle. The results can also be applied for satellite image segmentation and for medical image processing.

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