ENEE 739J Assignment 2

Submitted by Amit Agrawal

1 Problem Statement

Unsupervised and Supervised Texture Segmentation using Markov Random Fields

2 Supervised Texture Segmentation

In supervised texture segmentation, the classes of textures are known beforehand. In other words, model parameter estimation is easier. The texture is assumed to be modelled by a 5th order GMRF. From the given image,regions of each texture are extracted. From the interior pixels for each such regions, a 5th order GMRF is fitted using least squares.

Once parameter estimation is done, the energy function U corresponding to each pixel for every texture is estimated. For each pixel a k*k window is taken and the energy function is calculated as given in [1]. Using this prior, initial labels for each pixel can be calculated as the one which minimizes U among all texture classes for that pixel.

The labels or texture classes are also modelled as 5th order GMRF. The energy function UL for the labels is assumed to be the form given in 1 with beta = 1.4.

Bias w(L) for the textures plays a very important role. It is difficult to estimate the bias, so it was determined by trial and error.

A deterministic relaxation algorithm (ICM) was used for maximizing the posterior density of the labels given the image intensity and the labels of its neighbors. The batch algorithm was used where the labels for all pixels were changed simultaneously. The algorithm was stopped when the no. of label changes go below 1 percent of image size.

2.1 Results

Figure 1 shows the first texture image. For this image, the lower right texture has two different orientations and hence 6 textures are considered for the supervised case. The parameters were estimated as described above. The initial labels obtained from maximizing probability of image intensities given labels is shown in figure 2.

Running ICM using initial labels as starting configuration gives Figure 3 as the segmented image.

For second image (figure 4) , 8 textures corresponding to top half of the image were considered.

The initial labels obtained from maximizing probability of image intensities given labels is shown in figure 5.

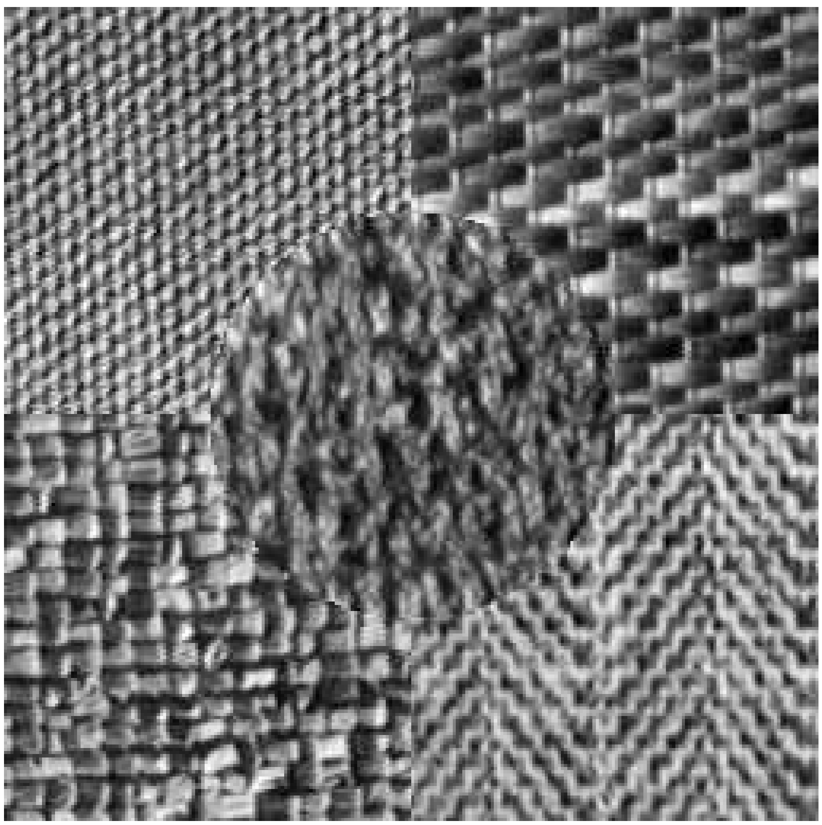

Figure 1: Mosaic 1

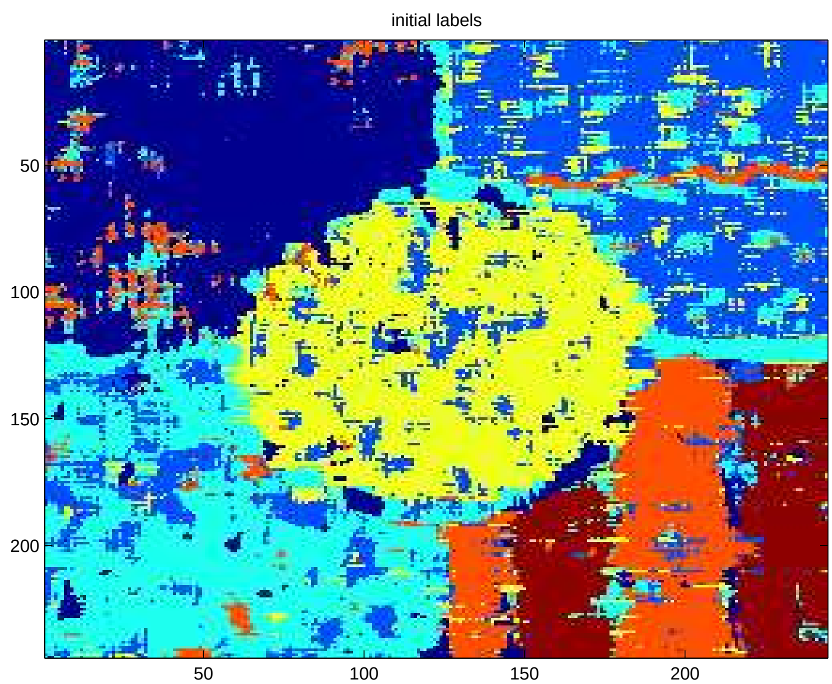

Figure 2: Mosaic 1 Labels based on Priors

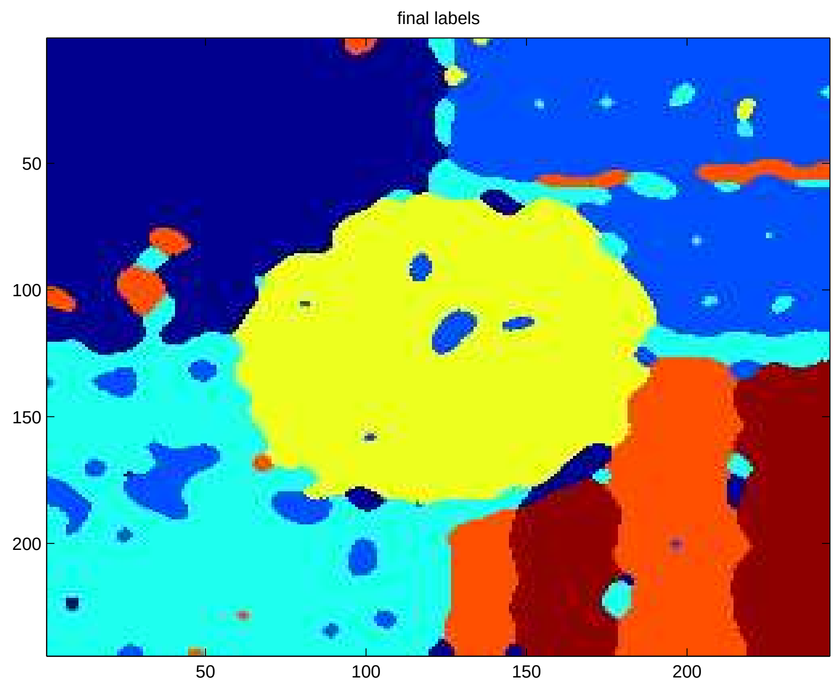

Figure 3: Mosaic 1: final segmentation

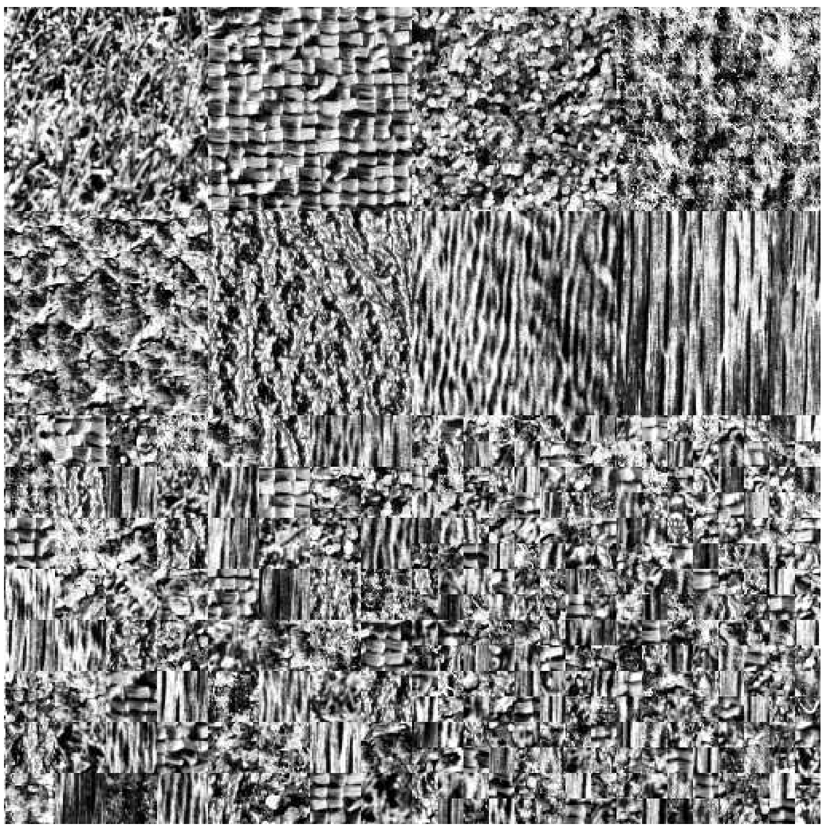

Figure 4: Mosaic 2

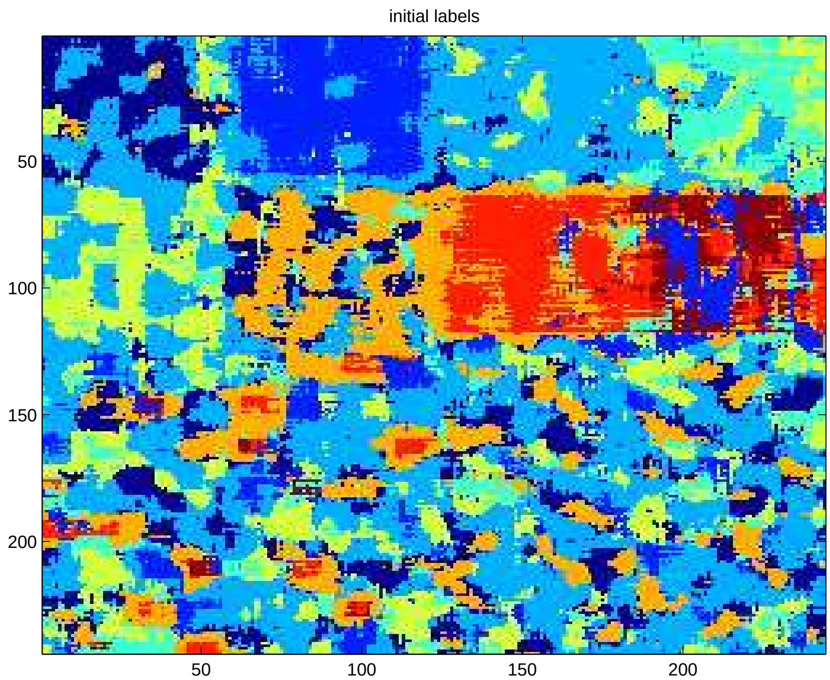

Figure 5: Mosaic 2: Labels based on prior

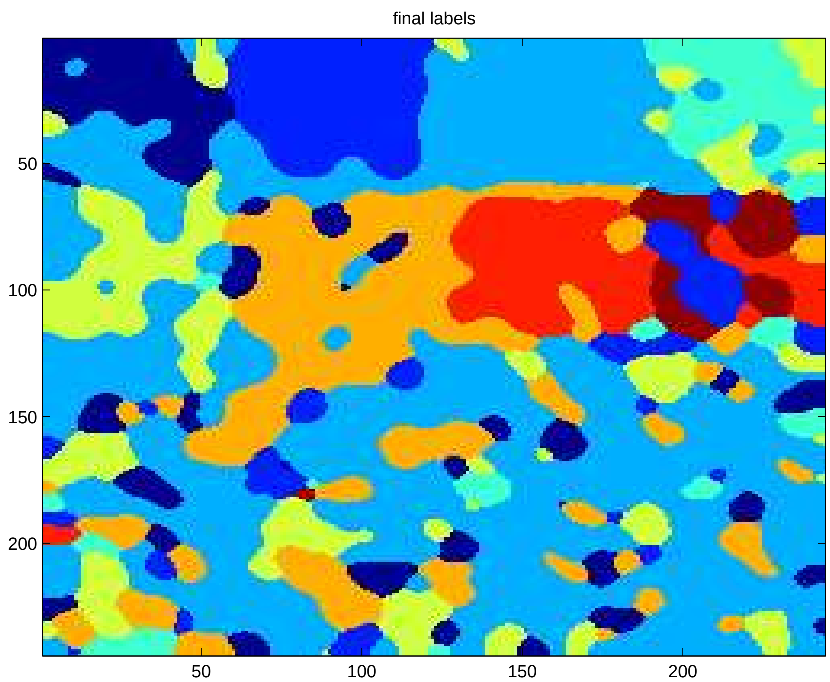

Figure 6: Mosaic 2: Segmented

Running ICM using initial labels as starting configuration gives figure 6 as the segmented image.

3 Unsupervised Texture Segmentation

In unsupervised texture segmentation, the class of each texture is not know beforehand. But here we assume that we know the no. of textures present in the image.

The image is segmented into non-overlapping blocks of size 32*32 and a 5th order GMRF is fitted assuming that the block is homogeneous. The feature vector for each block consist of the model parameters and the mean and variance of the block. A simple clustering scheme as described in [2] is used where clusters are formed on the basis of the distance between the feature vectors in the clusters being less than a threshold. In such scheme, many blocks at the texture boundaries will not be assigned to any cluster.

Using the blocks assigned to a cluster, the parameters are recomputed and then the supervised approach discussed above can be used for segmentation.

3.1 Results

Figure 7 shows the clustering result on mosaic1. The blue regions represent ambiguous blocks which are not part of any cluster.

Note that all the texture regions are properly accounted for.

Figure 8 shows the final segmentation. All textures are properly segmented except for the lower right hand one which as discussed above has two different orientation. In this case, since only 5 textures were used, it couldn't differentiate between one of them but the other has been segmented out.

Figure 9 shows the clustering result on mosaic2. The blue regions represent ambiguous blocks which are not part of any cluster. Figure 10 shows the final segmentation for the second image. The segmentation is not very good as in the lower part, several textures are grouped together closely. Getting a good bias estimate can improve the results.

References

[1] Chellappa R, Manjunath BS, "Stochastic and Deterministic Networks for Texture Segmentation", IEEE Trans. on Acoustics, Speech and Signal Processing, Vol. 38, No.6 June 1990

[2] Chellappa R, Manjunath BS, "Unsupervised Texture Segmentation Using Markov Random Field Models", IEEE PAMI, Vol. 13, No. 5 , May 1991

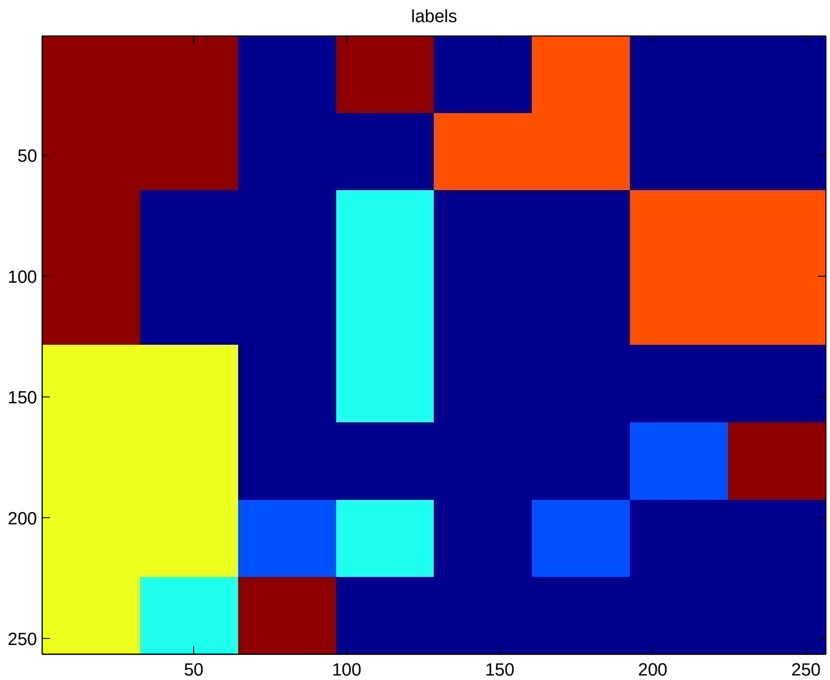

Figure 7: Mosaic 1: Clusters

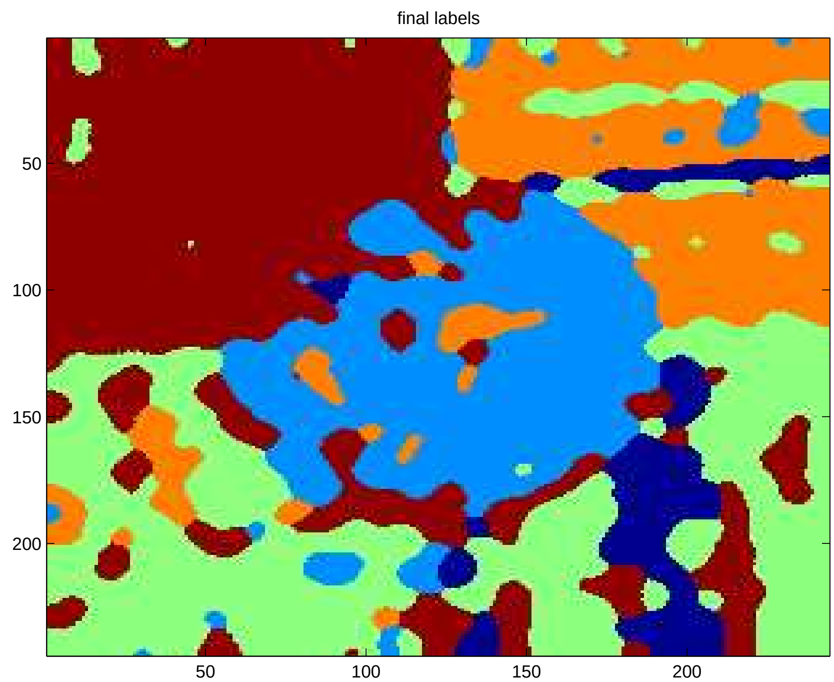

Figure 8: Mosaic 1: Unsupervised Segmentation

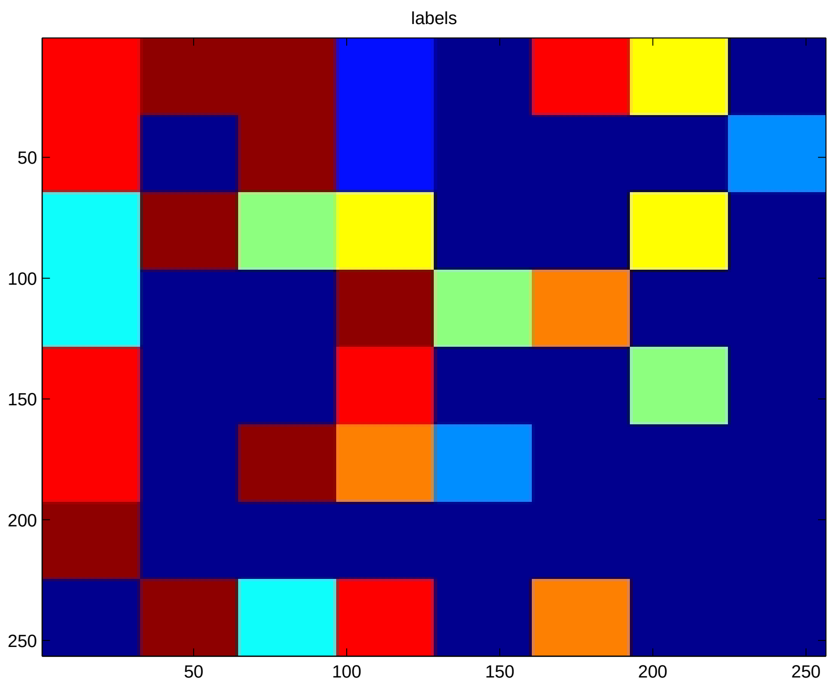

Figure 9: Mosaic 2: Clusters

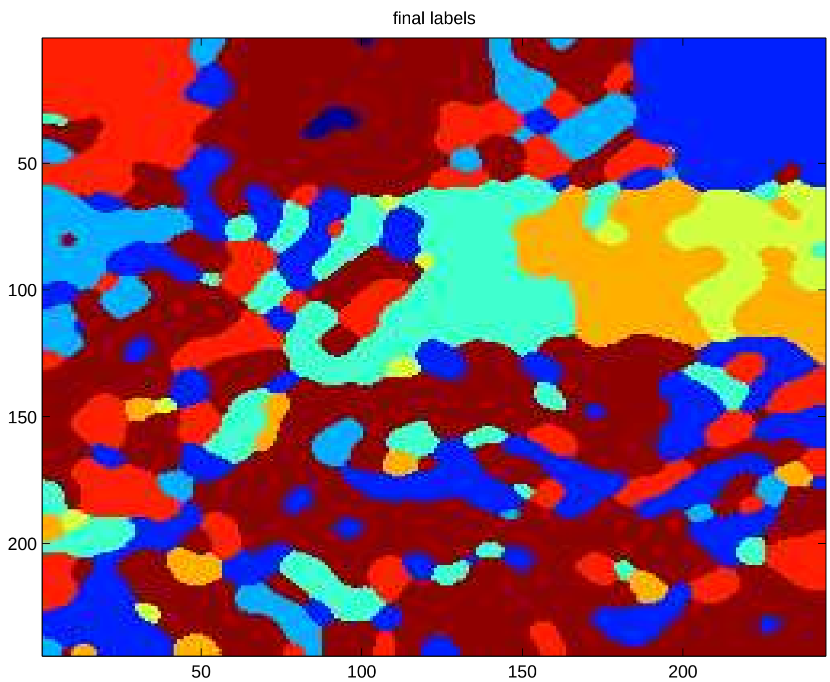

Figure 10: Mosaic 2: Unsupervised Segmentation