CS5340 Project Report

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1 Problem 1 : Data Denoising

1.1 Potential function

For data denoising using Gibbs Sampling, we used the following pairwise potential term:

$$\psi_t(x_t, x_s) = e^{J*x_t*x_s} \tag{1}$$

Where J is a constant parameter which can control the influence of neighboring pixels on the current pixel. Setting J = 3 gave us good results as can be seen in section 1.3.

For local evidence, we used gaussian distribution with mean as the original pixel value and variance as $sqrt(1/2)$. Thus we defined local evidence as follows:

$$\psi_t(x_t) = e^{-(x_t - y_t)^2} \tag{2}$$

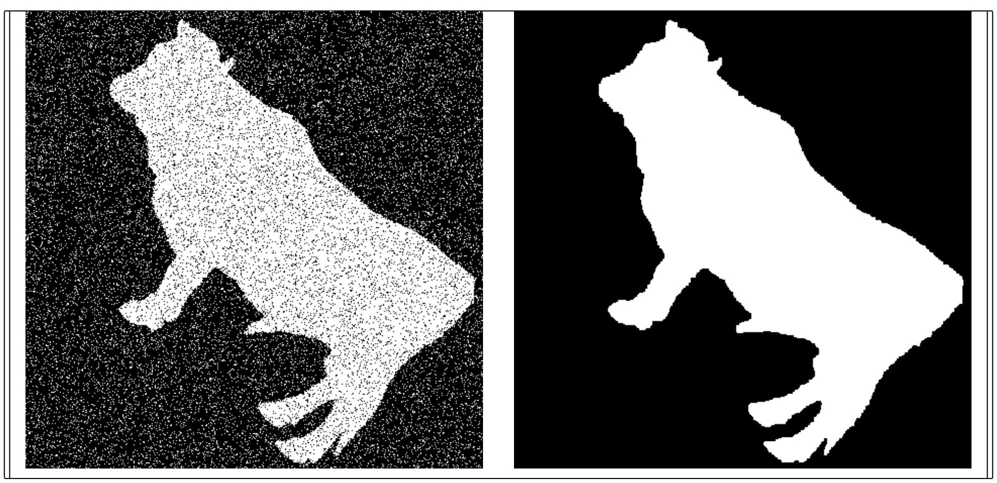
1.2 Algorithm

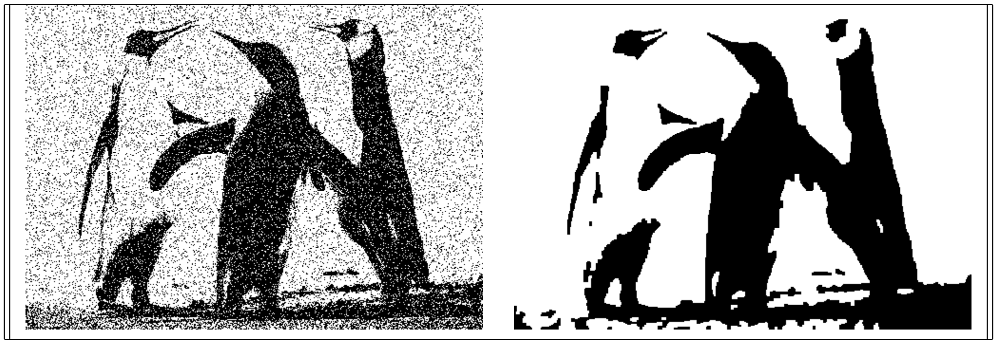
Using these potential functions, we could calculate $p(x_t = 1|x_{-t}, y, \theta)$ as follows:

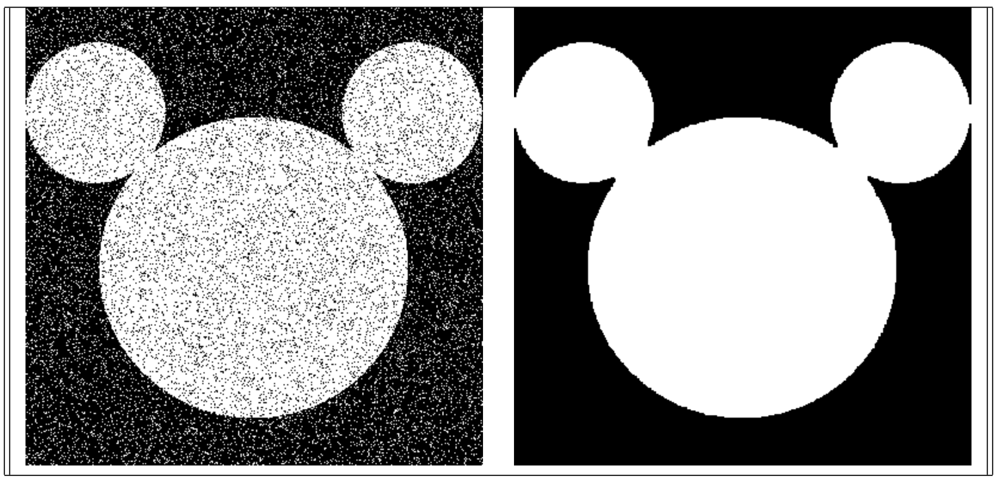
$$p(x_t = 1|x_{-t}, y, \theta) = \frac{\psi_t(x_t = 1)\Pi_{s \in nbr(t)}\psi_t(x_t = 1, x_s)}{\psi_t(x_t = 1)\Pi_{s \in nbr(t)}\psi_t(x_t = 1, x_s) + \psi_t(x_t = -1)\Pi_{s \in nbr(t)}\psi_t(x_t = -1, x_s)} \tag{3}$$

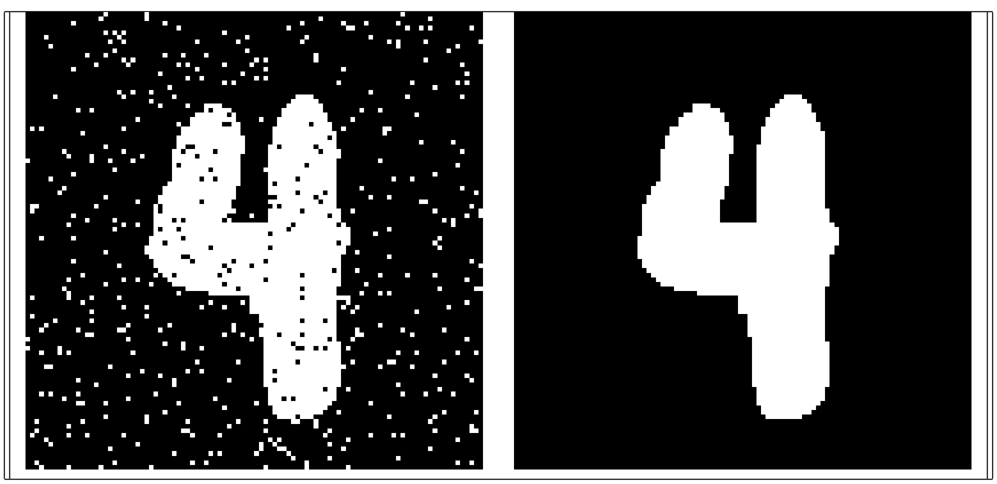
Using the above probability distribution for each pixel, we did gibbs sampling with 1100 iterations out of which first 100 iterations were set as burn-in.

1.3 Results









2 Problem 2 : Expectation-Maximization Segmentation

2.1 Features

We tried 3 different features for image segmentation.
1) Lab features : The L, a and b values for each pixel
2) Lab features with neighbour difference :
3) Lab features with avg neighbour :

From the results, we can see that Lab features with avg neighbour perform better that just Lab features as with the help of neighbours, small noise is filtered out more efficiently. However in case of zebra, this leads to worse results as white stripes of zebra are also filtered out. This shows the importance of correctly defining features.

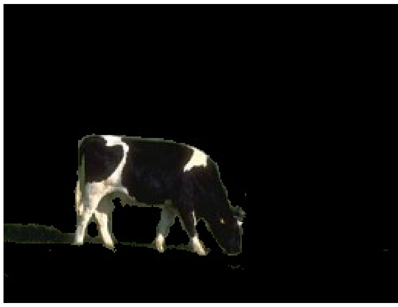
2.2 Algorithm

For a given feature set, we first initialize the mean and covariance parameters of 2 gaussians by setting the covariance as covariance of the features for whole image and mean as a random value which is not very far from the actual mean for the whole image.

Then we calculate the probabilities for all pixels belonging to a given segments using gaussian functions as described in problem definition. Then we update parameters of gaussians by calculating weighted mean and covariances using probabilities calculated in E-step as weights. We update the mixing parameters by summing up the probabilities for each segment. We do this iteratively until the change in parameters is very small.

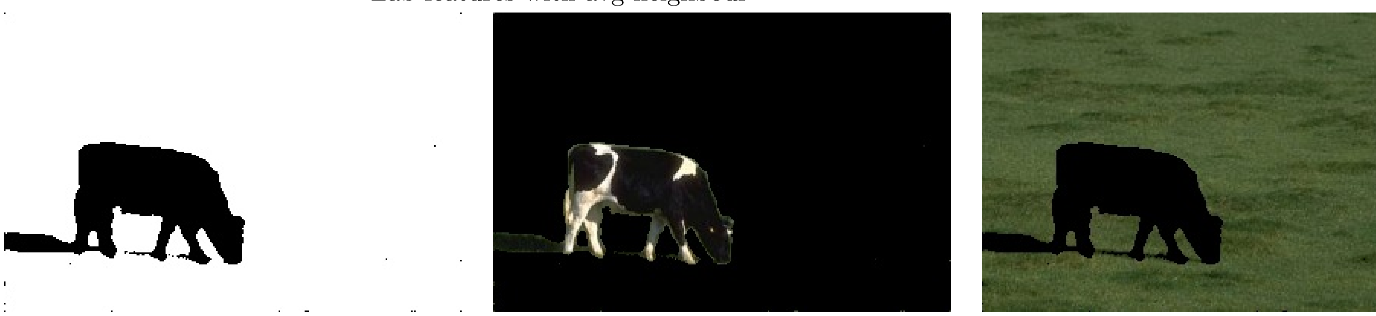
2.3 Results

Lab Features

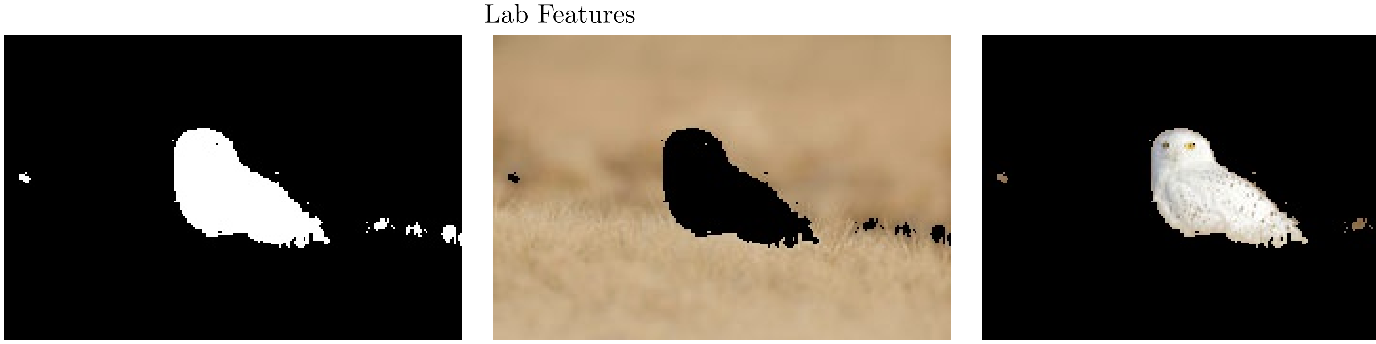


Lab features with neighbour difference

Lab features with avg neighbour

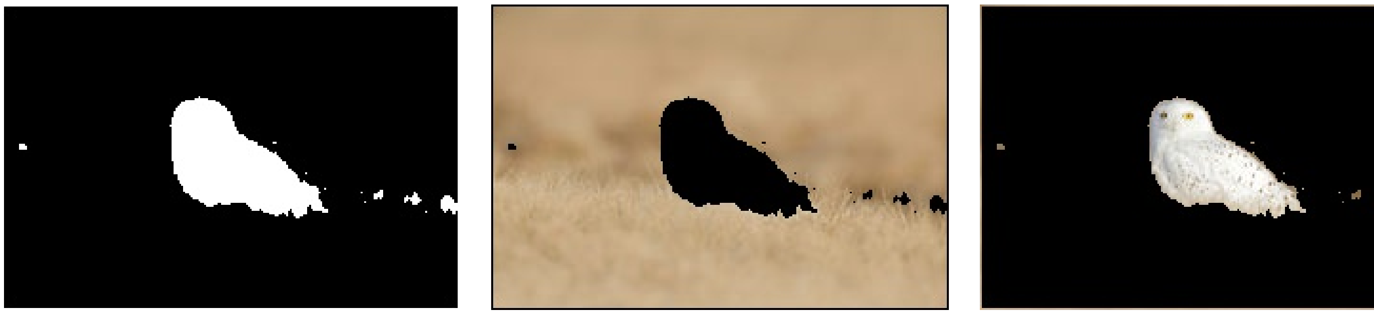


Lab Features

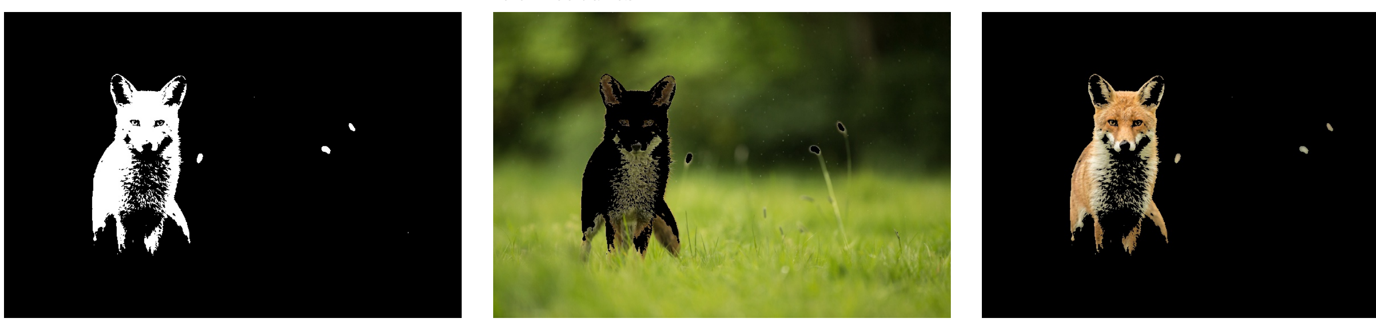


Lab features with neighbour difference

Lab features with avg neighbour



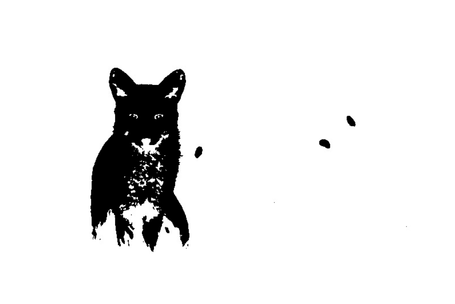
Lab Features



Lab features with neighbour difference

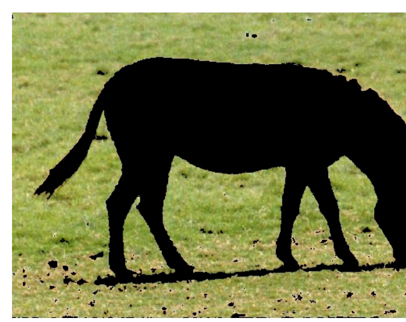


Lab features with avg neighbour



Lab Features





Lab features with neighbour difference

Lab features with avg neighbour