LEARNING GAUSSIAN CONDITIONAL RANDOM FIELDS

FOR LOW-LEVEL VISION

Poster Presentation By:
Rahul
Sunil Chaudhary

Marshall F. Tappen,
University of Central Florida,
Ce Liu, Edward H. Adelson, William T. Freeman
MIT CSAIL

INTRODUCTION

Gaussian Conditional Random Field (GCRF) model is a tool for vision and image processing, which is better than some other models in the same category. GCRF models are variation of Gaussian MRF model which are particularly easy to work with because they can be implemented using matrix and linear algebra routine. This paper describes the GCRF model which can be adapted easily to different trade-off between efficiency and image quality. The authors have shown how the parameters of GCRF can be efficiently trained for low level vision task.

DESCRIPTION

GCRF model can be motivated in two ways:

- **Probabilistically as a Conditional Random Field**

  It is defined by a set of linear features that are convolution kernels. For a set of features f_1 , f_2 …. f_n , the probability density of an image X, conditioned on an observed image O is defined to be

estimated value of ($X*f_i$)(x, y)

$$p(\chi) = \frac{1}{Z} exp\left(-\sum_{i=1}^{N_i} \sum_{x,y} \omega_i\,(x,y;O,\theta)\big((\chi * f_i)(x,y) - r_i(x,y;O)\big)^2 \right)$$

positive weighting function that uses the observed image O to assign a positive weight

value at location (x, y) in the image produced by convolving X with f_i

➢ An estimator based on minimizing a cost function

From a cost function perspective the estimate is the image X that minimizes the equation

$$\sum_{i=1}^{N_i} \sum_{x,y} \omega_i(x,y;O,\theta)\big((\chi * f_i)(x,y) - r_i\big)^2$$

The minimum can be computed using the pseudo-inverse, which can be expressed as

$$h(O;\theta) = (F^T \underbrace{W(O;\theta)}F)^{-1} F^T W(O;\theta) r$$

Diagonal Matrix which is a function of the observed image and parameter θ

Before the model can be used, the parameters of the weighting function must be chosen. These are found by maximizing the likelihood of the training data.

Transforming the equation into linear algebra routines

$$\sum_{i=1}^{N_i} \sum_{x,y} \left((\chi * f_i)(x,y) - r_i(x,y;O) \right)^2$$

This exponent can be written in matrix form as under:

$$(F\chi - r)^T (F\chi - r)$$

Above equation can be rewritten in the standard form of the exponent of a multivariate normal distribution $(\chi - r)^T \Lambda^{-1} (\chi - r)$ by setting the precision matrix, Λ^{-1}, to be $F^T F$ and the mean, μ ,to be $(F^T F)^{-1} F^T r$

Reason for adding Weight

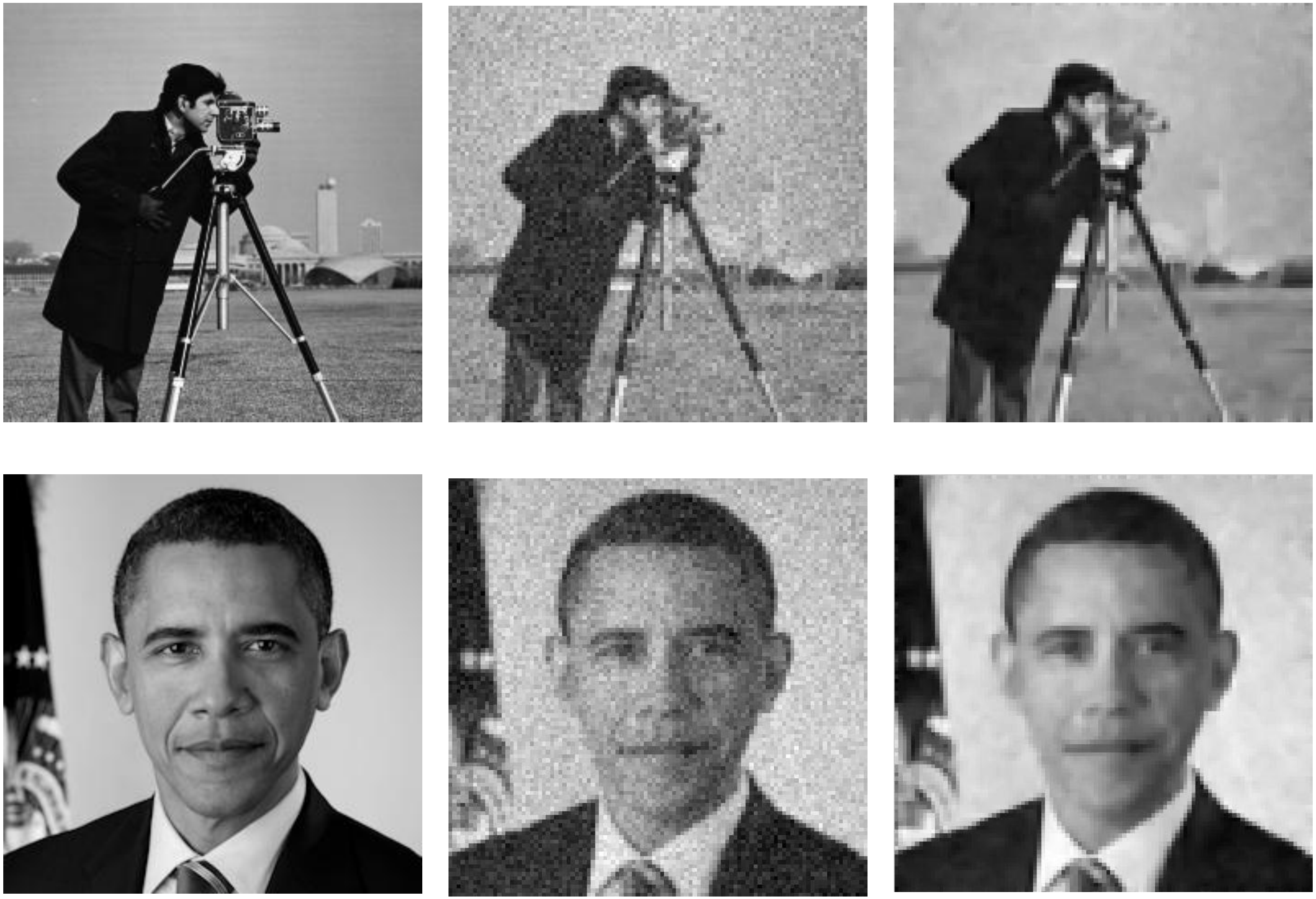
Assigning a weight to each quadratic term improves the model's ability to handle strong edges. For a term based on a derivative filter, the weight could be increased in flat regions of the image and decreased along edges. This will enable the model to smooth out noise, while preserving sharp edges.

EXAMPLE

Original | **Noisy Input** | **De-noised Image**

a:

b:



After executing the given code in MATLAB (Intel 2nd gen Core-i5 CPU @ 2.4GHz) following results have been observed.

a. *Image dimensions* : 256x256, *Number of iterations* : 600, *Time taken*: 161.79 sec

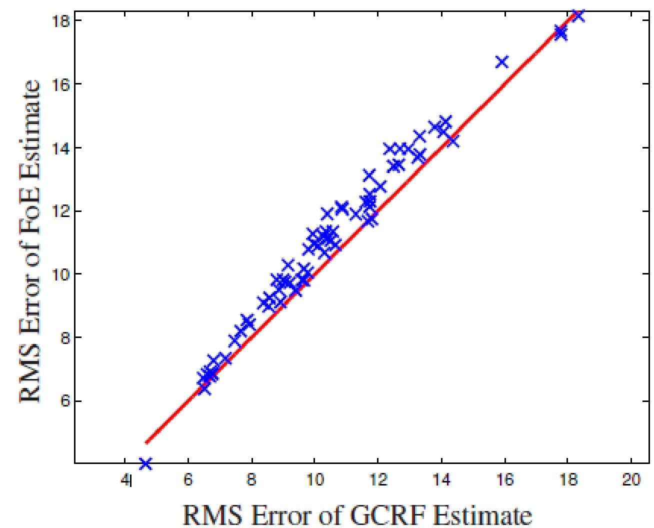
b. *Image dimensions* : 256x256, *Number of iterations* : 300, *Time taken*: 75.70 sec

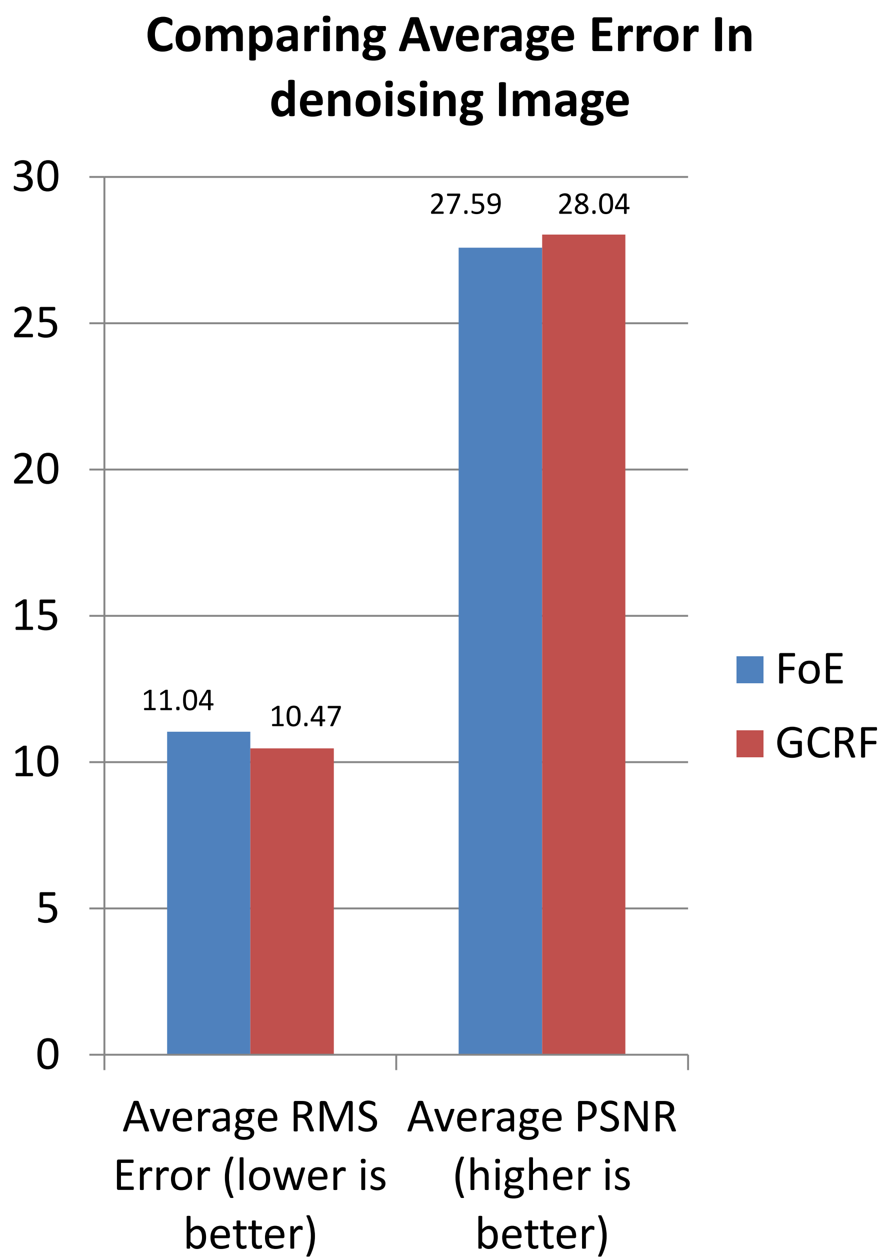
COMPARISON WITH FIELD OF EXPERTS

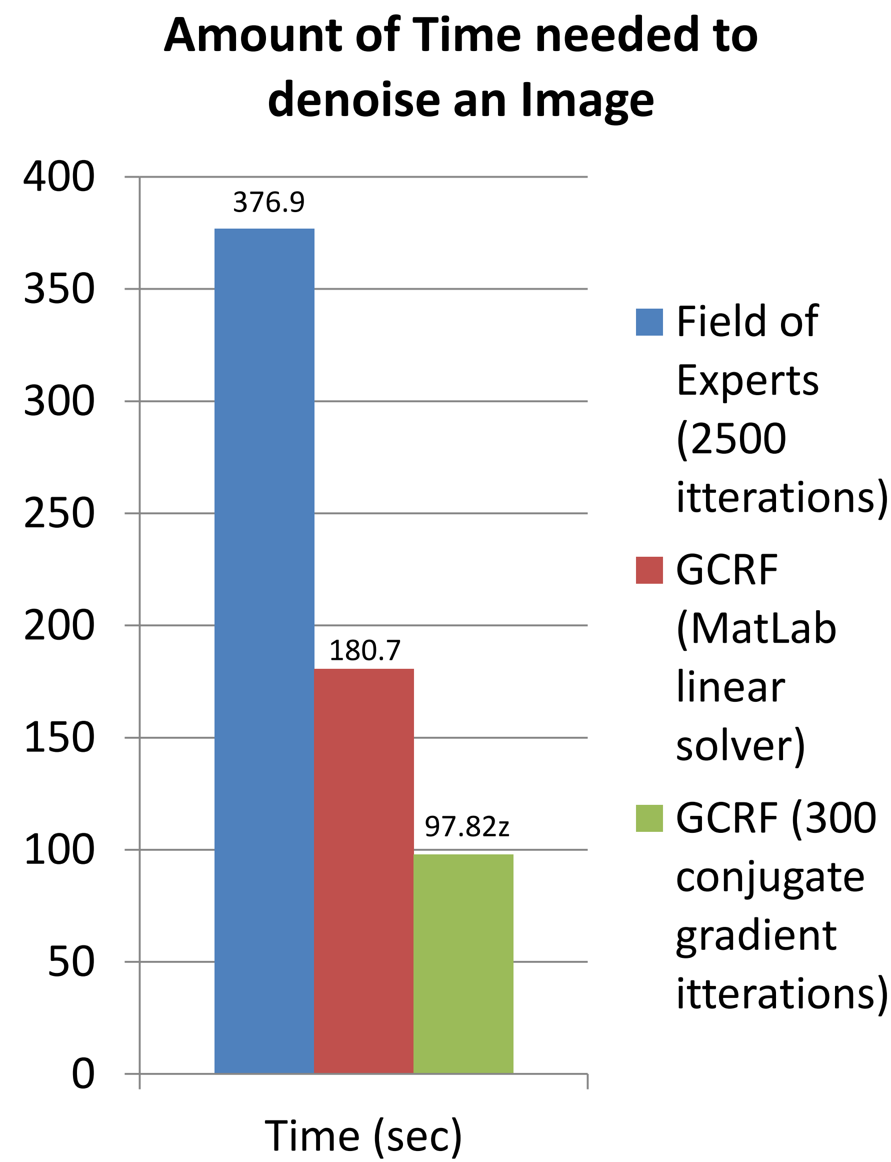
The results of GCRF model were compared with the Field of Expert (FoE) model. The implementation were run on 68 test images from the Berkeley segmentation database. The observed images were created by adding White Gaussian noise with standard deviation of 25 to each image. The FoE model de noises images by using gradient decent algorithm.

The following results were observed:

- The GCRF model produces denoised images with a lower error than FoE model.
- The GCRF model produces the better estimate for majority of images.
- GCRF model requires nearly half the time (for 2500 iterations in FoE model) to produce a de noise 481x321 images.




Comparing Average Error In denoising Image
30
25
20
15
10
5
0
27.59
28.04
11.04
10.47
FoE
GCRF
Average RMS Error (lower is better)
Average PSNR (higher is better)


Amount of Time needed to denoise an Image
400
350
300
250
200
150
100
50
0
376.9
180.7
97.82z
Field of Experts (2500 itterations)
GCRF (MatLab linear solver)
GCRF (300 conjugate gradient itterations)
Time (sec)

ADVANTAGES

- GCRF model is convenient to work with because it can be implemented using standard numerical algebra routine. Algorithms for numerical linear algebra are well understood, and efficient implementations are available.
- It is faster and easier than some methods.
- This can be trained on relatively larger images.
- It does a better job at preserving the fine scale textures.

DISADVANTAGES

- It relies on input data for the weight function. Therefore, if the data is not proper then it may lead to poor quality (such as over smoothing).
- GCRF model is trained for special noise level.

- When using log likelihood to fit the GCRF parameters, we have to do matrix inversion which requires $O(N^3)$ operational time. For 256*256 image storing the matrix in the memory with single precision values will require 16 GB of memory.

RELATED WORK

Several other works in the same field are

- Field of Expert (FoE) : A frame work for learning image prior (2005)
- Estimating intrinsic component images using non-linear regression (2003)
- Structure prediction via the extra gradient method (2006)
- Hidden Markov support vector machine (2003)
- Discriminative training of energy-based model (2005)
- Statistical modeling of images with field of Gaussian scale mixture (2007)

- Size:270x380
- Itterations:300