Facial Image Deblurring using a Sparse Representation Based Iterative Incremental Method

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***Abstract*—Deconvolution finds many applications in the Signal Processing domain. A variety of Signal Processing problems such as image blurring in shaky camera, echoes in long distance call, etc. can be modeled as convolution. Deconvolution tries to recreate the original signal as it was before convolution. Several factors need to be taken into account, such as noise, point-spread function (PSF), etc. before formulating an algorithm to effectively deconvolve a signal. This paper describes an efficient iterative incremental image deblurring algorithm, which exploits the sparse nature of natural images and helps is restoring noisy and blurry facial images. The main goal of this project is to deblur facial images which ultimately aid in better face recognition. The results demonstrate superiority of this algorithm over traditional deblurring methods.**

***Keywords*—Deconvolution, Deblurring, Image Processing, Sparse, K-SVD**

I. INTRODUCTION

The focus of this paper is deconvolution of blurry and noisy images using an iterative incremental algorithm that takes into account the sparse nature of natural images, and combines this information with an optimization algorithm to perform the restoration task [1]. The paper compares the result with famous deblurring methods such as the Lucy-Richardson [4] method and the Wiener method.

The problem of deonvolution can be modeled as finding a sharp, clean image x, given a blurred image y and a filter f, such that:

$$y = h * x \tag{1}$$

It is convenient to notice that convolution is a linear operator and hence Eq 1 can be written as:

$$y = Hx \tag{2}$$

where H is the convolution matrix of dimesnion NXN, and the images x and y are each described by an $NX1$ elements vector. For the future reference of this paper, it is also useful to denote the convolution in the frequency domain. Hence Eq 1 can be written as:

$$Y(\omega) = H(\omega)X(\omega) \tag{3}$$

where $H(\omega)$ is the fourier transform of h, and is a diagonal matrix. $Y(\omega)$, $X(\omega)$ are the fourier transforms of y and x respectively.

If H is a full rank matrix and there is no noise involved, the deconvolution task can be easily done by simply inverting the convolution matrix and defining $x = H^{-1}y$, or in the frequency domain by $X(\omega) = Y(\omega)/H(\omega)$. This, however is not applicable for practical scenarios. For example, $H(\omega)$ might be zero for some values of ω, and the inverse will not be defined at those frequencies. The inverse is also very sensitive to noise. Suppose, if we have noise in the signal, the inverse will be $Y(\omega)/H(\omega) = X(\omega) + n/H(\omega)$. We can clearly see that for very small values of $|H(\omega)|$, the contibution of noise will be very large, and the results wil be poor.

Many methods try to tackle this problem of image restoration by introducing a regularization term that penalizes the unwanted solutions (such as noise), and hence try and stay away from bad solutions. The central idea of such algorithms is to find an appropriate regularizer term that would provide the best possible result. But designing a regularized optimization problem is not easy, and often leads to image artifacts if the regularization term is not conditioned properly. Another problem that comes to light while discussing the potential solutions to deblurring is the pixel-level restoration methods, which many times overfit the results [7]

This paper describes a method that works at an intermediate level (higher than pixel level, and lower than parametric methods) for image restoration, which is more general than pixel-level methods and not as specific as the paramteric ones. The rest of the paper is organised as follows. In section 2, the basic of sparse representation of images are covered; in section 3, the process of dictionary learning is described; in section 4, the proposed deblurring algorithm is explained; analysis of the results is done in section 5. The work is concluded in section 6.

II. SPARSE REPRESENTATION OF IMAGES

Sparse representation can be thought of as expressing some thought with the fewest of words possible. In terms of images it can be expressed as given an image $\mathbf{x} \in \mathbb{R}^n$, it can be represented as:

$$x = D\alpha \tag{4}$$

where $\mathbf{D}$ is the dictionary chosen by us and α is the sparse representation of the image $\mathbf{x}$. The dimension of $\mathbf{D}$ are nXN. Each column of the dictionary can be thought of as a word and so there are N words in total. Some of the most commonly used dictionaries are wavelet, fourier, curvelet, DCT, etc. Usually the dictionary is selected from the above list, but to get better results, the paper adopts a different method, which is described in the next section

III. DICTIONARY LEARNING

Selecting the right dictionary is essential, not only for better sparse representation but also in efficient image restoration. The dictionaries mentioned in the last section all cater to different varities of signals. While fourier is a good choice for vibrations, curvelet is better for piecewise smooth signals, and wavelet does a good job in isotropic properties [8]. But to represnt the image as a whole in a more general and desirable manner, no single dictionary does a good job. Thus designing a flexible and adaptive dictionary that provides better representation than single methods becomes essential.

Learning a dictionary using image samples that are similar in content to the images that we need to deblur provides a desirable dictionary which satisfies the above mentioned requirements. One of the most famous methods of learning a dictionary is the K-SVD method [2]. The basic mathematical formulation of K-SVD is:

$$\min_{D,\alpha} ||\alpha||_0 \;\; \mathrm{s.t.} \;\; ||x - D\alpha||_2^2 < \epsilon \tag{5}$$

where $||\alpha||_0$, the L_0 norm is defined as $\sum_j \alpha_j^0$, and $||A||_2$ is the L_2 norm defined as $\sqrt{\sum_{ij} A_{ij}^2}$. The K-SVD algorithm cosists of two steps

- The sparse coding stage, where it finds the sparse representation for the samples.
- The Dictionary update stage that updates the dictionary in each iteration using SVD Decomposition.

Thus the overall process is an alternate updation of the sparse representation and the dicitonary. We trained the dictionary on latent sharp similar facial images, and the size of the dictionary is designed to be n=64 and N=256. The obtained dictionary is as shown in Figure 1.

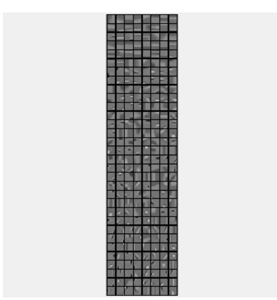

Fig. 1. Learned Dictionary

IV. SPARSE ITERATIVE INCREMENTAL DEBLURRING

Using the concepts describe in the previous section, the minimization problem can be formulated as follows:

$$\min ||y - Hx|| \tag{6}$$

$$\mathrm{s.t.} (x)_i \geq 0 \tag{7}$$

$$x = D\alpha, ||\alpha||_0 \leq \epsilon \tag{8}$$

where **y** is the noisy and blurry image, **x** is the latent sharp image. The only two constraints are the non-negative and the sparsity constraints. The non-negative constraint is an effective cnstraint used widely for image restoration and the sparsity constarint enables the maintains the sparsity of the codes.

The algorithm that was followed for the deblurring process was:

Algorithm 1 Sparse Iterative Incremental Deblurring

Initialization : Initialize x_0, prepare dictionary D
while algorithm converges **do**
- Obtain $X_k\omega$, the fourier transform of x_k, the k-th estimate
- Calculate the frequency error: $S_k(\omega) = Y(\omega) - X_k(\omega)H(\omega)$
- Update equation becomes: $X_{k+1}(\omega) = X_k(\omega) + \dfrac{H^*(\omega)S_k(\omega)}{|H(\omega)|^2 + \gamma}$
- Get inverse fourier transform x_{k+1} fromX_{k+1}
- Enforce non-negative constraint to x_{k+1} to get $x_{k+1,p}$
- Get the sparse representation using Orthogonal Matching Pursuit (OMP) [6] for α and then get $x_{k+1,p,s}$ through Equation 8
- Set $x_{k+1,p,s}$ as the current estimate

For our facial images, the algorithm converged at 5 iterations. For the sparsity constraint ϵ is taken to be equal to 0.7σ where σ is the noise variance. The calculations were done in the freqeuncy domain as it is easier to implement and is computationally faster than spatial domain calculations.

V. RESULTS AND COMPARISON

The experiment was performed on a new facila image which was not included while learning the dictionary. We used a variety of filters to blur the image and then added noise to it. The results were compared with the famous Lucy-Richardson deconvolution and the Wiener deconvolution methods. Following are the comparative results.

The first filter that we used was a Gaussian 15X15 filter with $\sigma = 2$. Figure 2 shows the result.

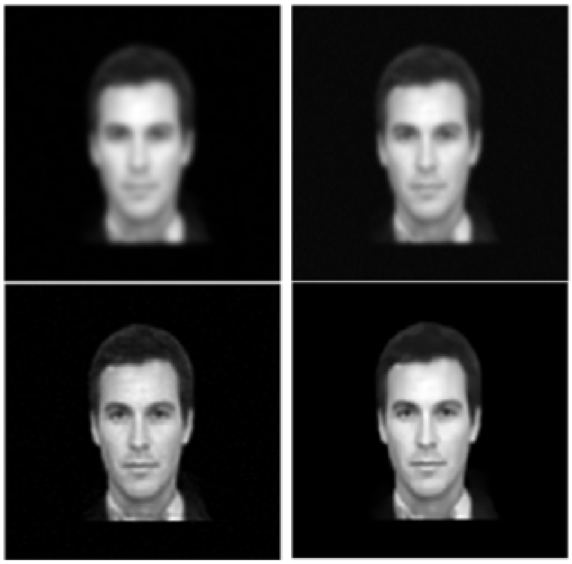

Fig. 2. Clockwise from top-left (a) Captured Image, (b) Wiener, (c) Richardson-lucy, (d) Our

Thus we see that Lucy-Richardson and our algorithm do an equally good job in this case.

Upon using a motion filter of length 20 and angle of 45 the results were as shown in Figure 3

Fig. 3. Clockwise from top-left (a) Captured Image, (b) Wiener, (c) Richardson-lucy, (d) Our

Thus we see that Lucy-Richardson the result of Lucy-Richardson has started deteriorating as we blur the image further. Our algorithm has visually better results.

Upon worsening the blur further, using a motion filter of length 30, and an angle of 0 the results were as shown in Figure 4

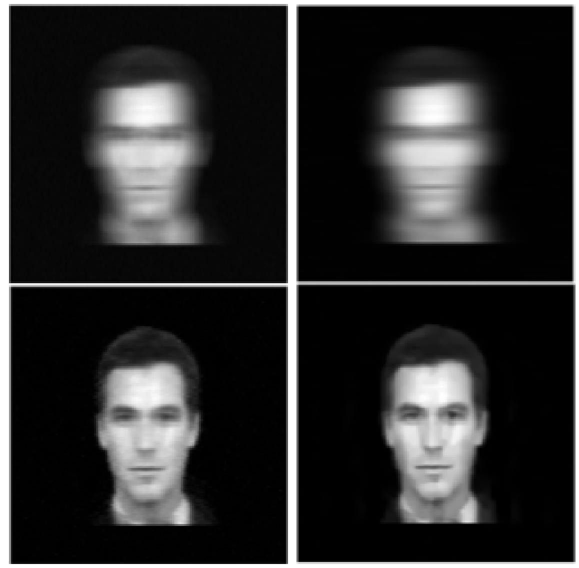

Fig. 4. Clockwise from top-left (a) Captured Image, (b) Wiener, (c) Richardson-Lucy, (d) Our

Again we see that our algorithm gave the best result in terms of retrieving back the facial features such as eyes. The wiener method did nto perfrom well at all in any of the cases.

Thus visual results prove that our implementation of the algorithm described in [**insert reference our**] outperformed the traditional deblurring methods such as the Richardson-Lucy method and the Wiener filtering method.

VI. Conclusion and Future Work

We were able to successfully implement the algorithm described in the paper [1]. The paper proposes an intermediate level image restoration method that avoids under/over fitting the results. Thus we have sharper images even for the worst cases of blurring. But this method involves providing the blur kernel to the algorithm to deblur the images. The future work hence becomes estimation of the blur kernel and perform a blind deconvolution [3]. There is also room for providing more constraints in the minimization problem to get better results. We would also like to test this algorithm with face-detection softwares to test the practicability of the algorithm.

Acknowledgment

We would like to express their gratitude towards Prof. Yao Wang for doing an exemplary job in teaching the nuances of Digital Signal Processing in a very intuitive manner, and instilling the confidence in us to do this project. The project couldn't have been completed without her guidance and resourcefulness. We would also like to thank our mentor Yilin Song for providing us valuable inputs and correcting us whenever necessary. Lastly, we would like to thank Haichao Zhang and Yanning Zhang for conceptualizing such an efficient method of image deblurring.

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