Adaptive Deblurring and Parameter Estimation Using Dictionary Learning and Whiteness Measures

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Abstract: ***The blurring of the image is a common scenario as the digital devices become popular. Often these images will be blurred due to camera shake and out of focus. Image deblurring is so becoming so important and this paper proposes an adaptive method of image deblurring by using dictionary learning method. We also carry out an comparative study with an existing method in which deblurring is done by estimating a parameter for the deblurring filter by using an iteration method. As iterations require a stopping criteria this method also makes use of a whiteness criteria to stop the iterations and obtaining the filter and then image will be deblurred. A comparative study between these two methods will be carried out.***

Keywords: Deblurring, Blindeblurring, Adaptive learning Dictionary updation, Residual whiteness

1. Introduction

Present days, as the digitalization has reached its maximum peak every now and then a new digital device is launched with a powerful camera. At every second in every corner of the world a photo is clicked by us. But most often these images will be blurred due to many reasons. These reasons include addition of noise, motion of camera etc. Also as the space expeditions are widely carried out in nowadays the picture taken by the space ships will be most often be blurred due to the presence of noise.

Image deblurring is broadly classified into two: blind and non-blind. If there is enough information regarding the original image and we only need to estimate only blur kernel such type is called as non-blind deblurring. If there is no information about both image and the blur kernel then its classified to be under the blind category. Non-blind deblurring is easy to be carried out and there are enough methods to carry out non-blind deblurring. Whereas blind deblurring is the most difficult technique to be done.

In ID problems we have designed our degraded images as y=h*x+n im which y is considered as the degraded image, h is the blur kernel, x is the original image and n is the additive Gaussian noise.

In NBID problems our aim is to find 'x' from 'y' and ' h' and in case of BID problems our aim is to find 'x' and 'h' from the given degraded image 'y'. The previous method of such image deblurring problems included the estimation of a regularization parameter and gradually gets the information about the image by slowly decreasing the regularization parameter. From this it is crystal clear that such method requires iteration method in which it includes large number of iterations so here we want to provide a efficient stopping criteria also for this method. This is given on the basis of an whiteness measure. This type of deblurring technique has limited use because of its complexity and hence we had moved on to new methods. This method also greatly depends on the type of the blurness caused. As the technology is advancing we require an adaptive method which will be suitable for every type of blur with a less much complexity.

In this paper we propose an adaptive method which can be used in image deblurring using an dictionary learning method. In this method the image blur is modeled as B=K*I+n, where B is the blurred image, K is the blur kernel; I is the original image and n is the additive Gaussian noise. Here we makes use of an sparse representation using a dictionary learned directly from the blurred image. This method exploits sparsity constraints to estimate the blur kernel and makes use of standard method to get the original image.

This paper has divided in to six sections in which second section contains the literature survey. Third section comprises an outline of the previous method of deblurring by parameter estimation. Fourth section explanation of the algorithm of our adaptive method. Fifth section involves an comparative study. Last we will present results and conclusions.

2. Literature Survey

The image deblurring is not a new problem it has gained attention of scientists pretty much earlier so here we are just giving a brief description about the previous methods of image deblurring. In [2] the image deblurring is done with the help of an parameter estimation method which is well explained in the coming sections. In [3] the dictionary updation by using KSVD algorithm is explained. After this dictionary updation is done by KSVD we can deblur the image by making use of any state of art methods. This algorithm is proved to be better in case of dictionary updation as well as for sparse representation of these dictionaries. In this case we can improve the efficiency of overall algorithm by making use of any efficient deconvolution method so that after dictionary updation we can easily and simply deconvolve the kernel, obtained from this ID problem which is estimated from the dictionary updated and sparse coefficients, from the blurred image to get a deblurred image. In [4] the blind deblurring of natural images is taken into consideration. In this a method similar to that of parameter estimation is done which involves a cost function which is to be minimized. First assumption of blur filter is necessary in this case from which a filter can be calculated. By using this filter deconvolution is done to get a new image and the process continues. In [5] the author made use of the same algorithm as mentioned above in a bayesian approach to deblur the image. Both of these approaches involves large number of iterations which makes the problem complex. So we want to move to an algorithm which makes the problem less complex with less number of iterations. Where as in [6] a new algorithm for parameter estimation is proposed from the results its less efficient compared to other methods mentioned above. So from all these we are now describing a new adaptive method which is explained in the coming sections.

3. Parameter Estimation and Whiteness Measures

A. Parameter estimation

In Image deblurring problems we have designed our degraded images as y=h*x+n in which y is considered as the degraded image, h is the blur kernel, x is the original image and n is the additive Gaussian noise and * is the blur from an image is called as the deconvolution operation. Here we make use of an equation for the cost function given by

$$C(x,\lambda)=1/2 \;\| y-h*x \| + \lambda \;\phi\,(x) \qquad (1)$$

The first term in the equation is the classical data and the λ is the regularization parameter. The value of the regularization parameter will affect the image properties for small values the recovered image will be under regularized with high influence of the noise where as for higher values we get over regularized images.

In NBID as h is known an x can be calculated from above equation which satisfies that this x will minimize the cost function for some value of λ.

In case of BID first an regularization parameter value is chosen and at the initial stage the x is made equal to y so that the equation for cost function will yield a h for us. We represent it as h'. By using this h' we can calculate new x' in which the cost function will be minimum. This is repeated step by step to retrieve our original image. Initial images obtained will be cartoon like based upon these initial images further iterations will be carried out. The main drawback of this method is that we need a manual stopping mechanism to stop the iterations. In this method we make use of a whiteness criterion.

B. Whiteness criteria

In this we make use of a whiteness measure or rationale r which can be calculated by

$$r=y-h'*x' \qquad (2)$$

this rational will be calculated for each iteration, and the final iteration is considered which will maximizes one of the whiteness measure introduced below. It may be also stated as the final iteration will make the measure r spectrally white; i.e mean of r will be zero. The first step of our method is to normalize the residual image3 to zero mean and unit variance.

$$r = r -/ r \sqrt{\mathrm{var}(r)} \qquad (3)$$

The auto-correlation can be estimated by using

$$R_{rr}(m, n) = K\Sigma_{i;j}r(i, j)\; r(i - m, j - n) \qquad (4)$$

If the residual measure becomes spectrally white then the autocorrelation function will become equal to a delta function. One of the approaches for the calculation of whiteness is referred above. Other measures for r can also be utilized such that we can find an estimate for its mean such that if our whiteness rationale becomes spectrally white then the mean of r will be equal to zero. Auto co-variance and other measures can also found out for r such as power spectral density etc, and the result can be compared with that of white Gaussian noise and when the measure is same as that can be obtained from a white noise then the iterations can be concluded.

4. Adaptive Deblurring Using Dictionary Learning

The images can be modeled with sparse representation in a complete dictionary. The initial dictionary of the latent image is formed by applying discreet cosine transform to the blurred image. Our input image is divided into different patches. So that a single patch can be viewed as

$$Ip=D\alpha \qquad (5)$$

Where Ip is the image patch, D is the dictionary formed from the image, and α is the sparse coefficients.

We consider the image deblurring problem as an optimization problem so that we make use of an equation to find out blur kernel K

$$\min \|B - K \otimes DA\| + \lambda\; \Sigma\,\Theta(\alpha), \qquad (6)$$

The proposed algorithm had to find D, K, α from the above equation. We will obtain initial D from the input image, which later will be updated. We will assume a suitable value for α. With the estimated kernel we can use any conventional method to deblur the image. Sparse coefficients for each image patch can be found by using

$$\alpha^{(n+1)} = \arg\min \|\alpha\|_1, \quad \text{s.t.} \quad b = (K^{(n)} \otimes D^{(n)})\alpha,$$
$$\alpha^{(n+1)} = \arg\min \|\alpha\|_1, \quad \text{s.t.} \quad b = \hat{D}^{(n)}\alpha,$$

where ^D(n) is the blurred dictionary at iteration n. Here, we use b to represent a block of blur image.

When the kernel is estimated from the initial dictionary and sparse coefficients next step is to update the dictionary. This is done by the following methods first we will produce a deblurred image from the estimated kernel and then makes it into patches and produce the dictionary by using an algorithm like KSVD algorithm. Similarly the image can be recovered by estimating the blurring kernel.

5. Results

As we had described two methods for deblurring we can now compare both these methods by using some usual parameters as ISNR etc. In case of the parameter estimation method the number of iterations involved is too much larger which makes the whole process complex where as in adaptive method we can effectively reduce the number of iterations. As we compare the output images we can see that the difference in blurrness between images. In order to get a fully deblurre image we require almost 100 iterations in case of parameter estimation but same result can be obtained by just 8 iterations in adaptive method.

a) original image

b) blurred image

c) output image of parameter estimation method at iteration 8

d) output image of our adaptive method at iteration 8

The output images obtained are given above from these images we can understand the deblurring of both the methods in a better way. The parameter estimation method has shown least efficiency when compared with that of adaptive method because it has done only pure deblurring at iteration 8 where for adaptive method almost all blurness has removed from the picture by the same number of iterations i.e. by 8^{th} iteration we have almost deblurred the whole image. So from this it is clear that adaptive method is more efficient than that of the parameter estimation method.

e) output image of parameter estimation method in 100 iteration.

By the parameter estimation method deblurring is done by doing the iterations a hundred times. i.e. at the 100^{th} iteration only we could obtain a better deblurred image.

6. Conclusion

The image deblurring is a very challenging problem now a days and the removal of blurness often is a complex process. Here we are introducing a new algorithm for image deblurring by using an adaptive method. Previous method of deblurring using parameter estimation and whiteness measures is also taken into consideration and both of these measures are carried out in the same deblurred image. The results are also compared from which its obviously clear that the adaptive method is far better than the parameter estimation method, since the same amount of blurrness is removed from the image by adaptive method in a very less iterations whereas the same thing is done by parameter estimation with the help of large number of iterations. Adaptive method also helps to remove the blurrness in image caused by any of the reasons. Hence paper presents a new better an efficient deblurring technique. It can be made better by including any easier method of deconvolution to it.

References

[1] SINGLE IMAGE DEBLURRING WITH ADAPTIVE DICTIONARY LEARNING Zhe Hu Jia-Bin Huang Ming-Hsuan Yang Electrical Engineering and Computer Science University of California at Merced Merced, CA 95344, USA

[2] Parameter Estimation for Blind and Non-Blind Deblurring Using Residual Whiteness Measures Mariana S. C. Almeida and M´ario A. T. Figueiredo, *Fellow, IEEE*

[3] M. Aharon, M. Elad, and A. Bruckstein. K-SVD: an algorithm for designing overcompletes dictionaries for sparse representation. IEEE Transactions on Signal Processing, 54(11):4311–4322, 2006

[4] “Blind and semi-blind deblurring of natural images,” *IEEE Trans. Image Processing*, vol. 19, pp. 36–52, 2010.

[5] M. S. C. Almeida and L. B. Almeida, “Blind deblurring of natural images,” in *IEEE Int. Conf. Acoustics, Speech, and Signal Processing -ICASSP*, 2008, pp. 1261–1264.

[6] N. P. Galatsanos and A. K. Katsaggelos, “Methods for choosing the regularization parameter and estimating the noise variance in image restoration and their relation,” *IEEE Trans. Image Processing*, vol. 1, pp. 322–336, 1992.