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Restoring Motion Blur from Vehicle License Plates

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Abstract - Image restoration is the process of estimating the clears original image given just a degraded observed image. The degradation can occur because of noise, motion blur, out of focus blur or atmospheric disturbance. The loss of information due to such degradation could be immense in field like the degraded license plates of vehicles that break speed limits or traffic rules. Various approaches try to remove the motion blur from such motion blurred images to retrieve the license plate number to charge the owner of the vehicle. This paper uses forward backward splitting technique implemented using wavelet transform to retrieve restored image of license plates of vehicles for enforcement of traffic laws.

Keywords— Regularization, Restoration, Motion Blur, Data Fidelity

I. INTRODUCTION

This paper concentrates on a method for removing the blur from recorded image, caused by relative motion between the camera and the original scene. Image Restoration tries to perform an operation on the image that is the inverse of the imperfections in the image formation system. Other names for Image Restoration are Image Deblurring or Image Deconvolution. The loss of information due to degradation makes the degraded image wrong target for analysis.

Considering one such field is the recognition of license plate's numbers of vehicles speeding above an allowed limit. Imaging devices are used to capture images for the identification of license plates of speeding vehicles that break speed limits or traffic rules. The surveillance camera has been used on the road for traffic for a long time, but the resolution of the images is not fine enough to recognize the letters on the license plate of speeding vehicles. Addition to this there is the motion blur and noise effects which makes it becomes difficult to recognize the letters on the license plate of speeding vehicles. This paper focuses on the restoration of the motion blurred and noisy image of license plate of vehicles.

II. LITERATURE SURVEY

Bayesian Estimation is discussed in [1] where both the kernel and image are taken as samples from some probability spaces and solve for the unknowns that minimize the expected value of a loss function also called as maximum a posterior (MAP) estimator. But Bayesian estimator is built for a specific blur model and cannot handle other types of blurs without adaptation and performance highly depends on the sample number and statistics. Artificial Neural Network (ANN) has been used for restoring images in [4]. Algorithm such as the Back propagation and the Perceptron use gradient decent techniques to tune the network parameters to best-fit a training set of input-output examples and is capable of learning complex non-linear functions and is expected to produce better structure especially in high frequency regions of the image.

An efficient and effective motion blur removal method based on long and short exposure images presented in [12] merges the two images with taking into account the detected motion pixels. It has low computational complexity and low memory requirements. In [13] a single image captured with vehicle motion is used for speed measurement. Segmentation followed by edge detection is then applied on the subimage to find the left and right blur regions. Ideally, there will be two edges with the same width in each image scanline. Thus, the blur length can be obtained by taking the average of the ramp edge widths from those image scanlines.

Another method called the Adaptive Sparse Domain Selection (ASDS) in [14] considers the fact that the optimal sparse domains of natural images can vary significantly across different images and different image patches in a single image. The dictionaries that were pre-learned from a dataset of high quality example patches for each local patch were selected adaptively. The ASDS improves significantly the effectiveness of sparse modeling and consequently the results of image restoration.

III. RESTORATION BASICS

If we denote f the desired ideal spatially discrete image that does not contain any blur or noise, then the recorded image g is modeled as:

$$g = H * f + n \tag{1}$$

f - Original Image
g - corrupted image
*H - convolution kernel or point-spread function (**PSF**)*
n - noise that corrupts the blurred image

An alternative way of describing blurring is through its spectral equivalence. By applying discrete Fourier transforms, we obtain the following representation

$$G(u, v) = H(u, v)*F(u, v) + N(u, v) \tag{2}$$

where (u,v) are the spatial frequency coordinates, and capitals represent Fourier transforms.

The restoration of motion blurred license plates will be achieved by following two Image Deblurring Techniques referred in [10].

A. Regularization Technique

Regularization techniques have been proposed to add some form of a priori knowledge about the original image to be estimated. The general form of regularization methods is to find an estimate u of f that solves the minimization problem, i.e:

$$\min_{u \in R^N} F(\lambda, u) = \min_{u \in R^N} \{\mathcal{H}(u) + \lambda J(u)\} \tag{3}$$

where the functional $\mathcal{H}$(u) is given by :

$$\mathcal{H}(u) = \frac{1}{2}\|Hu - g\|_2^2 \tag{4}$$

$\mathcal{H}$(u) represents the data fidelity term, whereas $J(u)$ is a regularization functional (also called the penalization functional). It stabilizes the problem by introducing prior information into the solution, which encourages it to have some desirable properties (or equivalently, penalizes undesirable behaviour of the solution). Parameter λ is known as the regularization or the penalization parameter. It maintains the balance between the data fidelity and regularization terms.

B. Forward–Backward Splitting

In L1 image restoration problems, one seeks to find a solution to the following optimization problems: Given λ >0 evaluate:

$$\min_{u \in R^N} \left\{ F(\lambda, u) = \frac{1}{2}\|Hu - g\|_2^2 + \lambda \|W\, u\|_1 \right\} \tag{5}$$

where W represents the wavelet transform matrix.

A class of efficient iterative algorithms for the minimization of the sum of two convex functionals, where one of which is nonsmooth, has been recently introduced within the general framework of proximal splitting methods(prox).

Algorithm for Forward Backward Splitting (FBS)

A. Initialization Step

$\tilde{u}_0 = u_0 = g$

reldiff=1,k=2,t_1=1, zero=10^{-5}

Define functions:

f1=L1 norm of input image

*f2= L2 norm of difference image (H*x-g)*

$$v_1 = u_0 + H^T (g - H u_0) \tag{6}$$

$u_1 = prox(v_1)$

$\tilde{u}_1 = u_1$

B. while reldiff >=zero

1. Forward Updating Step:

$v_k = u_{k-1} + H^T (g - H u_{k-1})$

2. Backward minimization step:

$$\begin{aligned}\tilde{u}_k &= prox_{\beta\lambda J}(v_k) \\ &= \arg\min_{u \in R^N} \{\lambda J(u) + (1/2)\|u - v_k\|_2^2\}\end{aligned} \tag{7}$$

3. Evaluation Step:

$$t_k = (1 + \sqrt{1 + 4 * t_{k-1}^2}) / 2 \tag{8}$$

$$\tau_k = (t_{k-1} - 1) / t_k$$

$$u_k = \tilde{u}_k + \tau_n (\tilde{u}_k - \tilde{u}_{k-1}) \tag{9}$$

4. Reduction Step:

$$F(\lambda_k, u_{\lambda_k}) = \text{f1}\,(u_k) + \text{f2}\,(u_k); \tag{10}$$

5. Calculate stopping criteria reldiff and increase iteration variable.

$$reldiff = \frac{F(\lambda_k, u_{\lambda_k}) - F(\lambda_{k-1}, u_{\lambda_{k-1}})}{F(\lambda_k, u_{\lambda_k})} \tag{11}$$

$$k = k + 1$$

C. End while

C. Algorithm for Forward -Backward Minimization

1) Wavelet:

The term "wavelets" is used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ.

The orthonormal basis or wavelet basis is defined as:

$$\psi_{(j,k)}(x) = 2^{j/2}\psi(2^j x - k) \tag{12}$$

The scaling function is given as:

$$\phi_{(j,k)}(x) = 2^{j/2}\phi(2^j x - k) \tag{13}$$

where ψ is called the wavelet function and j and k are integers that scale and dilate the wavelet function. The factor 'j' in equations is known as the scale index, which indicates the wavelet's width. The position is given by the location index k. The wavelet function is dilated by powers of two and is translated by the integer k. In terms of the wavelet coefficients, the wavelet equation is:

$$\psi(x) = \sum_k^{N-1} g_k \sqrt{2\phi(2x - k)} \tag{14}$$

where $g0, g1, g2, \ldots$ are high pass wavelet coefficients.

The scaling equation in terms of the scaling coefficients is given below:

$$\phi(x) = \sum_k^{N-1} h_k \sqrt{2\phi(2x - k)} \tag{15}$$

The function φ *(x)* is the scaling function and the coefficients *h0, h1, h2,…* are low pass scaling coefficients.

The wavelet and scaling coefficients are related by the quadrature mirror relationship, which is:

$$g_n = (-1)^n h_1 - n + N \quad (16)$$

The term *N* is the number of vanishing moments. The wavelet equation produces different wavelet families. For Haar wavelet transform, $h_0=h_1=1/\text{sqrt}(2)$ and $g_0 = - g_1= 1/\text{sqrt}(2)$.

One half of the output is produced by the low pass filter function defined by Equation 15 and the other half is produced by the high pass filter function defined by Equation 14. The low pass outputs contain most of the information of the input signal and are known as "coarse" coefficients. The outputs from the high pass filter are known as "detail" coefficients. The coefficients obtained from the low pass filter are used as the original signal for the next set of coefficients. This procedure is carried out recursively until a trivial number of low pass filter coefficients are left. The final output contains the remaining low pass filter outputs and the accumulated high pass filter outputs. This procedure is termed as decomposition.

2) Wavelet Thresholding:

The term wavelet thresholding is explained as comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. This is called as Soft thresholding. It is defined as follows:

$$T_s = \begin{cases} sign(x)\ (|x| - t) & for\ |x| > t \\ 0 & in\ all\ other\ regions. \end{cases} \quad (17)$$

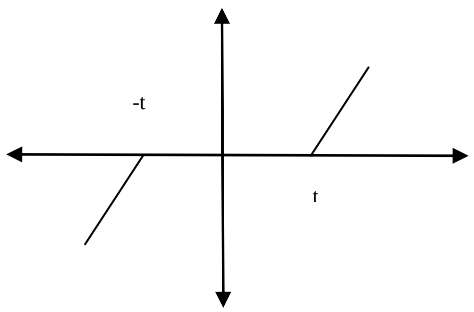

Fig 1. Soft thresholding

The soft method is much better, results in more visually pleasant images and yields a smaller minimum mean squared error compared to hard form of there holding. The inverse discrete wavelet transform is applied to build back the modified image from its coefficients.

IV. METHODOLOGY USED

- Step 1: Read License Plate IMAGE
- Step 2: Image Preprocessing
  Select motion length and bsnr for blurring using motion blur and Apply to obtain Blurred Image.
- Step 3: Apply Forward Backward Splitting Algorithm
  A. Initialization step

  B. Implement Forward Updating Step & Backward Minimization Step

  1. The image is first subjected to a discrete wavelet transform, which decomposes the image into various sub-bands. It calculates DWT wavelet coefficients for a finite set of input data, which is a power of 2.
  2. This input data is passed through two convolution functions. One half of the output is produced by the low pass filter and the other half is produced by the high pass filter.
  3. The coefficients obtained from the low pass filter are used as the original signal for the next set of coefficients. This procedure is carried out recursively until a trivial number of low pass filter coefficients are left.
  4. Soft Thresholding is now applied to the detail components to remove the noise.
  5. Once the processing is done, the image is built back from the coefficients.

     In the inverse discrete wavelet procedure, quadrature mirror filters equations 15 and 14 are supplied with the coarse coefficients and the accumulated detail coefficients. The so obtained outputs of the two filters are added and are considered as the coarse coefficients for the next stage of reconstruction. This procedure is continued until the complete image is obtained.

  C. Evaluation Step
  D. Reduction Step
  E. Calculate stopping criteria reldiff and increase iteration variable.
  F. End while
- Step 4: Calculate performance measures
- Step 5: Perform Localization
  1. Dilate the image to fill boundary gaps.

2. Erode the image to remove false thin connecting lines.
3. Perform edge detection using canny operator
4. Obtain the rectangles formed and save in s[ ] alongwith its area information
5. Sort rectangles areawise in descending order and store in HH[ ] and ii array holds corresponding rectangle's index in ss[ ].
6. Among the topmost 12 largest rectangle frames obtain one with highest contrast from reconstructed image which represents license plate.
7. Display the license plate.

➢ Step 6: Display deblurred license plate image

V. PERFORMANCE EVALUATION

We need to assume that the PSF of the blur is satisfactorily known. Now, if the recorded image is *g* and the point-spread function of the linear restoration filter, denoted by *h* and the restored image is given by *u*. In image restoration the improvement in quality of the restored image over the recorded blurred one is measured by the signal-to-noise-ratio improvement.

A. The Improved Signal to Noise Ratio (**ISNR**) is given by:

$$ISNR = 20\log_{10}\left(\frac{\|g-f\|_2}{\|u-f\|_2}\right) \quad (db) \qquad (18)$$

The ISNR is basically a measure that expresses the reduction of disagreement with the ideal image when comparing the distorted and restored image.

B. Peak Signal to Noise Ratio (**PSNR**) is given by:

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \qquad (19)$$

$$MSE = \frac{1}{MN}\sum_{n1=0}^{N-1}\sum_{n2=0}^{M-1}(u-f)^2 \qquad (20)$$

where *MSE is* Mean Square Error.

C. Blurred Signal to Noise Ratio (**BSNR**) is given as:

$$BSNR = 20.\log_{10}\left(\frac{\|g-\bar{g}\|_2}{\sigma\sqrt{N}}\right) \qquad (21)$$

$\bar{g}$ denotes the mean of *g* and σ is the standard deviation of the error.

VI. EXPERIMENTAL RESULTS

A. Restoring license plate blurred with BSNR=30 & Motion Length=11

Fig 2.Original License Plate

Fig 3. Blurred with BSNR=30 & Motion Length=11

Fig 4.Restored by Proposed Method

Fig 5. Restored by ASDS

TABLE I: PSNR and ISNR values of different methods for the car3 image degraded by Blur Kernel of BSNR=30 & Motion Length=11

Parameters	Proposed Method	ASDS
PSNR	34.8531 db	39.0686 db
ISNR	10.562 db	14.7656 db
TIME	20.2293 sec	431.758 sec

Fig 6. Localization

B. Comparative analysis of Proposed Method and ASDS

TABLE II: Comparative analysis of different approaches for combinations of length of motion and bsnr:

Blur Details	Method	ISNR db	PSNR db	Time sec
BSNR=20 db, Length=9	Proposed	9.9704	33.275	12.282
	ASDS	16.3321	39.640	485.788
BSNR=40 db & Length=9	Proposed	14.3768	37.686	13.039
	ASDS	17.6014	40.910	473.279
BSNR=20 db & Length=15	Proposed	8.7887	30.353	23.599
	ASDS	14.9195	36.480	479.441
BSNR=40 db & Length=15	Proposed	11.3984	32.966	24.926
	ASDS	15.6622	37.230	475.519
BSNR=40 db & Length=20	Proposed	7.4185	28.331	26.129
	ASDS	12.9783	33.890	465.807

C. Effect of input image being smooth on PSNR and ISNR

Fig 7. Smooth Original Image

Fig 8. Blurred Image of the smooth image

Fig 9. Restored Image using Proposed Method

D. Effect of input image being bright on PSNR and ISNR

Fig 10. Bright Original Image

Fig 11. Blurred version of the bright image

Fig 12. Restored Image using Proposed Method

TABLE III: Comparison of Performance measures in scenarios where original image is smooth and when image is bright:

Parameters	Original	Smooth	Bright
PSNR	34.327 db	38.1833 db	36.3204db
ISNR	10.6158db	4.5066 db	8.8727 db

Observing the outputs when the image is smoother or brighter than original, it is seen that when the image is smoother than original or brighter than original then the PSNR increases slightly but the ISNR reduces. For smooth image the decrease in ISNR value is significant.

VII. CONCLUSION

In this paper, an approach for restoring vehicle license plate is used based on a single motion blurred image taken by a stationary camera. For the motion blurred license plate image, image restoration provides a way to make the image clear by removing motion blur and noise.

The improved signal to noise ratio for a constant length of motion increases as the BSNR value is increased. Also it is observed that there is decrease in the ISNR for a constant BSNR and increasing values of motion blur. The ISNR values of ASDS method is better than the proposed method but it takes much more time since ASDS method uses the training set to restore images.

It is seen that when the image is smoother than original or brighter than original then the PSNR increases but the ISNR reduces. Thus though it seems to increase PSNR the visual quality degrades than when the original image is taken as it is. This is the limitation of the proposed method.

The proposed method exploits the information yielded by the iterative method to converge to a seemingly optimal value. The resulting Forward Backward Splitting algorithm does not require any information about the perturbation process.

VIII. Future Scope

When the input image is very smooth then the ISNR is reduced significantly. This limitation degrades the performance of the proposed method for restoring motion blurred image. Thus further research can be performed to improve the ISNR of a motion blurred image even if the input image is very smooth.

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