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AN ITERATIVE SUPER-RESOLUTION RECONSTRUCTION OF IMAGE SEQUENCES USING A BAYESIAN APPROACH AND AFFINE BLOCK-BASED REGISTRATION

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ABSTRACT

Due to translational registration, traditional super-resolution reconstructions can apply only on the sequences that have simple translation motion. This paper reviews the super-resolution algorithm in these two decades and proposes a novel super-resolution reconstruction that that can apply on real sequences or complex motion sequences. The proposed super-resolution reconstruction uses a high accuracy registration algorithm, the fast affine block-based registration [42], in the stochastic regularization technique of Bayesian MAP estimation used to compensate the missing measurement information. The experimental results show that the proposed reconstruction can apply on real sequence such as Suzie, Mobile Calendar and Foreman.

1. INTRODUCTION

Typically, theoretical and practical limitations constrain the achievable resolution of any devices. SR (Super-Resolution) image reconstruction algorithms investigate the relative motion information between multiple LR (Low Resolution) images (or a video sequence) and increase the spatial resolution by fusing them into a single frame. In doing so, it also removes the effect of possible blurring and noise in the LR images [7], [20], [22], [37]. Recent work relates this problem to restoration theory [34]. As such, the problem is shown to be an inverse problem, where an unknown image is to be reconstructed, based on measurements related to it through linear operators and additive noise. This linear relation is composed of geometric warp, blur and decimation operations. The super-resolution problem is modelled by using sparse matrices and analyzed from many reconstruction methods [20] such as the Non-uniform Interpolation, Frequency Domain, Maximum-Likelihood (ML), Maximum A-Posteriori (MAP), and Projection Onto Convex Sets (POCS).

The super-resolution restoration idea was first presented by T. S. Huang and R. Y. Tsan [39] in 1984. They used the frequency domain approach to demonstrate the ability to reconstruct one improved resolution image from several downsampled noise-free versions of it, based on the spatial aliasing effect. A frequency domain recursive algorithm for the restoration of super-resolution images from noisy and blurred measurements is proposed by S. P. Kim, N. K. Bose, and H. M. Valenzuela [31] in 1990. The algorithm using a weighted recursive least squares algorithm, is based on sequential estimation theory in the frequency-wavenumber domain, to achieve simultaneous improvement in signal-to-noise ratio and resolution from available registered sequence of low-resolution noisy frames. In [32], S. P. Kim and Wen-Yu Su also incorporated explicitly the deblurring computation into the high-resolution image reconstruction process in 1993 because separate deblurring of input frames would introduce the undesirable phase and high wavenumber distortions in the DFT of those frames. Although the frequency domain methods are intuitively simple and computationally cheap, the observation model is restricted to only global translational motion and LSI blur. Due to the lack of data correlation in the frequency domain, it is also difficult to apply the spatial domain a priori knowledge for regularization. The POCS formulation of the SR reconstruction was first suggested by Stark and Oskoui [37] in 1987. Their method was extended by Tekalp [37] to include observation noise in 1992. Although the advantage of POCS is that it is simple and can utilize a convenient inclusion of a priori information, these methods have the disadvantages of nonuniqueness of solution, slow convergence, and a high computational cost.

Due to MRF (Markov Random Field) that can model the image characteristic [29-30] especially on image texture, their super-resolution approach using MAP estimator (or the Regularized ML estimator), with the HMRF (Huber-Markov Random Field) prior was presented by Richard R. Schultz and Robert L. Stevenson [27-28] in 1996. The blur of the measured images is assumed to be simple averaging, and the measurements additive noise is assumed to be independent and identically distributed (i.i.d.) Gaussian vector.

M. Elad and A. Feuer [16] proposed the hybrid method combining the ML and nonellipsoid constraints for the super-resolution restoration in 1997 and the adaptive filtering approach for the super-resolution restoration in 1999 [17]. Later, the special case of super-resolution restoration (where the warps are pure translations, the blur is space invariant and the same for all the images, and the noise is white) are proposed for a fast super-resolution restoration in 2001 [18]. A. J. Patti and Y. Altunbasak proposed [2] a super-resolution reconstruction using ML estimator with POCS-based regularization in 2001 and Y. Altunbasak, A. J. Patti, and R. M. Mersereau [45] proposed a super-resolution restoration for the MPEG sequences in 2002. They proposed a motion-compensated, transform-domain super-resolution procedure that directly incorporates the transform-domain quantization information by working with the compressed bit stream. Later, B. K. Gunturk and Y. Altunbasak and R. M. Mersereau [3] proposed a ML super-resolution with regularization based on compression quantization, additive noise and image prior information in 2004.

S. Baker and T. Kanade [33] proposed another super-resolution algorithm (hallucination or recognition-based super-resolution) in 2002 that attempts to recognize local features in the low-resolution image and then enhances their resolution in an appropriate manner. Due to the training data base, this algorithm performance depends on the image type (such as face or character) and this algorithm is not robust enough to be sued in typical surveillance video. J. Sun, N. N. Zheng, H. Tao and H. Y. Shum [12] proposed hallucination super-resolution (for single image) using regularization ML with primal sketches as the basic recognition elements in 2003. D. Rajan and S. Chaudhuri [7-8] proposed super-resolution approach, based on ML with MRF regularization, to simultaneously estimate the depth map and the focused image of a scene, both at a super-resolution from its defocused observed images in 2003. P. Vandewalle, Sabine S. Susstrunk and M. Vetterli [24] propose a fast super-resolution reconstruction based on a non-uniform interpolation using and a frequency domain registration in 2004. Although this method has low computational load and can use in the real-time system, the degradation models are limited. The alternate super-resolution approach, L1 Norm minimization and robust regularization based on a Bilateral Total Variance, was presented by S. Farsiu and M. Dirk Robinson [34] in 2004. This approach performance is superior to what proposed earlier in [16], [17] and [18] because this approach proper to deal with different data and noise models and this approach has fast convergence.

All the above super-resolution restoration methods [2], [3], [7], [12], [16], [17], [18], [20], [22], [24], [27], [28], [29], [30], [31], [32], [33], [34], [37], [39], [45] are restricted to global or local uniform translational displacement between the measured images or sequences therefore, unfortunately, the pure translation model can not represent the real complex motion effectively therefore image super-resolution applications can apply only on the sequences that have simple translation motion.

This paper proposed a novel super-resolution framework that can apply on real sequences or complex motion sequences. Due to the limitation of the translation model, we present a high accuracy registration algorithm, the fast affine block-based registration [42] that can model the high complex motion. This proposed registration algorithm divides the current frame into overlapping blocks then it searches all possible affine modelled blocks within a search windows in the reference frame to find the best matched blocks. The affine parameter of the best matched block is called an affine motion parameter or affine motion vector. To reduce the tremendous computation cost due to the large frame-size, a modified three step search (M3SS) is used to estimate the affine parameter. The proposed super-resolution is based on L2 norm minimization with three different regularizations: Laplacian, MRF and BTV. Therefore, the super-resolution reconstruction can apply on real sequences or complex motion sequences such as the standard sequence (Foreman, Carphone or Suzie).

The organization of this paper is as follows. Section II introduces briefly the proposed affine block-based registration that can improve the accuracy performance of translational registration and a modified three step search (M3SS) that is developed to alleviate the heavy computations of Full Search (FS). Section III introduces the super-resolution using the affine block-based registration and a Bayesian approach with BTV regularization function as a prior function. Section IV outlines the proposed solution and presents the comparative experimental results. Finally, Section V provides the summary and conclusion.

2. INTRODUCTION OF SUPER-RESOLUTION

This section starts our presentation with a brief description of the problem and the model used. Consider a sequence of images $\{\underline{Y}(t)\}$, each image is of $M \times M$ pixels, as our measured data. We wish to generate a sequence $\{\underline{X}(t)\}$ of images of higher resolution, each image of $L \times L\ (L > M)$ pixels and of improved quality. For convenience of notation, all images will be presented as vector, ordered column-wise lexicographically. Namely, we have $\underline{Y}(t) \in \mathbf{R}^{M^2}$ and $\underline{X}(t) \in \mathbf{R}^{L^2}$. At each time instant we assume that the two images are related via the following equation.

$$\underline{Y}(t) = D \cdot H \cdot \underline{X}(t) + \underline{N}(t) \qquad (1)$$

where $\underline{X}(t)$ is blurred, decimated (namely, down sampled) and contaminated by additive noise, giving $\underline{Y}(t)$. H is the blur matrix, a space and time invariant, D the decimation matrix is depend on the camera characteristic thus D is assumed constant, and $\underline{N}(t)$ is a zero mean Gaussian noise. For traditional image sequence, the sequence $\{\underline{X}(t)\}$ satisfied the following equation:

$$\underline{X}(t) = F(t) \cdot \underline{X}(t-1) + \underline{V}(t) \qquad (2)$$

The matrix $F(t)$ stands for the geometric warp between the images $\underline{X}(t)$ and $\underline{X}(t-1)$, and $\underline{V}(t)$ is the system noise.

3. AFFINE BLOCK-BASED REGISTRATION [42]

Typically, the translational block-based registration can detect only pure translational motion along the image plane and fails to consider any complex motions that arise due to rotation, zooming, etc. An efficient way of detecting several complex motions is by using the combination of the block-base technique and affine model. In this section, we propose a scheme for estimating affine block-based motion vectors suitable for several complex motions. The estimation can be separated to 2 stages. At the first stage of the estimation algorithm, the current and reference frames are divides into overlapping blocks (16x16). This stage is divides the image into small areas in order to detect and estimate the local motions. The advantage of this stage is to reduce the computational load and to support parallel calculation. Next, the second stage computes the affine motion vector of each block between the current and reference frame using M3SS that will be discussed in the later section.

Due to a very high computational load in affine motion vector estimation, the M3SS is proposed to reduce that load. The 3SS (Three Step Search) is one of the popular fast algorithms used in the translational registration therefore this paper develops the 3SS, that can estimate 2 motion parameters as in (3), to be M3SS that can estimate 6 motion parameters as in (4).

$$mv_{x,tran}(x,y) = a \text{ and } mv_{y,tran}(x,y) = b \qquad (3)$$

$$mv_{x,affine}(x,y) = ax + by + c \text{ and}$$
$$mv_{y,affine}(x,y) = dx + ey + f \qquad (4)$$

For the 7x7 displacement window (translation deformation) and $\pm 20^\circ$ degree (rotation, extraction or expansion deformation), the proposed M3SS algorithm utilizes a search pattern with $3^6 = 729$ check points on a search window in the first step as shown in (5). Next, the center of the search window is then shifted to the point with minimum Block Distortion Measure (BDM) and the search window size of the next step is reduce to the half of the previous step. Finally, the search algorithm processes until the search window is reduce to (6). The M3SS algorithm for each block is summarized as follows.

Step 1: A minimum BDM (Block Distortion Measure) point is found from a check point pattern at the center of the searching area as shown in (5)

$$[a,b,c,d,e,f] = [\pm 0.16, \pm 0.16, \pm 2 \pm 0.16, \pm 0.16, \pm 2] \qquad (5)$$

Step 2: The search window is reduced to half in all dimensions of the previous search window and a minimum BDM (Block Distortion Measure) point is found from a 729 check point pattern at the center of the new searching area. It will go to step 3.

Step 3: If the search window is equal to (6) then the process stop otherwise go to step 2.

$$[a,b,c,d,e,f] = [\pm 0.01, \pm 0.01, \pm 0.125 \pm 0.01, \pm 0.01, \pm 0.125] \tag{6}$$

(The criterion for parameter selection in this paper was to choose parameters which produce most PSNR results for 4 standard sequences, Foreman, Carphone, Suzie and Stefan that have different BG and FG motion characteristic. Therefore, to ensure fairness, each experiment was repeated several times with different parameters and the best result of experiments was chosen [42]).

From the table 1, the total number of the M3SS check points is fixed at 3.65E+3. Compared with the classical block-based estimation method (translation block-based estimation method) at 0.25 pixel accuracy and w=9, the total number of the M3SS check points has more computational load the classical approach about 3 times.

Table I. Performance Comparison of Registration Method

Block-Based Registration Method	BMA (Block Matching Algorithm)	Search Points
Affine	FS (Full Search)	1.29E+09
	M3SS	3.65E+03
Translation	FS (Full Search : 0.25 Pixel)	1.09E+03
	FS (Full Search : 1 Pixel)	2.56E+02

4. THE PROPOSED SUPER-RESOLUTION

The problem of estimating the high-resolution image $\underline{X}$ given the low-resolution sequence $\{\mathbf{Y}\}$ is ill-posed since a number of solutions could satisfy the video sequences observation model constraints. A well posed problem will be formulated using the stochastic regularization technique of Bayesian MAP estimation, resulting in a constrained optimization problem with a unique minimum. The gradient descent method will be used to compute the estimate.

The MAP estimate maximizes the a-posteriori probability $\mathrm{P}\left(\underline{X} \middle| \{\mathbf{Y}\}\right)$ given by:

$$\hat{\underline{X}}_{\text{MAP}} = \arg\max_{\underline{X}} \left\{ \mathrm{P}\left(\underline{X} \middle| \{\mathbf{Y}\}\right) \right\} = \arg\max_{\underline{X}} \left\{ \frac{\mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right)\mathrm{P}\left(\underline{X}\right)}{\mathrm{P}\left(\{\mathbf{Y}\}\right)} \right\} \tag{7}$$

where the maximum independent of $\mathrm{P}\left(\{\mathbf{Y}\}\right)$, yields

$$\hat{\underline{X}}_{\text{MAP}} = \arg\max_{\underline{X}} \left\{ \mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right)\mathrm{P}\left(\underline{X}\right) \right\} \tag{8}$$

Taking the logarithm of Equation (8), yield

$$\hat{\underline{X}}_{\text{MAP}} = \arg\max_{\underline{X}} \left\{ \log\left(\mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right)\right) + \log\left(\mathrm{P}\left(\underline{X}\right)\right) \right\} \tag{9}$$

It remains to determine the form of the likelihood function $\mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right)$ and the prior $\mathrm{P}\left(\underline{X}\right)$.

$$\mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right) = \mathrm{P}_{\text{Noise}}\left(\sum_{k=1}^{N} \left(\underline{Y}_k - D_k H_k F_k \underline{X} \right) \right) \tag{10}$$

$$\mathrm{P}\left(\{\mathbf{Y}\} \middle| \underline{X}\right) = \left(\frac{1}{(2\pi)^{\frac{NMM}{2}} |K|} \right) \times \exp\left(-\frac{1}{2} \left(\sum_{k=1}^{N} \left(\underline{Y}_k - D_k H_k F_k \underline{X} \right) \right)^T K^{-1} \left(\sum_{k=1}^{N} \left(\underline{Y}_k - D_k H_k F_k \underline{X} \right) \right) \right) \tag{11}$$

From a statistic perspective, $\mathrm{P}\left(\underline{X}\right)$ regularization function is incorporated as a priori knowledge about the solution. A robust regularizer called bilateral-TV (BTV) was introduced in [34] therefore the prior $\mathrm{P}\left(\underline{X}\right)$ of the BTV is

$$\mathrm{P}\left(\underline{X}\right) = \frac{1}{k_p} \exp\left(- \underbrace{\sum_{l=-P}^{P} \sum_{m=0}^{P}}_{l+m \geq 0} \alpha^{|m|+|l|} \left\| \underline{X} - S_x^l S_y^m \underline{X} \right\| \right) \tag{12}$$

where matrices (operators), S_x^l and S_y^m shift $\mathbf{X}$ by l and m pixels in horizontal and vertical directions respectively, presenting several scales of derivatives. The scalar weight α, $0 < \alpha < 1$, is applied to give a spatially decaying effect to the summation of the regularization terms [34]. Combining the BTV regularization, we propose the solution of the super-resolution problem as follows:

Substituting the likelihood term in Equation (11) and the prior in Equation (12) into Equation (9) and removing constants independent off gives the objective function

$$\underline{X}(t) = \operatorname*{ArgMin}_{\underline{X}(t)} \left\{ \sum_{k=-N}^{N} \left(\begin{array}{l} \left\| D \cdot H \cdot G(k) \cdot \underline{X}(t) - \underline{Y}(k) \right\|_2^2 \\ + \left(\underbrace{\sum_{l=-P}^{P} \sum_{m=0}^{P}}_{l+m \geq 0} \alpha^{|m|+|l|} \left\| \underline{X} - S_x^l S_y^m \underline{X} \right\| \right) \end{array} \right) \right\} \tag{13}$$

We use steepest descent to find the solution to this minimization problem (13):

$$\hat{\underline{X}}_{n+1}(t) = \hat{\underline{X}}_n(t) + \beta \cdot \left\{ \begin{array}{l} \left(\sum_{k=1}^{N} F_k^T H_k^T D_k^T \left(\underline{Y}_k - D_k H_k F_k \hat{\underline{X}}_n \right) \right) - \\ \lambda \left(\underbrace{\sum_{l=-P}^{P} \sum_{m=0}^{P}}_{l+m \geq 0} \alpha^{|m|+|l|} \left(I - S_x^l S_y^m \right) \cdot \operatorname{sign}\left(\hat{\underline{X}} - S_x^l S_y^m \hat{\underline{X}} \right) \right) \end{array} \right\} \tag{14}$$

where β is a scalar defining the step size in the direction of the gradient and λ is a regularization factor. $F(k)$ is a forward affine registration and $F^T(k)$ is a inverse affine registration. Fig. 1 is the block diagram representation of (12). First, the current estimate of HR frame $\mathbf{X}(t)$ is warped by affine block-based motion matrix. Second, the warped HR frame $F(t)\mathbf{X}(t)$ are divides into overlapping-blocks ($\underline{X}(t)$) and each block are blurred and decimated. For each block, $\underline{Y}(t)$ will be compared to the warped, blurred, and decimated current estimate of HR frame $\underline{X}(t)$. Third, the residues of the comparison are upsampling (D^T), deblured (H^T) and comprised to entire images. Fourth, entire residue images are warped by inverse affine block-based motion matrix. Finally, the all warped residue images and BTV regularization are combined and the result is used to update the SR image.

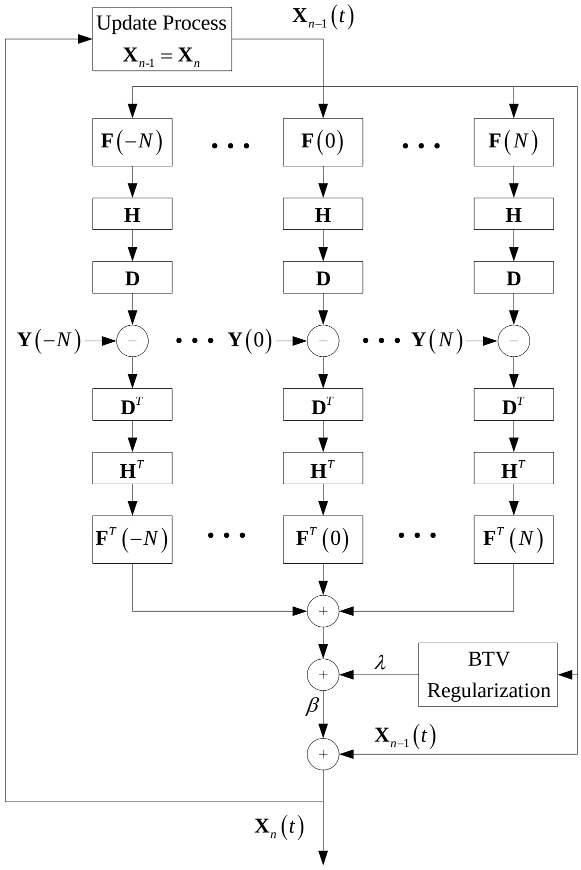


Fig. 1 - Block diagram representation of (14)

5. EXPERIMENTAL RESULT

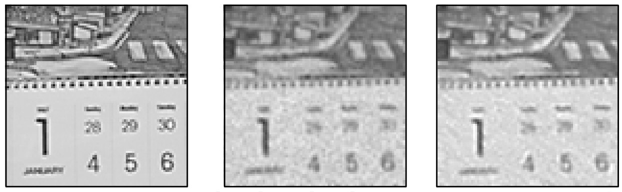
This section presents the experiments and results obtained by the super-resolution method using affine block-based registration using M3SS. These experiments are implemented in MATLAB and they perform results using Suzie sequence that is a QCIF format (176x144). The blurred and noisy LR frame (88x72) is generated for the original Foreman sequence at SNR = 25 dB. The block size is fixed at 8x8 (16x16 for overlapping block) and the search window w=7 for affine block-based registration. Fig. 2(c) shows the Suzie (Frame 40) result of applying our BTV regularization criterion with the following parameters $\lambda = 0.1$, P=2, α=0.7, $\beta = 0.5$ and $N = 2$ (or frame 38, 39, 40, 41 and 42). The result shows that Fig. 2(c) is more sharp edges and less noise than the LR image in Fig. 2(b). (The criterion for parameter selection in this paper was to choose parameters which produce visually most appealing results. Therefore, to ensure fairness, each experiment was repeated several times with different parameters and the best result of each experiment was chosen [34]).

Fig. 3(c) shows the Mobile Calendar (Frame 10) result of applying our BTV regularization criterion with the following parameters, $\lambda = 0.1$, P=2, α=0.7, $\beta = 0.5$ and $N = 2$ (or frame 8, 9, 10, 11 and 12). The result shows that Fig. 3(c) is more sharp edges and less noise than the LR image in Fig. 3(b).

Fig. 4(c) shows the Foreman (Frame 110) result of applying our BTV regularization criterion with the following parameters, $\lambda = 0.1$, P=2, α=0.7, $\beta = 1$ and $N = 2$ (or frame 108, 109, 110, 111 and 112). The result shows that Fig. 4(c) is more sharp edges and less noise than the LR image in Fig. 4(b).

(a) Original HR Image (Frame 40)	(b) Blurred and Noisy LR Image (SNR=25dB) (Frame 40)	(c) SR Image with BTV Regularization Function (Frame 40)

Fig. 2 - Suzie Simulation Result of proposed method



(a) Original HR Image (Frame 10)	(b) Blurred and Noisy LR Image (SNR=25dB) (Frame 10)	(c) SR Image with BTV Reg. Function (Frame 10)

Fig. 3 - Mobile Calendar Simulation Result of proposed method

(a) Original HR Image (Frame 110)	(b) Blurred and Noisy LR Image (SNR=25dB) (Frame 110)	(c) SR Image with BTV Reg. Function (Frame 110)

Fig. 4 - Foreman Simulation Result of proposed method

6. CONCLUSION

In this paper, we propose an alternate approach using a novel image registration, Affine Block-Based Registration, and a Bayesian approach with BTV regularization function as a prior function. Experimental results conducted clearly that the proposed algorithm can apply on the general sequence such as Suzie, Mobile Calendar and Foreman and the proposed algorithm can be improved remarkably.

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