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MULTI-FRAME SUPER-RESOLUTION IMAGE RECONSTRUCTION EMPLOYING THE NOVEL ESTIMATOR L1INV-NORM

Antigoni Panagiotopoulou

Electronics Laboratory, Physics Department, University of Patras, Rio 26500, Greece
email:anpanag@upatras.gr

ABSTRACT

In multi-frame Super-Resolution (SR) image reconstruction a single High-Resolution (HR) image is created from a sequence of Low-Resolution (LR) frames. This work considers stochastic regularized multi-frame SR image reconstruction from the data-fidelity point of view. In fact, a novel estimator named $L1inv-$norm is proposed for assuring fidelity to the measured data. This estimator presents the hybrid form of both $L1$ error norm and logarithm ln. The introduced $L1inv-$norm is combined with the Bilateral Total Variation (BTV) regularization. The proposed SR method is directly compared with an existing SR method which employs the Lorentzian estimator in combination with the BTV regularizer. The experimental results prove that the proposed technique predominates over the existing technique.

Index Terms— super-resolution, data-fidelity, hybrid form, $L1$ estimator, logarithm ln

1. INTRODUCTION

Multi-frame Super-Resolution (SR) image reconstruction techniques can serve for processing a number of Low-Resolution (LR) images of a scene to obtain a High-Resolution (HR) image. Basically, in SR reconstruction changes in the LR images caused by blur and motion provide additional data that can be employed to reconstruct the HR image from the observed LR images. SR techniques are applicable in fields like surveillance, remote sensing, medical and nano-imaging.

Concerning stochastic regularized SR image reconstruction [1-2], in the literature there have been presented several methods which employ different error norms or estimators [3] for the data-fidelity term. In fact, certain error norms distinguish between usable and not usable measurements. The latter are regarded outliers and treated specially. Thus, the specific estimators present outliers rejection threshold. Such estimators having already been employed for the SR reconstruction task are the Huber, Lorentzian, Tukey, Hampel, Andrew's sine and Gaussian-weighted L_2 [3-8].

This work presents a novel Bayesian regularized SR method. Actually, a new re-descending estimator [3] named $L1inv-$norm is proposed for employment in the data-fidelity term. The introduced estimator is hybrid between L_1 and logarithm ln, presenting an outliers rejection threshold. The Bilateral Total Variation (BTV) regularizer is added as a penalty factor to the data cost function. An HR image is created from a sequence of sub-pixel shifted, aliased LR frames. Experimentation is carried out employing frames corrupted by Gaussian, speckle and Poisson noise. The results obtained by means of the proposed method are compared with those coming from the technique in [5] which utilizes the Lorentzian error norm combined with the BTV regularizer. The proposed method exhibits greater robustness to outliers and proves better than the method in [5].

The SR image reconstruction problem is discussed in Section 2. Section 3 presents the proposed estimator $L1inv-$norm. The conducted experiments are given in Section 4 whilst the conclusions are drawn in Section 5.

2. THE PROBLEM OF SUPER-RESOLUTION IMAGE RECONSTRUCTION

SR image reconstruction is an inverse problem. In the context of stochastic regularized SR techniques the formulation of the SR problem takes place by means of two terms, the data-fidelity term and the regularization term [2]. The solution HR image, denoted X, can be expressed as follows:

$$X = \underset{X}{ArgMin}\left[\sum_{i=1}^{N}\rho\left(M_iX - Y_i\right) + \lambda r\left(X\right)\right] \tag{1}$$

where $\sum_{i=1}^{N}\rho\left(M_iX - Y_i\right)$ stands for the data-fidelity term. The specific term consists of a cost function named $\rho-$function or error norm which measures the difference between the projected estimate of the HR image M_iX and each LR frame Y_i. The operator M denotes the imaging system and the symbol N denotes the LR frames number. As far as $r\left(X\right)$ is concerned, it is the regularization term and consists of a cost function which poses a penalty on the estimated HR image with the intention to direct it to a better formed solution [2]. In this work the BTV regularization is employed [5]. With regard to the coefficient λ, it is called regularization parameter and determines the strength by

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which regularization imposes constraints on the HR estimate. By employing iterative solution method based on gradient, we obtain:

$$X_{n+1} = X_n - \beta\left\{\sum_{i=1}^{N} M_i^T \psi(M_i X_n - Y_i) + \lambda r'(X_n)\right\} \quad (2)$$

The function ψ stands for the influence function [3] of the ρ -function employed whilst r' is the derivative of r . The parameter β is a scalar that determines the step size in the direction of the gradient. Regarding the parameter n, it denotes the number of iterations.

3. THE PROPOSED ESTIMATOR $L1inv-$NORM

At the data-fidelity term of the SR problem formulation the LR frames that result from shifting, blurring and down-sampling the estimated HR image are compared with the corresponding measured LR frames, in order to assess the correctness of the HR estimate. Thus, the selection of the error norm that is utilized in the data-fidelity term is critical. Actually, the behavior of the employed $\rho-$function can be analyzed by means of its influence function ψ [3]. The latter is proportional to the derivative of ρ and characterizes the bias that is introduced in the solution by a particular measurement. The calculated difference between the projected estimate of the HR image and each LR frame stands for measurement. Certain estimators from the robust statistics [3] detect outliers and treat them specially. These estimators present outliers rejection threshold, called robust scale [5], and their influence functions characterize differently the bias introduced in the solution by each measurement in dependence on the considered usability of the measurement. To increase robustness and reject outliers, the $\psi-$function and hence the influence curve should be made to return to zero. Such an estimator is called a re-descending estimator. Outliers have diminishing effects on a re-descending estimator. The Lorentzian error norm is such an estimator [2-3, 5].

The estimator $L1inv-$norm that is proposed in this work is re-descending like the Lorentzian estimator and presents the following $\rho-$ and $\psi-$ functions:

$$\rho_{L_1inv}(x) = \begin{cases} |x|, |x| \le par \\ \ln(x), otherwise \end{cases} \quad (3)$$

$$\psi_{L_1inv}(x) = \begin{cases} sign(x), |x| \le par \\ \frac{1}{x}, otherwise \end{cases} \quad (4)$$

The $L1inv-$norm estimator is essentially the $L1-$norm estimator, but uses the natural logarithm ln for points that are considered outliers with respect to a certain threshold which is called L1inv parameter and is denoted by the symbol par .

The direct comparison of the two above-mentioned error norms can take place after dilating and scaling their influence functions to make them as similar as possible [5]. Thus, Fig. 1 depicts the aligned and scaled $\psi-$functions of the Lorentzian and $L1inv-$norm estimators. An estimator's influence function characterizes the bias that a particular measurement has on the solution. Herein regarding the measurements which are located on the positive x-axis before the outliers threshold, two different regions of treatment can be discerned. With concern to the smaller value specific measurements, the Lorentzian error norm gives to each measurement a weight that increases as the measurement value also increases. However, the introduced estimator $L1inv-$norm gives zero weight to these measurements. With regard to the greater value particular measurements, they receive a constant weight of one by the Lorentzian estimator whilst the proposed estimator gives them weights that increase as their values also increase. As far as the measurements placed on the x-axis after the scale parameter are concerned, they receive descending weights as their values increase by both error norms. These measurements are identified as outliers so their influence is reduced. Actually, the $L1inv-$norm estimator penalizes these great value measurements more strictly than the Lorentzian error norm. Concluding, the introduced estimator $L1inv-$norm exhibits a less consecutive influence function than the Lorentzian error norm, which results in more efficient handling of the measurements. Thereafter, the introduced estimator presents an influence function that treats all measurements more efficiently than the one of the Lorentzian error norm with regard to the characterization of their bias introduced in the solution.

4. EXPERIMENTS

Several simulated experiments are carried out to compare the performance of the proposed SR technique with that of an existing SR method [5]. A synthesized LR sequence of 16 frames, scene Lena, is utilized for SR image reconstruction by the factor of 4. Fig. 2a depicts the original HR image. Fig. 2b demonstrates one of the synthesized frames. Noise is also inserted in the frames. The experiments conducted here are simulated experiments but outliers are present since the noise inserted in the LR frames is ignored in the image acquisition model formulated for performing the SR image reconstruction task. Gaussian noise of mean 0 and variances 0.0012, 0.003 and 0.007 is employed. Fig. 2d-f demonstrate the specific noisy frames. Parts of the SR reconstructed images are shown in Fig. 3. Visual comparison asserts predominance of the introduced technique $L1inv-$norm + BTV over the technique in [5] that utilizes the Lorentzian error norm in combination with the BTV regularization, regarding resolution improvement and noise removal. With concern to the variance equal to 0.003, the following parameter values are employed $a = 0.4$, $\lambda = 0.009$ and $\beta = 0.2$, 0.1 regarding the techniques proposed, [5]. Experiments are conducted with Lena frames that are corrupted by speckle noise of different variances and by Poisson noise, as well. The particular noisy frames are given in Fig. 2c, g-i. Parts of the SR reconstructed images are depicted in Fig. 4. Visual inspection asserts that in all noise cases the proposed method performs superiorly to the method presented in [5].

Fig. 5 depicts plots of the numerical measures Xydeas and Petrovich as well as MSE versus the number of iterations of the SR reconstruction procedure. In all the experimental cases the $L1inv-$norm + BTV technique performs superiorly to the Lorentzian + BTV technique. Therefore, in the diagrams concerning the Xydeas and Petrovich measure the curve of the proposed technique remains at higher values than the curve of the technique in [5]. Also, the MSE plots demonstrate that the curve corresponding to the proposed technique retains lower values than the other curve. Actually, the plots demonstrate that early in iterations of the reconstruction procedure no comparison of the techniques can take place, because of the corresponding curves getting mixed. So, the direct comparison of the techniques can be performed only when these curves clearly show the ranking in the methods performance. Furthermore, in all the experiments the parameters β, a and λ vary and are specified manually through visual monitoring. With regard to the robust scale, it is estimated as described in [5].

5. CONCLUSIONS

This work presents a new Bayesian regularized SR image reconstruction method. In fact, a novel re-descending estimator named $L1inv-$norm is proposed for utilization in the data-fidelity term of the SR problem formulation. The newly presented estimator is hybrid between L_1 and logarithm ln, and presents an outliers rejection threshold. Particularly, the novel estimator $L1inv-$norm in combination with the BTV regularization is proposed for multi-frame SR image reconstruction. The experimentation carried out proves that the introduced method outperforms the existing SR method which employs the Lorentzian estimator combined with the BTV regularizer. Thus, the $L1inv-$norm estimator predominates over the Lorentzian estimator. Actually, the proposed error norm presents a less consecutive influence function than the Lorentzian error norm, which results in more efficient handling of the measurements regarding the characterization of their bias introduced in the solution.

6. REFERENCES

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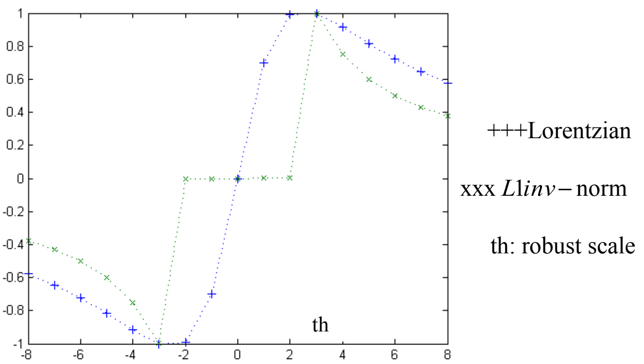

Fig. 1. The Lorentzian and $L1inv-$norm $\psi-$functions aligned and scaled. The direct comparison of the two error norms in rejecting outliers now can be performed.

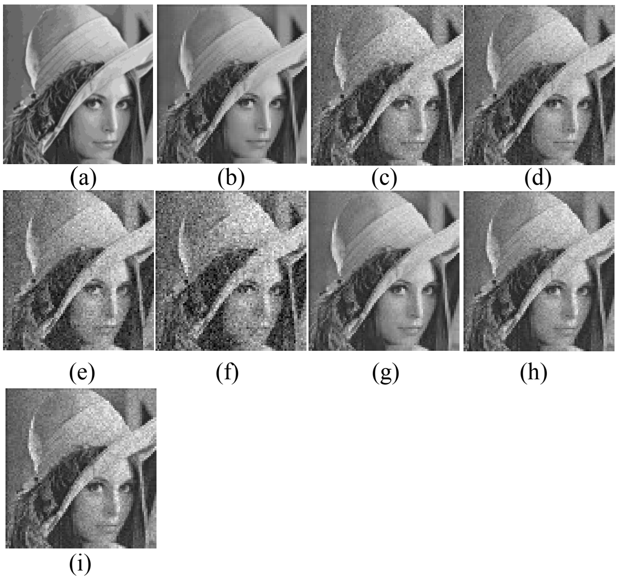

Fig. 2. Experimental data. (a) The original HR image. (b) A synthesized LR frame. (c) A Poisson noisy frame. (d)-(i) A frame corrupted by Gaussian noise of variance (d) 0.0012 (e) 0.003 (f) 0.007, by speckle noise of variance (g) 0.001 (h) 0.0035 (i) 0.006.

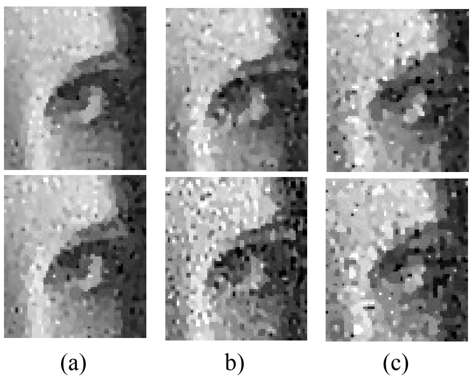

Fig. 3. Parts of the SR reconstructed images in case of frames corrupted by Gaussian noise of variance (a) 0.0012 (b) 0.003 (c) 0.007. First row: proposed technique. Second row: technique in [5]. The proposed technique performs best.

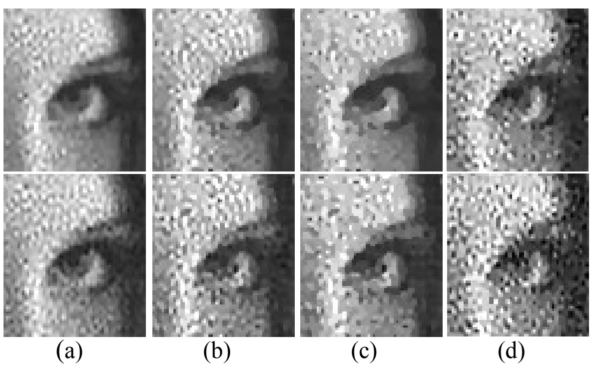

Fig. 4. Parts of the SR reconstructed images in case of frames corrupted by speckle noise of variance (a) 0.0012 (b) 0.003 (c) 0.007 and by Poisson noise (d). First row: proposed technique. Second row: technique in [5]. The proposed technique performs superiorly.

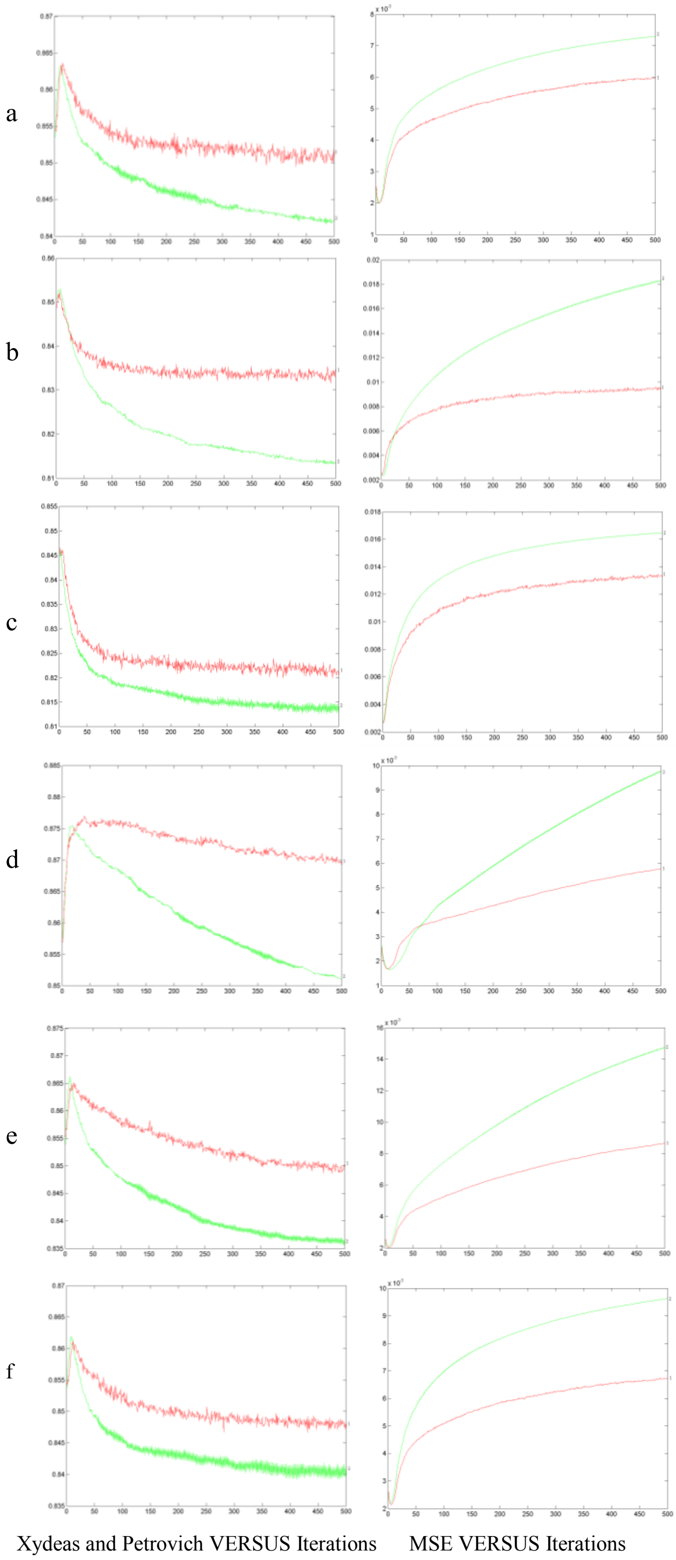

Fig. 5. Plots of numerical measures versus iterations number (curve 1: proposed technique, curve 2: technique in [5]) in case of Gaussian noise with variance: (a) 0.0012 (b) 0.003 (c) 0.007 and in case of speckle noise with variance: (d) 0.001 (e) 0.0035 (f) 0.006. Similar plots resulted for Poisson noise. The proposed technique performs best.