Int. J. Electron. Commun. (AEÜ) 65 (2011) 975–977

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.de/aeue

LETTER

Phase-driven spatially variant regularization for image resolution enhancement

Jing Tian [a,*], Li Chen [a], Lihong Ma [b], Weiyu Yu [c]

[a] School of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan, 430081, PR China
[b] Guangdong Key Lab of Wireless Network and Terminal, School of Electronic and Information Engineering, South China Guangzhou, 510641, PR China
[c] School of Electronic and Information Engineering, South China University of Technology, Guangzhou, 510641, PR China

ARTICLE INFO

Article history:
Received 5 July 2010
Accepted 17 February 2011

Keywords:
Image reconstruction
Regularization

ABSTRACT

A phase-driven spatially variant regularization approach is proposed in this letter to perform image resolution enhancement. The proposed approach adaptively adjusts the degree of regularization using the phase coherence measure of the local content of the image. This is in contrast to that a spatially invariant regularization parameter is exploited for the whole image in conventional approaches. Experiments are conducted to demonstrate the superior performance of the proposed approach.

1. Introduction

The objective of image resolution enhancement is to utilize a set of similar images acquired from the same scene to produce a single higher-resolution image with more details in order to improve content recognition ability. Motivated by the fact that the super-resolution (SR) computation is, in essence, an ill-posed inverse problem, numerous regularization-based approaches have been developed for addressing this issue, by incorporating the prior knowledge of higher-resolution image under reconstruction.

The major challenge inherent with the regularization-based approach is the determination of the regularization parameter, since it controls the degree of regularization, and consequently, determines the quality of the reconstructed high-resolution image [1]. Conventional approaches impose a spatially invariant regularization parameter to the whole image [2,3]. However, these approaches have limited adaptive capability in the process of image reconstruction and cannot balance the suppression of noise against the preservation of image details. Recently, several approaches have been proposed to exploit the spatially adaptive regularization parameters [4–7]. Li et al. proposed to use the fuzzy-entropy-based neighborhood homogeneous measure [4] to adjust the degree of regularization. Zhang et al. proposed a directional regularization approach [5] to impose smoothness constraint along the direction of edge, rather than across the edge.

To tackle the above challenge, this letter exploits the local phase coherence measure [8,9] to adjust the degree of regularization according to the local content of the image. This is motivated by the fact that the local phase coherence is able to provide a perceptual image representation that is fairly consistent to the human visual system, which has been supported by the physiological evidence that showed high human perception response to signal characteristics with high local phase coherence [10].

2. Problem formulation

The given low-resolution images can be viewed as warped, blurred, down-sampled and noisy versions from the original (unknown) high-resolution image (denoted as f). That is, their relationship can be mathematically expressed as

$$g^{(k)} = h^{(k)}f + \upsilon^{(k)}, \tag{1}$$

where $g^{(k)}$ represents the kth low-resolution image, $h^{(k)}$ represents the above-mentioned warping (i.e., shift and rotation), convolving and downsampling operations, and $\upsilon^{(k)}$ represents the additive white Gaussian noise. With such establishment, the goal of stochastic SR image reconstruction is to produce a single high-resolution image based on a set (say, cardinality N) of low-resolution observations $G=\{g^{(1)}, g^{(2)}, \ldots, g^{(N)}\}$.

3. Proposed image resolution enhancement approach

The proposed approach estimates the unknown high-resolution image (denoted as $\hat{f}$) by minimizing the following cost function

$$\hat{f} = arg\min_{f} \left\{ \sum_{i=1}^{N} ||f - g^{(i)}||^2 + \lambda_f \Gamma(f) \right\}. \tag{2}$$

where $\sum_{i=1}^{N} ||f - g^{(i)}||^2$ is the data term, representing the fidelity between the estimated high-resolution image with the observed

* Corresponding author.
E-mail addresses: eejtian@gmail.com (J. Tian), chenli@ieee.org (L. Chen), eelhma@scut.edu.cn (L. Ma), yuweiyu@scut.edu.cn (W. Yu).

1434-8411/$ – see front matter © 2011 Elsevier GmbH. All rights reserved.
doi:10.1016/j.aeue.2011.02.008

Table 1
The PSNR performance (in dB) comparison.

Regularization function	Regularization parameter	*Lena*	*Cameraman*
Total variation [2]	Spatially invariant	27.04	24.80
	Proposed spatially invariant	27.58	25.32
Bilateral total variation [3]	Spatially invariant	26.61	24.47
	Proposed spatially invariant	27.33	25.11

low-resolution images. On the other hand, $\Gamma(f)$ is the regularization term, which can be formulated using either the total variation model [2] or the bilateral total variation model [3].

The novelty of the proposed approach is to adaptively adjust the regularization parameter λ_f according to the local content of the image, more specifically, the local phase coherence measure. This is motivated by that the local phase coherence increases as the perceptual significance of signal characteristics increases. This has been supported by physiological evidence that showed high human perception response to signal characteristics with high local phase coherence [10]. Another advantage to the use of local phase coherence is the fact that it is insensitive magnitude variations caused by illumination conditions or noise incurred in image signals.

The proposed approach measures the local phase coherence based on the localized frequency information that is extracted using a Log-Gabor filter bank [10]. More specifically, the local phase coherence at the position (i, j) of the image is calculated as

$$c(i,j) = \frac{1}{2}\sum_{\theta} \left|(c(i,j,\theta)\sin(\theta))^2 + (c(i,j,\theta)\cos(\theta))^2\right| + \frac{1}{2}\sqrt{4\left(\sum_{\theta}(c(i,j,\theta)\sin(\theta)c(i,j,\theta)\cos(\theta))\right)^2 + \left(\sum_{\theta}\left[(c(i,j,\theta)\cos(\theta))^2 - (c(i,j,\theta)\sin(\theta))^2\right]\right)^2}, \quad (3)$$

where

$$c(i,j,\theta) = \frac{\sum_{n} W(i,j,\theta)|A_n(i,j,\theta)\Delta\varphi_n(i,j,\theta)|}{\sum_{n} A_n(i,j,\theta) + \xi}, \quad (4)$$

$$\begin{aligned}\Delta\varphi_n(i,j,\theta) = {} & \cos(\varphi_n(i,j,\theta) - \overline{\varphi}_n(i,j,\theta)) \\ & -|\sin(\varphi_n(i,j,\theta) - \overline{\varphi}_n(i,j,\theta))|,\end{aligned} \quad (5)$$

in which W represents the frequency spread weighting factor, A_n and φ_n represent the amplitude and phase at the wavelet scale n, respectively, $\overline{\varphi}_n$ represents the weighted mean phase, ξ is a small constant used to avoid the division by zero. All of these parameters are as same as that used in [10].

Since the response of the phase coherence is proportional to the high-frequency (i.e., edge) of the image, the degree of regularization should be reduced at positions which yield high phase coherence. Consequently, the edge is expected to be preserved. In view of this, the regularization parameter is proposed to be varied at each pixel position as

$$\lambda(i,j) = \lambda_f e^{-c(i,j)}, \quad (6)$$

where λ_f is the conventional spatially invariant regularization parameter, the $c(i,j)$ is defined in (3). It is further incorporated in to the cost function (2) to arrive a new cost function as

$$\hat{f} = \arg\min_{f} \left\{ \sum_{i=1}^{N} ||f - g^{(i)}||^2 + \sum_{i}\sum_{j} \lambda_f e^{-c(i,j)} \Gamma(f(i,j)) \right\}, \quad (7)$$

where the estimated high-resolution image $\hat{f}$ can be obtained using the gradient-based optimization algorithms. Comparing (2) and (7), one can see that the degree of regularization is spatially adjusted in the proposed approach (7), rather than being spatially invariant in conventional approaches (2).

Fig. 1. Various reconstructed high-resolution images: (a): ground truth; (b)–(d): spatially invariant regularization using [2] and [3], respectively; (c)–(e): proposed phase-driven spatially variant regularization using [2] and [3], respectively.

Table 2
The run-time performance (in seconds) comparison.

Regularization function	Regularization parameter	*Lena*	*Cameraman*
Total variation [2]	Spatially invariant	2.69	2.58
	Proposed spatially invariant	3.29	3.29
Bilateral total variation [3]	Spatially invariant	4.22	4.32
	Proposed spatially invariant	5.09	5.18

4. Experimental results

A *Lena* image and a *Cameraman* image are used as ground-truth test images in our simulation experiments. A series of operations are applied to each test image to generate four low-resolution images. We first shift the original image with the shift amount randomly drawn from a continuous uniform distribution over the interval (−2,2) in the unit of pixels. The shifted image is then convoluted with a point spread function, which is a Gaussian low-pass filter with a window size of 4×4 and the standard deviation of 2, followed by a down-sampling operation with a decimation factor of two in both horizontal and vertical directions, respectively. Lastly, each processed image is added with a zero-mean white Gaussian noise to yield a noisy low-resolution image with a SNR 20 dB.

The proposed spatially variant regularization approach is compared with the conventional approaches with spatially invariant regularization parameters. In our simulations, both the total variation [2] and bilateral total variation [3], which have an experimentally selected regularization parameter $\lambda_f = 0.15$, are independently exploited to utilize four low-resolution images to produce a 2×2 high-resolution image and compare it with the ground-truth image to calculate the PSNR performance (presented in Table 1). Furthermore, the subjective performance is compared in Fig. 1. As seen from the above table and figure, one can see that the proposed approach outperforms the conventional approaches with spatially invariant regularization parameters.

The second experiment is to evaluate the computational complexity of the proposed approach. The above resolution enhancement approaches are implemented using the Matlab programming language and run on a PC with a Pentium 2.4 GHz CPU and a 3 GB RAM. Ten experiments are conducted for each approach and their averaging run time are presented in Table 2, where one can see that the complexity of the proposed approach is slightly higher than that of conventional approaches, due to the calculation of local phase coherence information and adaptive adjusting of regularization parameters in the proposed approach.

5. Conclusions

A phase-driven spatially variant regularization approach has been proposed in this letter to perform image resolution enhancement, by adaptively adjusting the degree of regularization using the phase coherence measure of the local content of the image. The proposed approach outperforms the conventional approach that imposes a spatially invariant regularization parameter for the whole image, as verified in our experiments.

Acknowledgements

This work was supported by Key Project of Chinese Ministry of Education (210139); SRF for ROCS, SEM; National Natural Science Foundation of China (60872123, 60972133); GDSF Team Project (9351064101000003); the Joint Fund of the National Natural Science Foundation and the Guangdong Provincial Natural Science Foundation (U0835001); the Fundamental Research Funds for the Central Universities (x2dxD2105260), SCUT; Fund of Provincial Key Lab for Computer Information Processing Tech.(No. KJS0922).

References

[1] Zibetti M, Bazan F, Mayer J. Determining the regularization parameters for super-resolution problems. Signal Processing 2008;88(December):2890–901.
[2] Ng MK, Shen H-F, Zhang L-P, Lam E. A total variation regularization based super-resolution reconstruction algorithm for digital video. EURASIP Journal on Applied Signal Processing 2007;2007. Article ID 74585.
[3] Farsiu S, Robinson D, Elad M, Milanfar P. Fast and robust multi-frame super-resolution. IEEE Transactions on Image Processing 2004;13(October):1327–44.
[4] Li X, Hu Y, Gao X, Tao D, Ning B. A multi-frame image super-resolution method. Signal Processing 2010;90(February):405–14.
[5] Zhang L, Zhang H, Shen H, Li P. A super-resolution reconstruction algorithm for surveillance images. Signal Processing 2010;90(March):848–59.
[6] An Y, Lu Y, Zhai Z. Spatially varying regularization of image sequences super-resolution. In: Proc. Asian Conference on Computer Vision. 1em plus 0.5em minus 0.4em Xian. 2009. p. 475–84.
[7] Omer O, Tanaka T. Image restoration based on adaptive directional regularization. IEICE Transactions on Fundamentals of Electronics Communications and Computer 2009;E92-A(December):3344–54.
[8] Ciancio A, Costa A, da Silva E, Said A, Obrador RSP. Objective no-reference image blur metric based on local phase coherence. Electronic Letters 2009;45(November):1162–3.
[9] Wong A, Scharcanski J. Phase-adaptive superresolution of mammographic images using complex wavelets. IEEE Transactions on Image Processing 2009;18(May):1140–6.
[10] Kovesi P. Image features from phase congruency. Videre: A Journal of Computer Vision Research 1999;1:2–27.