TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 12, No. 10, October 2014, pp. 7280 ~ 7286
DOI: 10.11591/telkomnika.v12i8.6455

Local Standard Deviation Based Image Quality Metrics for JPEG Compressed Images

Akshay Gore*[1], H.K.Kansal[2], Savita Gupta[3]
[1]Department of Electronics and Communication, Chandigarh University, Punjab, India
[2]Department of Mechanical Engineering, Panjab University, Chandigarh, India
[3]Department of Computer Science and Engineering, Panjab University, India
*Corresponding author, e-mail: akshaygore@live.com

Abstract

In this paper, we address the Full-Reference (FR) Image Quality Metric (IQM) to assess the quality of JPEG-coded images and we present a new effective and efficient IQA model, called Local Standard Deviation Based Image Quality (LSDBIQ). The approach is based on the comparison of the local standard deviation of two images. The proposed metrics is tested on four well-known databases available in the literature (TID2013, TID2008, LIVE and CSIQ). Experimental results show that the proposed metrics outperforms other models for the assessment of image quality and have very low computational complexity.

Keywords: *JPEG2000, human visual system (HVS), local standard deviation, image quality assessment (IQA)*

1. Introduction

As High-Resolution digital images that are used in image processing technologies, tend to be of large sizes and thereby consuming large storage space, large transmission bandwidth, and long transmission times. Therefore, image compression is required before storage and transmission. JPEG and JPEG 2000 are two important techniques used for image compression. JPEG image compression standard use Discrete Cosine Transform (DCT). The DCT is a fast transform. It is a widely used and robust method for image compression. It has excellent compaction for highly correlated data. JPEG2000 is the latest image compression standard that compresses and decompresses the images using wavelet transformation. Wavelet transform-based image compression algorithms allow images to be retained without much distortion or loss when compared to JPEG, and hence are recognized as a superior method. However, compression leads to loss of spatial and spectral features of the image and may lead to erroneous results. Thus, there is a need for image quality assessment (IQA) of compressed images at various compression stages. Lossy image compression techniques allow high compression rates, but only at the cost of some perceived degradation in image quality. For lossy JPEG compressed images, the main distortion that might be introduced is blurring and ringing. Therefore, it become imperative to develop a quality assessment method that can evaluate perceptual image quality as good as human subjective evaluation. This necessitates the development of objective IQA approaches that can automatically predict perceived JPEG-compressed image quality [1-5].

2. Image Quality Assessments

IQA techniques can be divided into two groups, namely subjective and objective, which are discussed in the following.

2.1. Subjective

The best way for assessing the quality of an image is the subjective quality measurement recommendations given by the ITU [6], which consists of Difference Mean Opinion Score (DMOS) from a number of expert observers by looking at image. However, for

Received June 1, 2014; Revised July 4, 2014; Accepted July 29, 2014

most applications the DMOS method is inconvenient because DMOS evaluation is slow and costly, since it employs a group of people in the evaluation process [7].

2.2. Objective

In order to solve this problem i.e. the need for people in the evaluation process, an objective approach is required. Such objective quality assessment system has great potential in a wide range of application environments. Usually the objective image quality approaches can be categorized into three groups depending on the availability of the original image. (1) Full Reference (FR) methods perform a direct comparison between the image under test and a reference or original image. (2) No Reference (NR) metrics, are applied when the original image is unavailable. (3) Reduced Reference (RR) metrics lie between FR and NR metrics and are designed to predict image quality with only partial information about the reference image [2]. Focusing on FR metrics, the methods can be targeted to estimate the presence of JPEG-compressed images.

3. Related Work

The conventional pixel-based metrics such as Mean Square Error (MSE), Signal-to-Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR) are most widely used in image processing as these metrics are simple to calculate and easy to use. However, these pixel-based metrics do not correlates well with human subjective evaluation, and researchers have been devoting much efforts in developing advanced Human Visual System (HVS) IQA models [8, 9]. Recently, Wang et al proposed Structural Similarity Index (SSIM) based on the assumption that HVS is highly accustomed to extract structural information from an image [1]. After the great success of SSIM, number of IQA metrics have been developed with attempt to mimic the HVS. However, until now not even a single IQA metric can completely mimic HVS for evaluation purpose. A comprehensive evaluation and survey of FR-IQA is available in [10-13]. It is still a challenging task to achieve 100% consistency a human like perception in IQA under different circumstances. Therefore, the objective of this research work is to develop such a quality assessment metric for JPEG-compressed images, which will work effectively and efficiently.

In practice, an IQA model should be not only effective but also efficient. Unfortunately, accuracy and efficiency are difficult to achieve simultaneously, and most previous IQA algorithms can reach only one of the two goals. To filling this need, in this paper we have considered the case of JPEG-distorted images, and we have proposed a model based on a local standard deviation of an image called a *LSDBIQ* model.

The paper is organized as follows: in Section IV the proposed LSDBIQ technique is presented. In Section V the experimental results (in terms of performance comparison and efficiency evaluation) are compared. Finally, the conclusions are drawn in Section VI.

4. Proposed Technique

A schematic overview of the LSDBIQ approach proposed here, is shown in Figure 1.

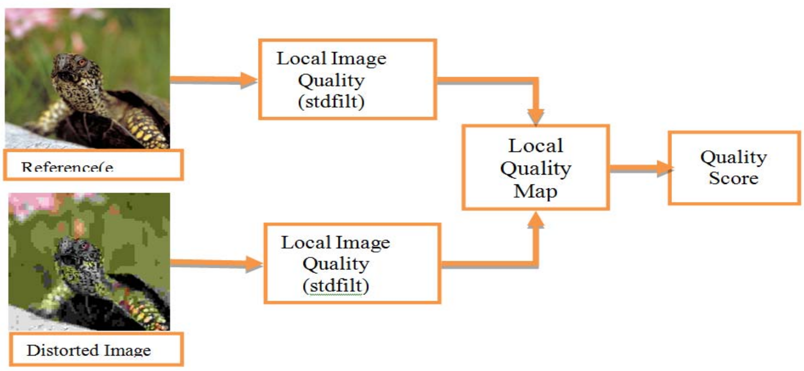


Figure 1. Overview of our LSDBIQ Model

4.1. Local Standard Deviation of an Image

Measures of local standard deviation have been widely used in image processing for texture measures and studies of spatial image structure [14, 15]. To calculate local standard deviation of an image *I*, a local standard deviation filter (stdfilt) is available in MATLAB software [16]. This tool performs a local standard deviation filter on a raster image, i.e. it calculates the standard deviation within a neighbouring area around each grid cell. A local standard deviation (σ) can be used to emphasize the local structure in an image and defined as:

$$\sigma = \sqrt{\frac{\sum(I-\bar{I})^2}{N}} \quad (1)$$

Where σ is standard deviation and *N* is number of pixels.

The local standard deviation of the reference (Ir) and distorted (Id) images is defined as:

Ir = stdfilt (Ir)
Id = stdfilt (Id)

With the help of Ir and Id standard deviation maps, we define the Local Quality Map (LQM) between two images Ir and Id as:

$$LSM = \frac{2\, I_r\, I_d + T}{I_r^2 + I_d^2 + T} \quad (2)$$

Where T is a small positive constant to stabilize the result and its proposed value is 0.0010. From Equation (2), if Ir and Id are equal, then LSM will achieve the maximum value 1.

5. Quality Score Measurement

We have applied our quality score measurement method to LSM values using standard deviation. The proposed metrics is called as LSDBIQ and define as:

$$\mathrm{LSDBIQ} = \left[\frac{1}{N}\sum_{i=1}^{N}(LSM(i) - \overrightarrow{LSM})^2\right]^{1/2} \quad (3)$$

Where $\overrightarrow{LSM}$ is:

$$\overrightarrow{LSM} = \frac{1}{N}\sum_{i=1}^{N} LSM(i) \quad (4)$$

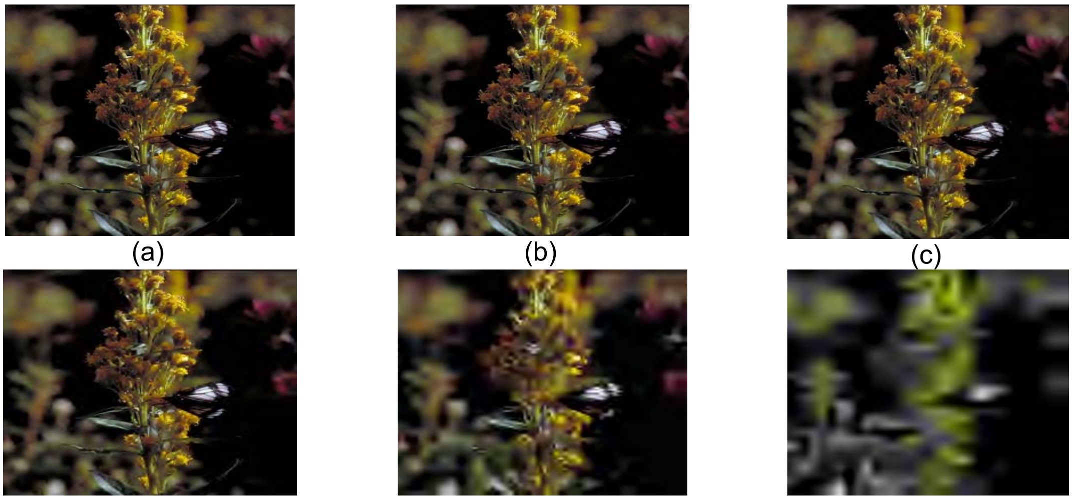
Where N is number of pixels in the image.

Values of objective LSDBIQ and human subjective *Difference Mean Opinion Scores (*DMOS) score also measures distortion, lower the value better will be the image quality.

6. Experiment Result

6.1. Demonstrative Results

Figure 2 shows some representative results from the CSIQ database where Flower image with different levels of JPEG2000 compression are compared. The subjective ratings of quality in term of DMOS are also shown for comparison. As can be seen in Figure 2, from (a) to (f), the level of JPEG2000 compression distortion increases and so does the DMOS subjective ratings of quality. This makes the LSDBIQ can predict quality of these images in a manner that is highly correlated with the subjective ratings of quality.



(a) (b) (c)

(d) (e) (f)

Figure 2. Comparison between LSDBIQ and DMOS as a subjective quality indicator. Note that like DMOS, JPEG-IQA is a distortion index (a lower DMOS/JPEG-IQA value means higher quality). (a) Original image Flower (DMOS= 0; LSDBIQ=0), (b) Image Flower, its JPEG2000 compression Level 1 (DMOS=0.028; LSDBIQ=0.0070), (c) Image Flower, its JPEG2000 compression Level 2 (DMOS=0.143; LSDBIQ=0.0235), (d) Image Flower, its JPEG2000 compression Level 3 (DMOS=0.460; LSDBIQ=0.0738), (e) Image Flower, its JPEG2000 compression Level 4 (DMOS=0.779; LSDBIQ=0.1630). (f) Image Flower, its JPEG2000 compression Level 5 (DMOS=0.926; LSDBIQ=0.2291).

7. Performance Comparison

The performance of LSDBIQ is compared with existing Image Quality Metrics (IQMs) including GMSD [17], FSIM [9], SSIM [1] and PSNR models. All the IQMs would be validated on four publicly available image databases that include JPEG2000-compressed images subsets: Tampere Image Database 2008 (TID2013) [18], Tampere Image Database 2008 (TID2008) [19], Laboratory for Image and Video Engineering (LIVE) [20] and Categorical Image Quality Database (CSIQ) [21]. We summarize in Table 1 these databases only for what concerned the JPEG compression.

To provide a complete evaluation of each IQMs, five commonly used performance correlation coefficient are employed as suggested in Video Quality Experts group [22]. These five performance metrics are the Spearman Rank-Order Correlation Coefficient (SROCC), Kendall Rank-Order Correlation Coefficient (KROCC), Pearson Linear Correlation Coefficient (PLCC), Root Mean Squared Error (RMSE) and Outlier Ratio (OR). In addition, we chose a five-parameter logistic function for nonlinear mapping as suggested in VQEQ [22].

$$G(x) = \beta_1 \left[\frac{1}{2} - \frac{1}{1+e^{\beta_2(x-\beta_3)}}\right] + \beta_4 x + \beta_5 \quad (5)$$

Where *x* denote the objective score and *G(x)* denotes the predicted subjective DMOS score. The five parameters are estimated by fitting the function to the subjective and objective data.

The Table 1 lists the SROCC, KROCC, PLCC, RMSE and OR results of LSDBIQ and other four IQMs on the TID2013, TID2008, LIVE and CSIQ databases. The best one metric producing the greatest correlations for each database are marked in boldface. The Table 1 show that the LSDBIQ performs best (effective) on all database in terms of correlation coefficients.

In order to provide a visual comparison of the five IQMs (PSNR, SSIM, FSIM, GMSD and LSDBIQ), there scatter plots of subjective DMOS (*G(x)*) versus objective DMOS scores obtained on LIVE database are shown in Figure 3, where each point represents one test image. The curves shown in Figure 3. are obtained by a nonlinear fitting function according to [23]. On comparison with other scatter plots, LSDBIQ’s points are more close to nonlinear fitting curve, which means that LSDBIQ correlates well with subjective DMOS score.

8. Efficiency Evaluation

At last, let us discuss the computation complexity of LSDBIQ with different IQMs, We thus analyze the computational complexity of LSDBIQ, and then compare the competing IQA models in terms of running time.

Suppose that an image has M*N pixels. The main operations in the proposed LSDBIQ model include calculating image local standard deviation, there by producing local quality map and quality score. Overall, it requires five lines code with 9 M*N multiplications and 8 M*N additions to yield the final quality score. Therefore, computation complexity of LSDBIQ is very low as compare GMSD, SSIM and FSIM.

In real time image-processing application running time of IQMs become crucial. We thus evaluated the running time of each four IQMs on a Toshiba Satellite PC with Intel Core i3 CPU and 8GB RAM and compared with LSDBIQ. The Software platform was MATLAB R2012. Table III list the running time of the four IQMs on an image of size 512*512 taken from CSIQ database. Clearly, from Table III, apart from PSNR, the LSDBIQ takes only 0.0193 second to process an image, which is 1.088 times faster than GMSD, 28.44 times faster than FSIM, 3.53 times faster than SSIM. Clearly, one very attractive advantage of LSDBIQ is their efficiency compared with other major IQA models such PSNR, SSIM, FSIM and GMSD etc.

Table 1. Databases that Contain jpeg-distortion Images

Database	Reference Images	Images Consider	Distortion Consider	Observer
TID2013	25	500	JPEG compression JPEG2000 compression JPEG transmission errors JPEG2000 transmission errors	971
TID2008	25	400	JPEG compression JPEG2000 compression JPEG transmission errors JPEG2000 transmission errors	838
LIVE	29	344	JPEG2000 compression JPEG	20
CSIQ	30	300	JPEG2000 compression Motion JPEG compression	35

Table 2. Performance of the Proposed LSDBIQ and the other Four Competing IQA Models Interms of SRC, PCC, KROCC, RMSE and or on the 4 Databases

DATABASE	Metrics	LSDBIQ	GMSD	FSIM	SSIM	PSNR
TID2013	**PLCC**	**0.9167**	0.9161	0.9004	0.8714	0.8683
(500)	**SROCC**	**0.9084**	0.9060	0.8929	0.9194	0.8713
	KROCC	0.7285	**0.7309**	0.6973	0.7381	0.6726
	RMSE	**0.5718**	0.5737	0.6226	2.1614	0.7097
	OR	**0.0740**	0.0700	0.1060	0.1700	0.1040
TID2008	**PLCC**	**0.8926**	0.8796	0.8712	0.8738	0.7918
(400)	**SROCC**	**0.9084**	0.8977	0.8850	0.8968	0.8145
	KROCC	**0.7291**	0.7152	0.6865	0.7088	0.6068
	RMSE	**0.7291**	0.7462	0.7702	0.7629	0.9581
	OR	**0.1225**	0.1300	0.1225	0.1225	0.1375
LIVE	**PLCC**	**0.9810**	0.9776	0.9389	0.9624	0.8701
(344)	**SROCC**	**0.9789**	0.9747	0.9357	0.9627	0.8718
	KROCC	**0.8662**	0.8572	0.7762	0.8249	0.6810
	RMSE	**5.6267**	6.1042	9.9855	7.8739	14.2944
	OR	**0.0523**	0.0523	0.0959	0.0872	0.1279
CSIQ	**PLCC**	**0.9575**	0.9541	0.8570	0.9447	0.9039
(300)	**SROCC**	**0.9488**	0.9347	0.8472	0.9311	0.8957
	KROCC	**0.7956**	0.7667	0.6512	0.7638	0.7043
	RMSE	**0.0898**	0.0933	0.1605	0.1022	0.1332
	OR	**0.0867**	0.0833	0.1000	0.0767	0.0900

Table 3. Running Time of the Competing IQA Models

IQA Models	LSDBIQ	GMSD	FSIM	SSIM	PSNR
Running time (s)	0.0193	0.0210	0.5490	0.0683	0.0095

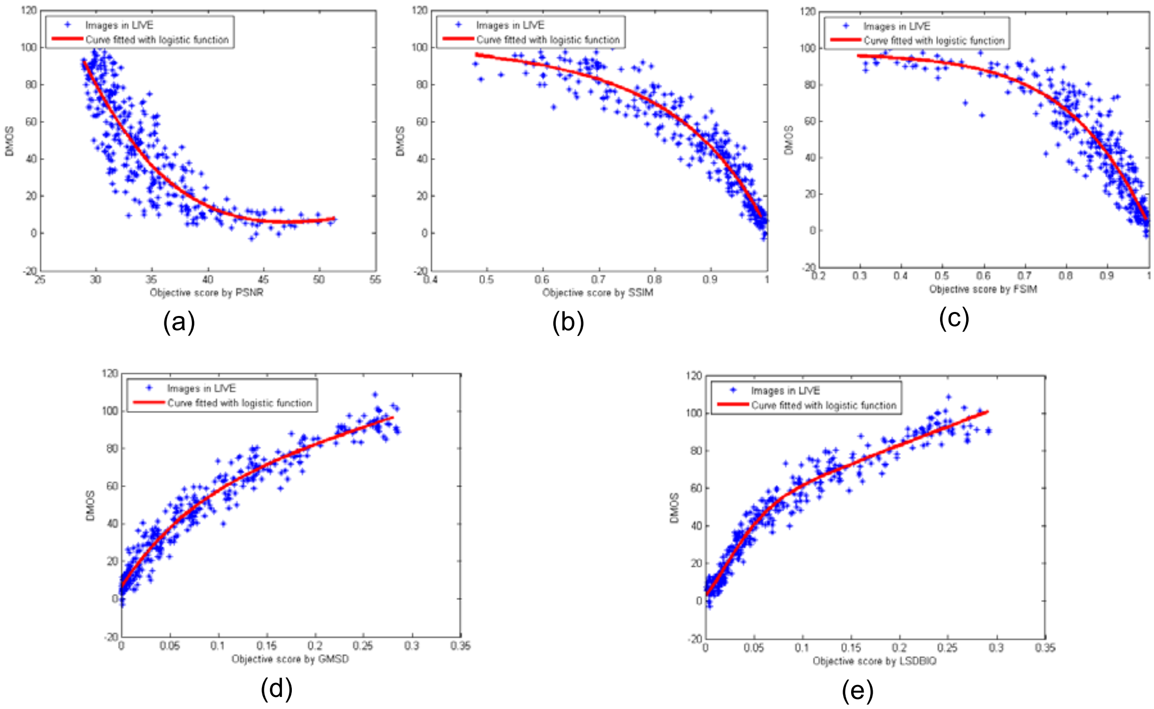


Figure 3. Scatter Plots of five IQMs on LIVE Database. (a) PSNR, (b) SSIM, (c) FSIM, (d) GMSD, (e) LSDBIQ

9. Conclusion

In this paper, we have considered the case of JPEG-compressed images, and we have proposed a FR-IQA model based on a local standard deviation in an image. Experimental results shows that the proposed ESDBIQ model performs better in terms of both accuracy and efficiency. The proposed new model is straightforward and can be easily generalized to other types of local feature. Further work includes extending the proposed algorithm to assess other kinds of distortion.

Acknowledgements

The authors would like to thanks Dr. Hua-Wen Chang from the Zhengzhou University of Light Industry, Zhengzhou, China for constructive pieces of advice that have prompted us for our research.

References

[1] Z.Wang, A.C Bovik, H.R Sheikh, and E.P Simoncelli, “Image Quality Assessment: From Error Visibility to Structural Similarity”, IEEE Transactions of Image Processing, vol. 13, pp. 1-12, April 2004.
[2] Z. Wang, and A. C. Bovik, “Modern Image Quality Assessment Synthesis Lectures on Image”, Video, and Multimedia Processing, vol. 2, no.1, pp. 1-156, 2006.
[3] Zhou Wang, “Applications of Objective Image Quality Assessment Methods”, IEEE Signal Processing Magazine [142], NOV 2011
[4] Zhou Wang and Alan C. Bovik, “A Universal Image Quality Index,” IEEE Signal Processing Letters, vol. 9, no. 3, pp. 81-84, Mar. 2002.

[5] M Chambah, S Ouni, M. Herbin, E. Zagrouba, “Towards an Automatic Subjective image Quality Assessment System”, SPIE-IS&T/Vol 7242 7242. M. Young, The Technical Writers Handbook. Mill Valley, CA: University Science, 1989.
[6] Recommendation 500-11: methodology for the subjective assessment of the quality for television pictures, ITU-R Rec. BT.500, 2002
[7] Z. Wang, A. C. Bovik, and L. Lu, “Why Is Image Quality Assessment So Difficult?”, IEEE International Conference on Acoustics, Speech, and Signal Processing, 2002.
[8] B. Girod, “What's wrong with mean-squared error?’’, Digital Images and Human Vision. MIT press, 1993.
[9] Lin Zhang, Lei Zhang, X. Mou and D. Zhang, “FSIM: A Feature Similarity Index for Image Quality Assessment,” IEEE Trans. Image Process., vol. 20, no. 8, pp. 2378-2386, Aug. 2011.
[10] Lihuo He, Fei Gao, Weilong Hou & Lei Hao, "Objective image quality assessment: a survey", International Journal of Computer Mathematics,Jun 2013.
[11] Lin Zhang, Lei Zhang, Xuanqin Mou, David Zhang: A comprehensive evaluation of full reference image quality assessment algorithms. ICIP 2012: 1477-1480.
[12] D. M. Chandler, M. M. Alam, and T. D. Phan "Seven challenges for image quality research," Proc. SPIE Human Vision and Electronic Imaging XIX, 901402 (February 25, 2014)
[13] D. M. Chandler, "Seven Challenges in Image Quality Assessment: Past, Present, and Future Research," ISRN Signal Processing, vol. 2013, Article ID 905685, 53 pages, 2013.
[14] Gonzalez, R. C., and Wintz, P., 1987. Digital Image Processing, Addison-Wesley, Menlo Park, CA, p. 414.
[15] Woodcock, C. E., and Strahler, A. H., 1987. The factor of scale in remote sensing, Remote Sensing of Environment, 21, pp. 311-332.
[16] MATLAB version 7.10.0. Natick, Massachusetts: The MathWorks Inc., 2010.
[17] Wufeng Xue, Lei Zhang, “Gradient Magnitude Similarity Deviation: A Highly Efficient Perceptual Image Quality Index”, IEEE Transactions On Image Processing, Vol. 23, No. 2, February 2014.
[18] N. Ponomarenko, O. Ieremeiev, V. Lukin, K. Egiazarian, L. Jin, J. Astola, B. Vozel, K. Chehdi, M. Carli, F. Battisti, C.-C. Jay Kuo, Color Image Database TID2013: Peculiarities and Preliminary Results, Proceedings of 4th Europian Workshop on Visual Information Processing EUVIP2013, Paris, France, June 10-12, 2013, pp. 106-111.
[19] N. Ponomarenko, V. Lukin, A. Zelensky, K. Egiazarian, M. Carli, F. Battisti, "TID2008 - A Database for Evaluation of Full-Reference Visual Quality Assessment Metrics", Advances of Modern Radioelectronics, Vol. 10, pp. 30-45, 2009.
[20] H. R. Sheikh, Z. Wang, L. Cormack, and A. C. Bovik. (2005) “Live Image Quality Assessment Database Release 2",http://live.ece.utexas.edu/research/quality.
[21] Eric C. Larson and Damon M. Chandler, “Most apparent distortion: full-reference image quality assessment and the role of strategy,” J. Electron. Imaging 19, 011006, Jan 07, 2010.
[22] VQEG, “Final report from the video quality experts group on the validation of objective models of video quality assessment”, http://www.vqeg.org, 2000.
[23] A. J. Bell and T. J. Sejnowski, “An information-maximization approach to blind separation and blind deconvolution,” Neural Comput., vol.7, no. 6, pp. 1129–1159, 1995.