Synthesis Sparse Modeling: Application to Image Compression and Image Error Concealment

Ali Akbari and Maria Trocan
Institut Supérieur d'Electronique de Paris (ISEP)
Paris, France
Email: ali.akbari@isep.fr and maria.trocan@isep.fr

Bernard Granado
Laboratoire d'Informatique de Paris 6
Pierre et Marie Curie University
Paris, France
Email: Bertrand.Granado@lip6.fr

Abstract

Signal models are a cornerstone of contemporary signal and image processing methodology. Two particular signal modeling methods, called analysis and synthesis sparse representation have been proven to be effective for many signals, such as natural images, and successfully used in a wide range of applications. Both models represent signals in terms of linear combinations of an underlying set, called dictionary, of elementary signals known as atoms. The driving force behind both models is sparsity of the representation coefficients. On the other hands, the dictionary choice determines the success of the entire model. According to these two signal models, there have been two main disciplines of dictionary designing; harmonic analysis approach and machine learning methodology. The former leads to designing the dictionaries with easy and fast implementation, while the latter provides a simple and expressive structure for designing adaptable and efficient dictionaries [1]. The line of research followed in this report is the synthesis-based sparse representation approach in the sense that the dictionary is not fixed and predefined, but learned from training data and adapted to data, yielding a more compact representation [2], [3]. We report recent and novel research results of two particular applications of this signal modeling: image compression and image error concealment.

Contributions

The first contribution of this report is addressing an adaptive sparse representation over a trained dictionary in order to efficiently compress the images [4]. Given a trained dictionary, the sparse representation of the image patches can be achieved by different ways such as the basis pursuit algorithms, matching pursuit techniques and other schemes [6]. However, the conventional sparse representation approaches consider a fixed number of atoms, called sparsity level, for all the image patches that can lead to a weak performance in the context of image compression. We adopt an adaptive sparse representation approach. From the view of biological vision and scientific analysis, the visual significance of each block (visual saliency) varies with its spatial position [7]. Some regions can be more sensitive to the Human Visual System (HVS) (salient regions), while others have a lower level of visual interest. Therefore, it is necessary to design an adaptive sparse representation scheme by joining the sparse representation and the HVS characteristics in order to achieve an efficient compression performance. Based on this representation, different sparsity levels are assigned to the image patches belonging to the salient regions of the image that are more conspicuous to the human visual system. Experimental results show that the proposed method outperforms the existing image coding standards, such as JPEG and JPEG2000, which use an analytic dictionary, as well as the state-of-the-art codecs based on the trained dictionaries. Rate-distortion graphs for the test images are presented in Fig. 1 for several baseline algorithms for comparison, including JPEG, JPEG2000, and an K-SVD based image compression algorithm, in which a fixed sparsity level is considered for all patches [3].

The second contribution is application of the sparse signal modeling for solving inverse problems, especially for image error concealment (EC) techniques [5], whose purpose is to reconstruct the original signal x from its degraded observed version y. Without prior knowledge on x, recovering x from y is an impossible task. Signal modeling is usually used as a prior knowledge about the signal to solve this NP-hard problem. Inspired by the synthesis-based sparse models as a prior, the EC challenge is transferred into a distinct sparse recovery frameworks. We use the learned dictionary in order to adaptively select the most relevant basis for representing each patch of the image, including the correctly received surrounding areas of the lost region. Then, these basis and corresponding coefficients are used to implicitly capture the correlation among the lost region and the correctly received pixels in its neighboring area and conceal the corrupted region. In fact, this correlation is modeled by means of the sparse representation of the correctly received neighboring area on a learned dictionary. Our approach is motivated by the recent results in the compressive sensing theory [8], which suggest that, under mild conditions, the sparse representation coefficients of a given zone, including both known and unknown pixels, can be correctly recovered from the sparse representation coefficients of its neighboring area. Compared with the state-of-the-art error concealment algorithms, experimental results show that the proposed methods show better reconstruction performance in terms of objective and subjective evaluations over a range of packet loss rates. The PSNR and SSIM results of concealed images obtained by different EC techniques are given in Tables I for 30% random loss pattern.

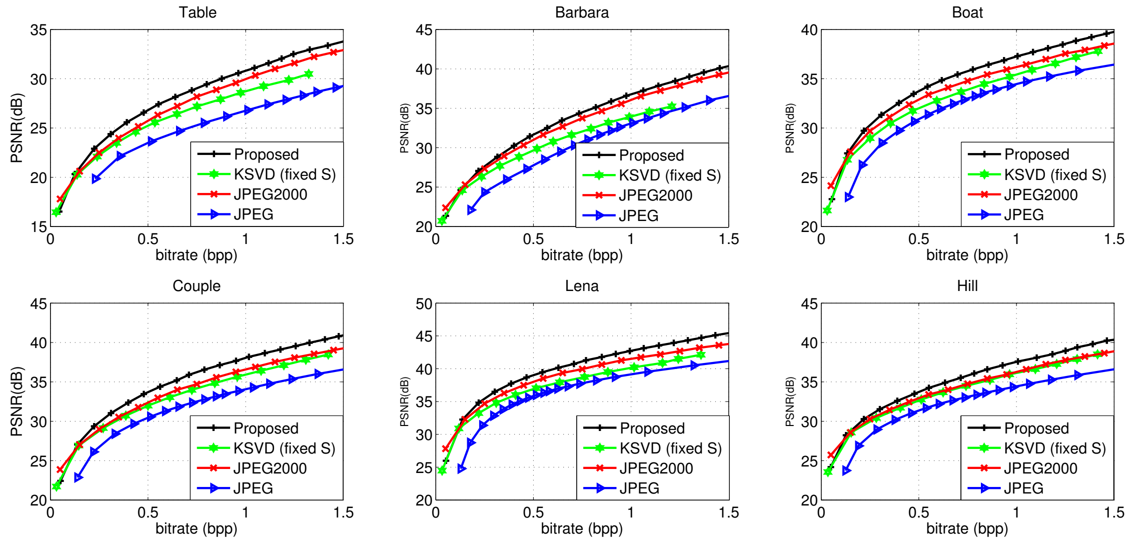

Fig. 1. Rate-distortion performance compared with JPEG, JPEG2000 and K-SVD based codec using fixed sparsity level in terms of PSNR for several test images (size 512×512, gray-level).

TABLE I
AVERAGE PSNR AND SSIM USING SEVERAL EC TECHNIQUES FOR 30% RANDOM LOSS (RAN.))

		EC Technique							
Loss		[9]	[10]	[11]	[12]	[13]	[14]	[15]	**Proposed**
		Lena							
Ran.	PSNR	28.88	25.95	17.98	31.45	30.77	29.42	30.21	**31.55**
	SSIM	0.926	0.913	0.652	0.955	0.940	0.838	0.943	**0.956**
		Peppers							
Ran.	PSNR	29.04	26.94	17.80	31.23	30.91	30.00	30.01	**31.68**
	SSIM	0.936	0.926	0.662	**0.959**	0.950	0.833	0.946	0.946
		Goldhill							
Ran.	PSNR	29.90	28.16	18.97	30.38	29.22	28.54	28.87	**30.97**
	SSIM	0.913	0.906	0.684	0.921	0.908	0.825	0.908	**0.925**

REFERENCES

[1] R. Rubinstein, A. M. Bruckstein, and M. Elad, “Dictionaries for sparse representation modeling,” *Proceedings of the IEEE*, vol. 98, no. 6, pp. 1045–1057, Jun 2010.

[2] A. Olshausen and D. J. Field., “Sparse coding with an overcomplete basis set: a strategy employed by v1?” *Vision Research*, vol. 16, no. 4, p. 33113325, Apr 1997.

[3] M. Aharon, M. Elad, and A. Bruckstein, “K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation,” *IEEE Transactions on Signal Processing*, vol. 54, no. 11, pp. 4311–4322, Nov 2006.

[4] **A. Akbari**, M. Trocan, and B. Granado, “Image compression using adaptive sparse representations over trained dictionaries adaptive saliency-based compressive sensing image reconstruction,” in *IEEE Workshop on Multimedia Signal Processing (MMSP)*, Sep 2016, (in press).

[5] ——, “Image error concealment using ssparse representations over a trained dictionary,” in *IEEE Picture Coding Symposium (PCS)*, Dec 2016, (Accepted to appear).

[6] G. Peyre, “A review of adaptive image representations,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 5, no. 5, pp. 896–911, Sep 2011.

[7] A. Borji, M. M. Cheng, H. Jiang, and J. Li, “Salient oobject detection: A benchmark,” *IEEE Transactions on Image Processing*, vol. 24, no. 12, pp. 5706–5722, Dec 2015.

[8] J. N. Laska, P. T. Boufounos, and M. A. Davenport, “Democracy in action: Quantization, saturation, and compressive sensing,” *Applied and Computational Harmonic Analysis*, vol. 31, no. 3, pp. 429–443, Nov. 2011.

[9] V. Varsa, M. M. Hannuksela, and Y.-K. Wang, “Non-normative error concealment algorithms,” *ITU-T SG16, VCEG-N62*, vol. 50, Sep 2001.

[10] Z. Rongfu, Z. Yuanhua, and H. Xiaodongl, “Content-adaptive spatial error concealment for video communication,” *IEEE Transactions on Consumer Electronics*, vol. 50, no. 1, pp. 335–341, Feb. 2004.

[11] J. Koloda, V. Sánchez, and A. M. Peinado, “Spatial error concealment based on edge visual clearness for image/video communication,” *Circuits Systems and Signal Processing*, vol. 32, no. 2, pp. 815–824, Apr. 2013.

[12] S. Shirani, F. Kossentini, and R. Ward, “An adaptive markov random field based error concealment method for video communication in an error prone environment,” in *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Phoenix, AZ, Mar. 1999, pp. 3117–3120.

[13] J. Koloda, A. Peinado, and V. Sanchez, “Kernel-based MMSE multimedia signal reconstruction and its application to spatial error concealment,” *IEEE Transaction on Multimedia*, vol. 16, no. 6, pp. 1729–1738, Jun. 2014.

[14] X. Li and M. T. Orchard, “Novel sequential error-concealment techniques using orientation adaptive interpolation,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 12, no. 10, pp. 857–864, Oct. 2002.

[15] J. Koloda, J. Ostergaard, S. H. Jensen, V. Sanchez, and A. M. Peinado, “Sequential error concealment for video/images by sparse linear prediction,” *IEEE Transaction on Multimedia*, vol. 15, no. 4, pp. 957–969, Jun. 2013.