DISTRIBUTED SOURCE CODING: THEORY AND APPLICATIONS

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ABSTRACT

Distributed source coding (DSC) refers to separate compression and joint decompression of mutually correlated sources. Though theoretical foundations were set more than thirty years ago, driven by applications such as wireless sensor networks, video surveillance, and multiview video, DSC has over the past few years become a very active research area. This paper provides an introduction to DSC theory, practical code designs and applications, and outlines current research trends while identifying challenges and opportunities in both theory and practice of DSC.

1. INTRODUCTION

Imagine a dense sensor network consisting of many tiny sensors deployed for information gathering. Readings from neighboring sensors will often be highly correlated. This can be exploited to significantly reduce the amount of information that each sensor needs to send to a central point, thus reducing power consumption and prolonging the life of the nodes and the network. Communication among sensors is often not feasible as it increases the complexity of the sensors that in turn leads to additional cost and power consumption. How then is it possible to exploit statistical dependency of the readings in different sensor nodes without information exchange among sensors? The answer lies in distributed source coding.

Distributed source coding (DSC) refers to separate compression and joint decompression of two or more physically separated sources. The sources are encoded independently (hence distributed) at the encoders and decompressed jointly at the decoder. DSC is thus a compression method that aims at exploiting mutual dependencies across different sources that need not communicate among each other.

DSC appeared as an information-theoretical problem in the seminal paper of Slepian and Wolf in 1973 [1]. Slepian and Wolf studied the simplest lossless case of DSC when two discrete sources are to be compressed independently and decompressed losslessly at the joint decoder, and provided an information-theoretical achievable rate region showing that asymptotically separate encoding is as good as joint encoding. This surprising result triggered a lot of information-theoretical research efforts that resulted in many extensions. For example, in 1976 Wyner and Ziv [2] considered a lossy version, with a distortion constraint, of a special case of the asymmetric Slepian-Wolf problem, where one source is available at the decoder as side information. Wyner and Ziv showed that for a particular correlation, where source and side information are jointly Gaussian, there is no performance loss due to the absence of side information at the encoder. The main message from these early information-theoretical works is that, in some special cases, side information present at the decoder and not at the encoder can be as helpful as if it were known to the encoder as well.

A possible realization of DSC via the use of conventional linear channel codes to approach the Slepian-Wolf bound was known as early as 1973, but due to the lack of any potential application of DSC, work on code designs, i.e., how to code the sources to approach given bounds given in [1, 2], started only at the end of the last century. The launch of wireless sensor networks (WSNs) ignited practical DSC considerations since WSNs naturally call for distributed processing. Closely located sensors are expected to have correlated measurements; thus in theory the DSC setup fulfills the requirement of power-efficient compression for distributed sensor networks.

The first practical DSC design was reported in 1999 in [3] followed by many improved solutions. The key beauty of these designs is that conventional channel coding can be used for compression. Thus, in a communication system, the same code can be used for compressing and protecting the source! Powerful code designs, developed since 1999, have paved the way towards practical applications. However, despite tremendous achievements in both theory and practice, the true potential of DSC has yet to materialize.

Nowadays, DSC has grown into a research field of its own right bringing together information and coding theory, signal/image processing, computer engineering and communications, and receiving attention by academics and industry. This is no wonder as DSC has many diverse potential applications ranging from WSN, ad-hoc networks, to video surveillance, stereo/multiview video, high-definition television, hyper-spectral and multi-spectral imaging. This paper provides an introduction to DSC theory and practice, critically reviews current research efforts and proposed applications, and identifies many research opportunities.

2. UNDERLYING PRINCIPLES OF DSC

DSC considers source coding or compression of correlated sources. The adjective *distributed* stresses that the compression occurs in a distributed or non-centralized fashion. For example, the sources to be compressed could be distributed across different nodes in a network. The task is to compress these sources and communicate compressed streams over noiseless channels to a decoder for joint decompression. The basis of DSC is that the compressions take place *independently*, that is, the nodes do not exchange their infor-

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mation, whereas decompression is *joint*.

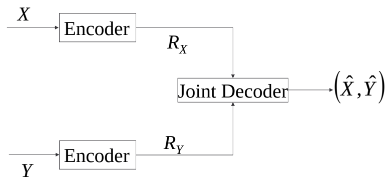

Figure 1: DSC concept with two separate encoders who do not talk to each other and one joint decoder. X and Y are discrete, correlated sources; R_X and R_Y are compression rates.

Slepian and Wolf [1] considered the simplest case of DSC with two discrete sources X and Y and lossless compression (Fig. 1), and showed that it is possible to have no performance loss of independent encoding compared to the case when joint encoding is done. Indeed, Slepian and Wolf showed that two discrete sources X and Y can be losslessly decoded as long as:

$$R_X \geq H(X|Y), R_Y \geq H(Y|X), R = R_X + R_Y \geq H(X,Y), \quad (1)$$

where R_X and R_Y are rates used for compressing X and Y, respectively. The above set of equations, known as the Slepian-Wolf (SW) coding region, shows that the sum-rate R can be as low as the joint entropy of the sources, which is the same as if the source were encoded together. A special case of SW coding is when one source, e.g., Y, is known at the decoder. Then, a rate not higher than $H(X|Y)$ suffices for compressing X. This case is known as asymmetric SW coding, or SW coding with decoder side information Y.

The remarkable result of [1] triggered significant information-theoretical research resulting in solutions - in the form of achievable rate regions - for more involved lossless source coding networks, e.g., networks with more than two sources, zig-zag network etc. (see [4] and references therein).

In 1976, Wyner and Ziv [2] considered a lossy version, with a distortion constraint, of the asymmetric SW coding problem and showed that for a particular correlation where source and side information are jointly Gaussian, there is no performance loss due to the absence of side information at the encoder. The lossy case of the general non-asymmetric SW setup shown in Fig. 1, known as *multiterminal (MT) source coding*, was introduced by Berger and Tung in 1977 [5] together with information-theoretical bounds on the achievable rate region.

DSC theory is still a very active information-theoretical area of research. Indeed, only the simplest DSC problems are solved and for many realistic MT source coding networks we still do not know exact compression limits.

Lossless DSC is considered together with network coding to provide limits for conveying sources over noiseless networks (see [6] and references therein). Lossy MT source coding problems [5] with two non-jointly Gaussian sources are unsolved. Other research challenges include addressing time-varying statistics, noisy channels and quantifying the rate loss compared to optimal or joint encoding.

3. DSC: CODE DESIGN

Slepian and Wolf's proof [1] is based on non-constructive information-theoretical tools, such as random binning and Fano's inequality, and thus does not give an insight on how to design an efficient binning scheme. A possible realization is proposed in a 1974 paper [7] where the use of linear channel codes was suggested for asymmetric SW coding.

In a nutshell, to encode X given Y at the decoder, bins are generated as "cosets" of a linear channel code. For example, suppose that both X and Y are binary sources with n-bit realizations. Then an (n,k) binary linear block code C can be used to generate 2^{n-k} coset codes each indexed by unique syndrome of C, $s_0,\ldots,s_{2^{n-k}}$. By definition a coset i contains a set of 2^k binary words of length n which when multiplied by the parity-check matrix of C, $\mathbf{H}$, give syndrome s_i. For example, the first coset is code C itself as it contains n-words that give syndrome $s_0 = 0$. Then, to compress, x is multiplied by $\mathbf{H}$, mapping it thereby into its corresponding $(n-k)$ syndrome bits, which is sent to the decoder achieving a compression ratio of $n:(n-k)$. The decoder applies conventional channel decoding on the side information y with the coset code whose syndrome is received, to recover $\hat{x}$ as the codeword closest to y.

Another variant of the above method is to send parity bits of a channel code (instead of syndromes) to compress. Specifically, to compress with the "parity-based" approach, x is encoded by a systematic linear channel code and only parity bits are sent to the decoder. The decoder "sees" side information y as received systematic part of the codeword and appends it to the received parity before conventional decoding. The main advantages of parity-based binning are better performance with transmission over noisy channels, while syndrome-based schemes can in theory achieve higher compression with shorter channel codes and do not require systematic codes. Both approaches are popular and the choice of the approach rests very much on the application.

Note that the above methods look at correlation between the sources as a virtual communication channel, and a good code for this channel will provide a good SW code by using coset codes as bins. Thus, the seemingly source coding problem of SW coding becomes a channel coding one, and near-capacity channel codes such as turbo and low-density parity-check (LDPC) codes [8] can be used to approach the SW limit. This "syndrome-based" approach is extended to non-asymmetric SW coding and compression of more than two sources (see [4] and references therein).

After the success of the first SW code designs, schemes for multiple non-uniform sources, non-binary sources, different correlation models, with rate compatible codes, transmission over noisy channels appeared (see, for example, [9, 10, 11, 12, 13, 14] and references therein). Moreover, the original DSC framework assumes that the correlation statistics are stationary and known to the encoders and decoder. Some initial attempts have been made to forego this assumption and recover the sources at the decoder without prior statistical knowledge (for example, see [15]).

WZ and MT source coding can be realized via quantization followed by SW coding of quantization indices based on channel coding. Quantization is used to tune rate-distortion performance, while the SW coder can be seen as a conditional entropy coder. The SW coder applies a linear channel code to generate cosets, and sends only the index of the coset to the decoder. The WZ decoder comprises an SW decoder, which uses the received coset index together with side information and performs "error-correction" decoding against "errors" introduced by the virtual correlation channel between the two or more correlated sources. The SW decoder is followed by a minimum-distortion reconstruction of the source using side information. This allows compression with some distortion. Capacity-approaching designs proposed in [16] based on trellis-coded quantization followed by advanced channel coding, with turbo codes and LDPC codes, come very close to the bounds for two jointly Gaussian sources.

The latest code designs that come very close to the theoretical bounds assume binary symmetric or jointly Gaussian correlations and use long block length, which is unacceptable in many applications. Thus, there is a need for developing efficient designs for non-stationary sources with more realistic mutual dependency and low block size (< 1000 bits). Though channel codes have been proposed as a natural solution for DSC from its foundations, the demands imposed by latest video applications might be better addressed via alternative solutions. One such very promising method is Distributed Arithmetic Coding (DAC) [17].

4. DSC: APPLICATIONS

Whilst the recent rediscovery of DSC was triggered by the need for efficient data gathering in WSNs, very quickly another application emerged - low-complexity video encoding. In this section we give an overview of the applications of DSC.

The inception of WSNs ignited practical DSC considerations in the early years of this century since WSNs naturally call for distributed processing. Closely located sensors are expected to have correlated measurements; thus DSC is the most effective compression method. However, many practical problems are in the way, including a complex correlation structure of real signals, non-stationary non-Gaussian sources, and high complexity of current source-channel DSC designs that require long codeword length.

4.1 WZ Video Coding

In WZ video coding or distributed video coding, the DSC paradigm is used to avoid a computationally expensive temporal prediction loop at the encoder. As the name suggests, WZ video coding exploits inter-frame video correlation with WZ coding, thus avoiding the need for motion search and storage of previous frames at the encoder. It relies on the fact that with WZ coding, side information is not needed at the encoder. That is, predictive coding can still be accomplished though the encoder does not know/use the previous frames, which will be used at the decoder. Thus, WZ video coding essentially comprises intra-frame encoding and interframe decoding. WZ coding also improves robustness to errors/losses in the channels; information-theoretical analysis of robustness of WZ video coding under some assumptions is given in [18] and references therein.

In classical video coding motion search is computationally the heaviest encoding operation. Thus, WZ coding can reduce complexity of the video encoder at the expense of increased complexity at the decoder side. This leads to low-complexity encoders and high-complexity decoders, quite an unusual video architecture. Indeed, the traditional video concepts with heavy encoders situated at strong servers and light decoders (e.g., PC, TV) are ideal for broadcasting/multicasting/video-on-demand applications where a single encoding is done, and multiple decoders at users' equipment are performed. However, some other applications may require multiple encodings and a single decoding. Such applications range from video surveillance, rescue and exploration missions, multiview camera arrays, to cellphone-to-cellphone conversation.

The WZ video framework appeared in a US patent [19] in 1980, but to the best of the authors' knowledge it remained without software implementation until only recently [20, 21]. WZ coding can be applied in the pixel domain [20], or in the transform domain [21, 22]. DCT-based coders perform better at the expense of a small increase in encoder complexity [22].

In pixel-domain WZ video coding [20], the pixels of a frame are directly input to a WZ coder and no image transform is applied. Video frames are divided into key frames and WZ frames. Key frames are intra-coded frames that are compressed and decompressed conventionally (for example, as intra-coded frames in H.264/MPEGx). Like I frames in conventional video coding, the key frames reduce compression efficiency, but are needed to stop possible error propagation and improve decoding of WZ frames.

Let $P_1, P_2, \ldots$ be a sequence of $n \times m$ pixel frames to be compressed by the video encoder. Let $P_i(x,y)$ be a pixel in the i-th frame at position (x,y). Each WZ frame, P_i, is first quantized pixel-by-pixel using 2^M quantization levels, and resulting quantization indices are fed into an SW encoder, which outputs parity-check symbols (parity-based binning). These output bits are sent to the decoder. Note that the number of output bits per frame (the information block length of the SW channel coder) is Mnm, which is usually enough for efficient use of turbo/LDPC codes.

The decoder consists of a classic WZ decoder which performs SW decoding on the received parity-check bits, using previously recovered frames to generate side information, followed by estimation.

Note that, a crucial difference between WZ video coding to the standard WZ setup lies in the fact that in the former the decoder can generate side information from all prior information available. The better the side information is, the higher the correlation and the better the compression. The process of side information generation resembles motion compensation at the decoder and is a key to efficient video compression. This correlation channel depends on the dynamics of the scene and varies from frame to frame. As correlation changes, the required WZ rate will also change from frame to frame. Thus, an efficient rate control algorithm is needed to ensure that: (i) a rate no higher than necessary is sent to the decoder; (ii) SW decoding is successful. It is natural to shift this rate control to the decoder side, in which case a feedback channel is needed for indicating the necessary rate to the encoder.

Great challenges of a decoder-driven video have made WZ video coding a very active research topic with many novel contributions appearing every year. Indeed, research has been going towards improving side information generation, correlation modelling [23], rate control, key-block selection, etc. Initial video coders proposed in 2002 [20, 21] have significantly evolved during the past eight years (see [24] for the latest overview), towards more flexible designs capable of distributing complexities between encoder and decoder depending on application and QoS demands.

However, despite all the achievements, performance wise WZ video coders still significantly lack behind best video coding standards, such as H.264/AVC. And obviously, due to non-stationarity of the sources, WZ video coders can never reach the performance of best conventional codecs. That is why probably, a "pure" WZ video coder [19, 20, 21] will remain only a neat research idea, but a place for WZ coding in conventional video whether for compression, resolution increase, or effective protection has yet to be found.

4.2 Multiview Video Coding

DSC naturally arises in the multiview video setup, where each camera *independently* compresses its view before transmission to a central decoder, which jointly decompresses all views. Indeed, since cameras observe the same scene only from different angles, it is expected that the captured views will be highly correlated and exploiting the correlation saves the rate compared to independent encoding and decoding. In the multiview setup, DSC can be used to reduce inter-view correlation, but also intra-view inter-frame correlation, thus ideally side information needs to be generated by combining past/current/future frames from all the views (see [25, 26]), which makes multiview WZ video coding very challenging.

In [27], two schemes are proposed: the first, asymmetric, setup uses H.264/AVC to compress one view which is exploited as decoder side information for reconstructing WZ coded second view. The second, symmetric, scheme resorts to source splitting (see [16]) to tradeoff the rates between the two cameras. To generate side information, a stereo matching algorithm based on loopy belief propagation is adopted at the decoder to produce pixel-level disparity maps between the corresponding frames of the two decoded video sequences on the fly. The obtained results were slightly better than using two independent H.264/AVC cameras.

Some other recent promising schemes include [28], where WZ coding is used for scene representation with omnidirectional image sensors to acquire a 3D scene, [29], and [30].

4.3 Video over Networks

WZ coding can be used to provide error protection of video or enable scalability. For example, in [31], a robust scalable video transmission over wireless networks was addressed and a solution proposed based on a single Raptor code for both compression (i.e., SW coding in DCT domain) and packet loss protection. Using the received packets together with a correlated video available at the decoder, an iterative soft-decision decoder was developed.

WZ coding has been also used for error protection in video communications channels (see [22, 32] and references therein). The idea is to compress independently video frame using both a conventional MPEG-like coder and a WZ video coder. MPEG provides a fine "description" but error prone, whereas WZ coding uses a coarser quantizer to provide a low-rate "description". The decoder first decodes the (corrupted) MPEG stream and then in case of errors after MPEG decoding, the decoder performs error concealment and then uses the obtained frame as side information for decoding the WZ stream.

WZ coding is embedded within compressive-and-forward - the best performing protocol for wireless relay channels when the relay is close to the destination (see [33]). In [34], DSC is proposed for video streaming in parallel from multiple servers. The source broadcasts signals to multiple servers, which employ MT source coding to compress the received bitstreams without decoding and send the result to a fixed client receiver over the Internet. Note that the signals at the servers are highly correlated since they are differently corrupted replicas of the same original data. Thus, DSC is natural solution to reduce the required rate. Following the basic ideas of compress-and-forward, the method of [34] was extended in [35] incorporating spreading codes.

4.4 Other Applications

DSC has been considered for compression of hyperspectral and multispectral images in [36, 37] and [38], respectively. For example, in [36] using DSC to exploit inter-band correlation, performance gains of up to a factor of three compared to 2D and 3D wavelet techniques are observed. Another application of DSC is proposed in [39], where it is used for wireless hearing aids. DSC is also proposed for biometrics and fingerprint feature extraction [40] and for cognitive radio spectrum sensing [41].

5. DISCUSSION AND CONCLUSION

The rediscovery of DSC at the end of the last century caused a research shift from information theory to coding and signal/image processing. The coding community has been excited by a novel marriage between source coding and channel coding that brought a plethora of new design problems that go far beyond current practice and require deep understanding of source-channel coding theory.

The image/video processing community was initially surprised with remarkable WZ video coding that completely revolutionizes the conventional way of thinking in video coding. This resulted in a search for better-performing code designs, novel side information generation techniques, rate control, and correlation modelling. The gap to the classic video coding standards has been reducing, and with comparable encoder complexities, WZ video coding is generally beating conventional coding solutions (see [24] and references therein).

Unfortunately, H.264/AVC performance is unreachable, and in an era of huge electronic advances and continuous chip-size and power-consumption reduction, pure complexity reduction probably cannot justify a complete technology shift. Thus, now after ten years of intense research, it might seem that we have reached a dead-end for WZ video coding. Consequently, initial excitement is slowly being replaced by disappointment and a slow decrease of interest until proposed applications have reached a higher level of maturity.

WZ video coding has a tremendous value as it has enhanced our understanding in video itself. It showed that video coding does not need to be centralized and encoder-driven; instead, it can be a play between the encoder and decoder and distributing the work in coding and processing could reduce overall power consumption, lead to better performance, and add necessary security guarantees. Indeed, with WZ coding, we know now that we can design an "intelligent" decoder which can do the job almost equally well as the encoder! But we are yet to discover how to use this.

And this brings us to the potentials of DSC. Though initially suggested to help communications in WSN, application of DSC to WSNs seem far away. Clearly, large block length requirements of efficient DSC designs and non-stationary source statistics are still huge obstacles. But more importantly, uncertainty introduced by probabilistic source coding is probably the price that accurate industrial sensor networks cannot pay. The exception might be camera and microphone arrays and visual sensors with known geometrical structures where high compression is a must and information sent might be recovered with some distortion. In video coding and processing, DSC can find its place as a supporting mechanism, for example, to increase resolution in super high-definition systems, encode colour information, provide protection, encode headers, etc.

Driven by all these applications, work on code designs is still equally important as it was 10 years ago: the search for efficient low-delay, low-complexity, application-layer codes is not over yet. Novel ideas are needed to bridge the gap between code design and practice. Thus, research into theory, designs and applications of DSC has strong potentials to lead to a killer-application soon. It is not just that DSC is so elegant that we cannot let it go.

REFERENCES

[1] D. Slepian and J.K. Wolf, "Noiseless coding of correlated information sources," *IEEE Trans. Inform. Theory,* vol. IT-19, pp. 471–480, July 1973.

[2] A.D. Wyner and J. Ziv, "The rate-distortion function for source coding with side information at the decoder," *IEEE Trans. Inform. Theory,* vol. IT-22, pp. 1–10, Jan. 1976.

[3] S.S. Pradhan and K. Ramchandran, "Distributed source coding using syndromes (DISCUS): design and construction, " in *Proc. DCC Data Compression Conf.*, Snowbird, UT, March 1999, pp. 158–167.

[4] V. Stanković, A. Liveris, Z. Xiong, and C. Georghiades, "On code design for the Slepian-Wolf problem and lossless multiterminal networks," *IEEE Trans. Inform. Theory,* vol. 52, pp. 1495–1507, April 2006.

[5] T. Berger, *Multiterminal source coding: The Information Theory Approach to Communications.* G. Longo, Ed., New York: Springer-Verlag, 1977.

[6] Y. Wu, V. Stanković, Z. Xiong, and S.Y. Kung, "On practical design for joint distributed source and network coding," *IEEE Trans Inform. Theory,* vol. 55, pp. 1709-1720, April 2009.

[7] A. Wyner, "Recent results in the Shannon theory," *IEEE Trans. Inform. Theory*, vol. 20, pp. 2–10, Jan. 1974.

[8] A. Liveris, Z. Xiong, and C. Georghiades, "Compression of binary sources with side information at the decoder using LDPC codes," *IEEE Commun. Letters,* vol. 6, pp. 440-442, Oct. 2002.

[9] J. Garcia-Frias and Y. Zhao, "Compression of correlated binary sequences using turbo codes, *IEEE Commun. Letters*, vol. 5, pp. 417–419, Oct. 2001.

[10] Y. Zhao and J. Garcia-Frias, "Data compression of correlated nonbinary sources using punctured turbo codes" in *Proc. DCC Data Compression Conf.* March 2002, Snowbird, UT, pp. 242–251.

[11] J. Garcia-Frias and W. Zhong, "LDPC codes for compression of multi-terminal sources with Hidden Markov correlation," *IEEE Commun. Letters,* vol. 7, pp. 115–117, March 2003.

[12] M. Sartipi and F. Fekri, "Distributed source coding using short to moderate length ratecompatible LDPC codes: The entire Slepian-Wolf rate region," *IEEE Trans Commun.,* vol. 56, pp. 400-411, Aug. 2008.

[13] D. Varodayan, A. Aaron, and B. Girod, "Rate-adaptive codes for distributed source coding," *EURASIP Signal Proc. J.*, vol. 86, pp. 3123-3130, Nov. 2006.

[14] M. Fresia, L. Vandendorpe, and H. V. Poor, "Distributed source coding using Raptor codes for hidden Markov sources," *IEEE Trans. Signal Proc.,* vol. 57, pp. 2868-2875, July 2008.

[15] S. Cheng, S. Wang, and L. Cui, "Adaptive Slepian-Wolf decoding using particle filtering based belief propagation," in *Proc. The 47th Annual Allerton Conf.*, Oct. 2009.

[16] Y. Yang, V. Stanković, Z. Xiong, and W. Zhao, "On multiterminal source code design," *IEEE Trans. Inform. Theory,* vol. 54, pp. 2278-2302, May 2008.

[17] M. Grangetto, E. Magli, and G. Olmo, "Distributed arithmetic coding," *IEEE Commun. Letters,* vol.11, pp.883-885, Nov. 2007.

[18] A. Majumdar, R. Puri, P. Ishwar, and K. Ramchandran, "Complexity/performance trade-offs for robust distributed video coding," in *Proc. ICIP Int. Conf. Image Proc.,* Genoa, Italy, Sept. 2005.

[19] H.S. Witsenhausen and A. Wyner, "Interframe coder for video signals," *US Patent No. 4,191,970*, Match 1980.

[20] A. Aaron, R. Zhang, and B. Girod, "Wyner-Ziv coding of motion video," in *Proc. The 40th Annual Asilomar Conf.,* Pacific Grove, CA, Nov. 2002.

[21] R. Puri and K. Ramchandran, "PRISM: A new robust video coding architecture based on distributed compression principles," in *Proc. The 40th Annual Allerton Conf.,* Allerton, IL, Oct. 2002.

[22] B. Girod, A. Aaron, S. Rane, and D. Rebollo-Monedero, "Distributed video coding," *Proc. of the IEEE,* vol. 93, pp. 71–83, Jan. 2005.

[23] C. Brites and F. Pereira, "Correlation noise modeling for efficient pixel and transform domain Wyner-Ziv video coding," *IEEE Trans. Circuits and Sys. for Video Techn.,* vol. 18, pp. 1177–1190, Sept. 2008.

[24] C. Guillemot, et al., "Distributed monoview and multiview video coding: Basics, problems and recent advances," *IEEE Signal Proc. Magazine*, pp. 67-76, Sept. 2007.

[25] T. Maugey and B. Pesquet-Popescu, "Side information estimation and new symmetric schemes for multi-view distributed video coding," *J. Vis. Commun. Image R.* 19 (2008) pp. 589599.

[26] T. Maugey, W. Miled, M. Cagnazzo, and B.Pesquet-Popescu, "Fusion schemes for multiview distributed video coding", in *Proc. EUSIPCO 2009,* Glasgow UK, Aug. 2009.

[27] Y. Yang, V. Stanković, W. Zhao, and Z. Xiong, "Two-terminal video coding," *IEEE Trans. Image Proc.,* vol. 18, pp. 534-551, March 2009.

[28] I. Tosić and P. Frossard, "Geometry-based distributed scene representation with omnidirectional vision sensors," *IEEE Trans. Image Proc.,* vol. 17, pp. 1033-1046, July 2007.

[29] N. Gehrig and P.L. Dragotti, "Geometry-driven distributed compression of the plenoptic function: Performance bounds and constructive algorithms," *IEEE Trans. Image Proc.,* vol. 18, pp. 457-470, March 2009

[30] B. Song, E. Tuncel, and A.K. Roy-Chowdhury, "Towards a multiterminal video compression algorithm by integrating distributed source coding with geometrical constraints," *J. Multimedia,* vol. 2, pp. 9-16, June 2007.

[31] Q. Xu, V. Stanković, and Z. Xiong, "Distributed source-channel coding of video using Raptor codes," *IEEE J. Sel. Areas in Commun.,* vol. 25, pp. 851-861, May 2007.

[32] S. Rane, P. Baccichet, and B. Girod, "Systematic lossy error protection of video signals," *IEEE Trans. Circuits and Sys. for Video Techn.,* vol. 18, pp. 1347-1360, Oct. 2008.

[33] V. Stanković, A. Host-Madsen, and Z. Xiong, "Cooperative diversity for wireless ad hoc networks," *IEEE Signal Proc. Magazine,* vol. 23, no. 5, pp. 37-49, 2006.

[34] V. Stanković, Y. Yang, and Z. Xiong, "Distributed source coding for multimedia multicast over heterogeneous networks," *IEEE J. Sel. Topics in Sig. Proc.,* vol. 1, pp. 220–230, Aug. 2007.

[35] C. Khirallah, V. Stanković, L. Stanković, Y. Yang, and Z. Xiong, "Compress-spread-forward with multiterminal source coding and complete complementary sequences," *IEEE Trans. Commun.*, vol. 57, pp. 884-887, April 2009.

[36] N.-M. Cheung, C. Tang, A. Ortega, and C.S. Raghavendra, "Efficient wavelet-based predictive Slepian-Wolf coding for hyperspectral imagery", *Signal Processing,* vol. 86, pp. 3180-3195, Nov. 2006.

[37] A. Abrardo, M. Barni, E. Magli, and F. Nencini, "Error-resilient and low-complexity onboard lossless compression of hyperspectral images by means of distributed source coding," submitted to *IEEE Trans. Geoscience and Remote Sens.*

[38] J. Zhang, H. Li, and C. Wen Chen, "Progressive distributed coding of multispectral images," *Mobimedia-2009*, London, UK, Sept. 2009.

[39] O. Roy and M. Vetterli, "Rate-Constrained collaborative noise reduction for wireless hearing aids," *IEEE Trans. Signal Proc.*, vol. 57, pp. 645–657, Feb. 2009.

[40] Y. Sutcu, S. Rane, J.S. Yedidia, S.C. Draper, and A. Vetro, "Feature extraction for a Slepian-Wolf biometric system using LDPC codes", in *Proc. ISIT Int. Symp. Inform. Theory*, July 2008.

[41] S. Cheng, V. Stanković, and L. Stanković, "An efficient spectrum sensing scheme for cognitive radio," *IEEE Sig. Proc. Letters,* vol. 16, pp. 501-504, June 2009.