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(54) **MULTI-SOURCE DATA ENCODING,
TRANSMISSION AND DECODING USING
SLEPIAN-WOLF CODES BASED ON
CHANNEL CODE PARTITIONING**

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Bear LLP

(52) **U.S. Cl.** **714/752; 714/801**

(57) **ABSTRACT**

(58) **Field of Classification Search** **714/752,**
714/801

See application file for complete search history.

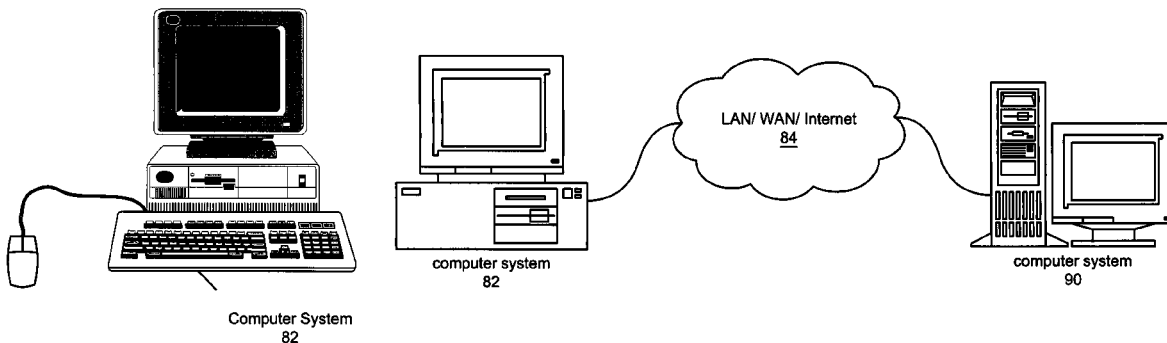
System and method for designing Slepian-Wolf codes by
channel code partitioning. A generator matrix is partitioned to
generate a plurality of sub-matrices corresponding respec-
tively to a plurality of correlated data sources. The partition-
ing is performed in accordance with a rate allocation among
the plurality of correlated data sources. A corresponding plu-
rality of parity matrices are generated based respectively on
the sub-matrices, where each parity matrix is useable to
encode data from a respective one of the correlated data
sources.

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41 Claims, 11 Drawing Sheets

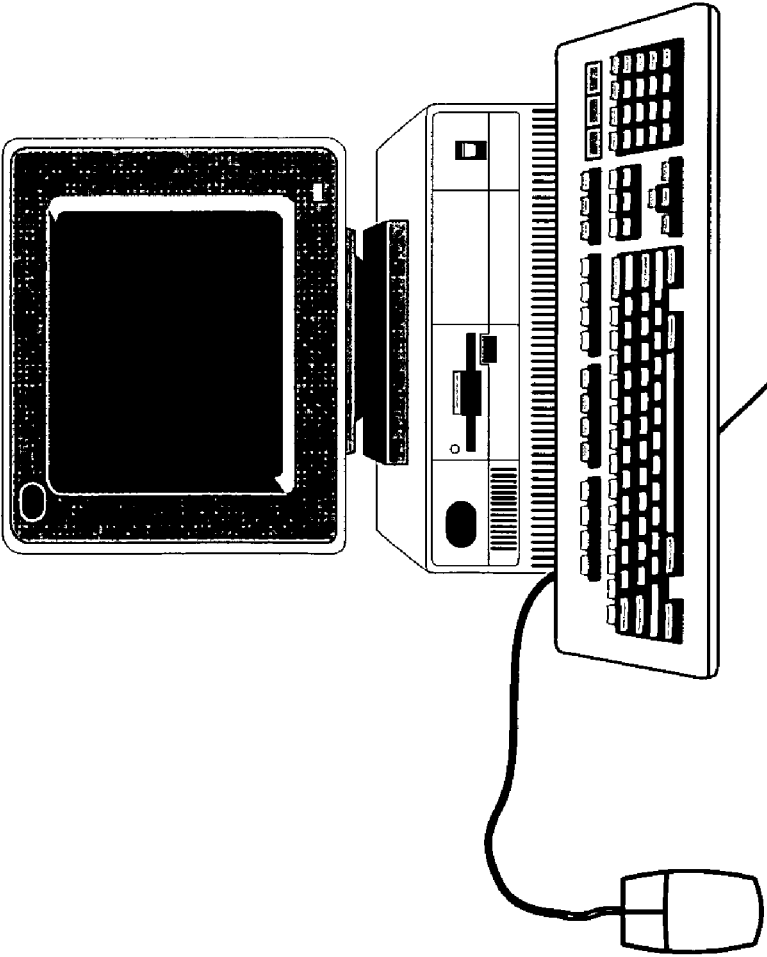


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Computer System
82

Figure 1A

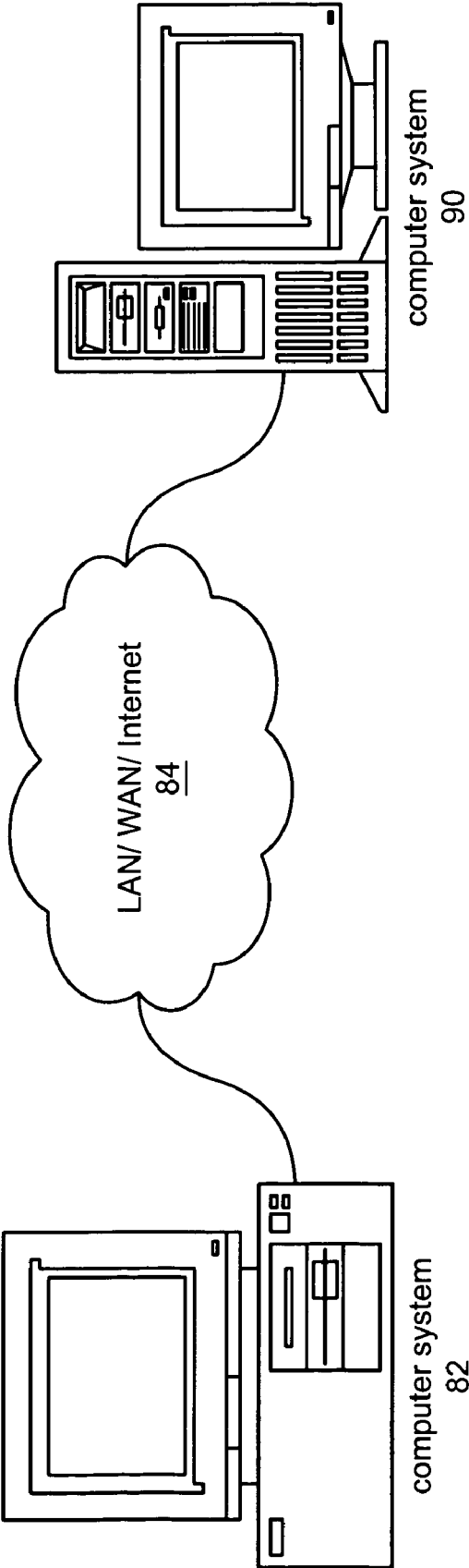


Figure 1B

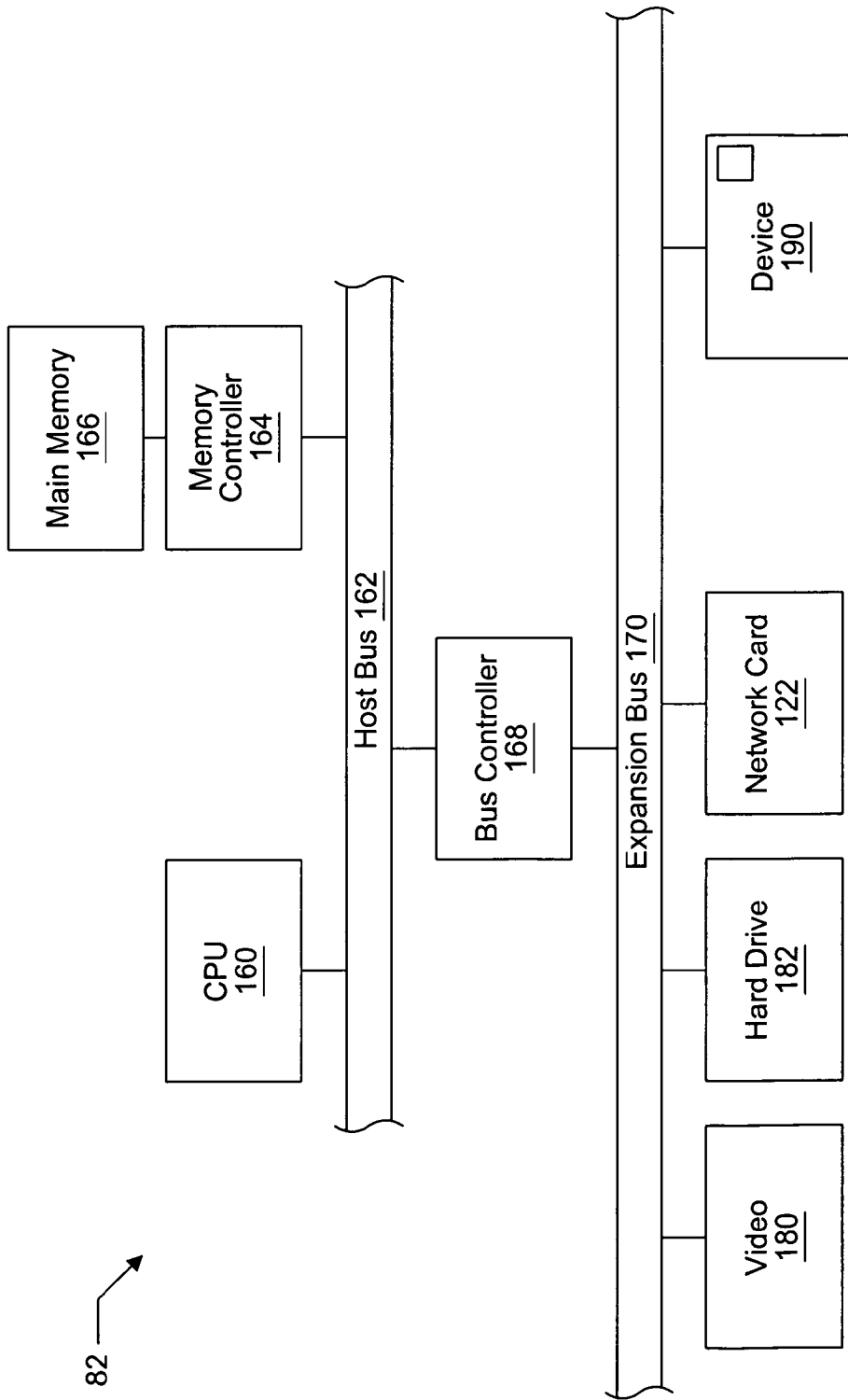


Figure 2

Distributed
Sensor System
302

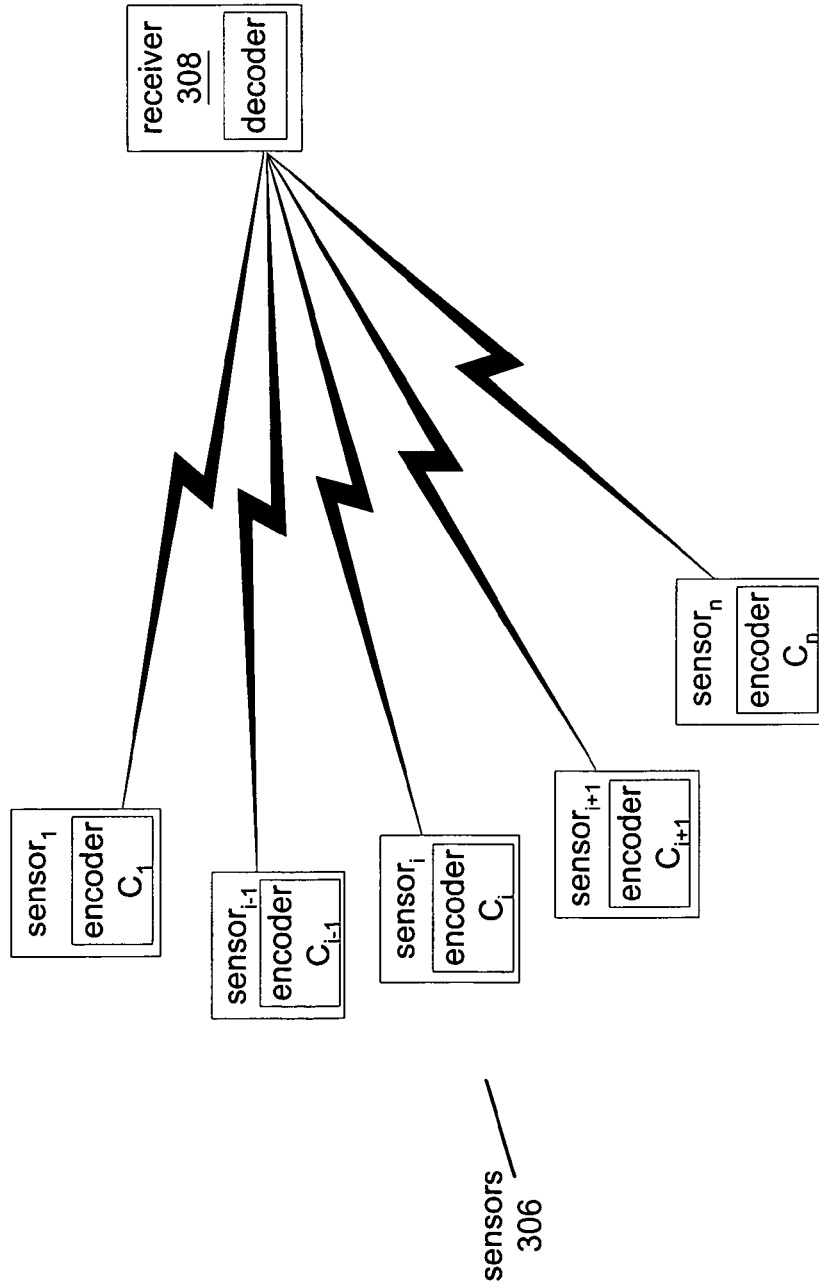


Figure 3A

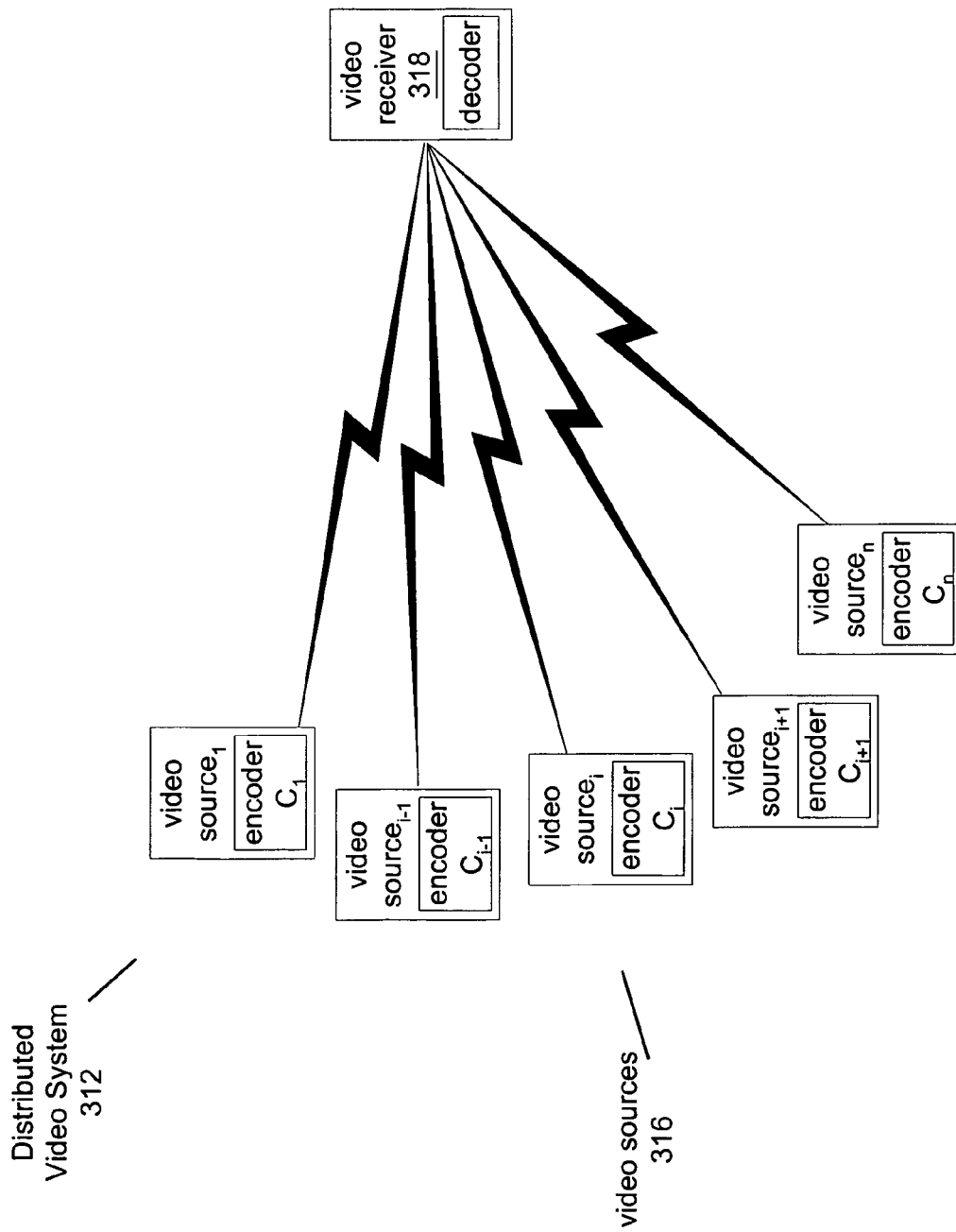


Figure 3B

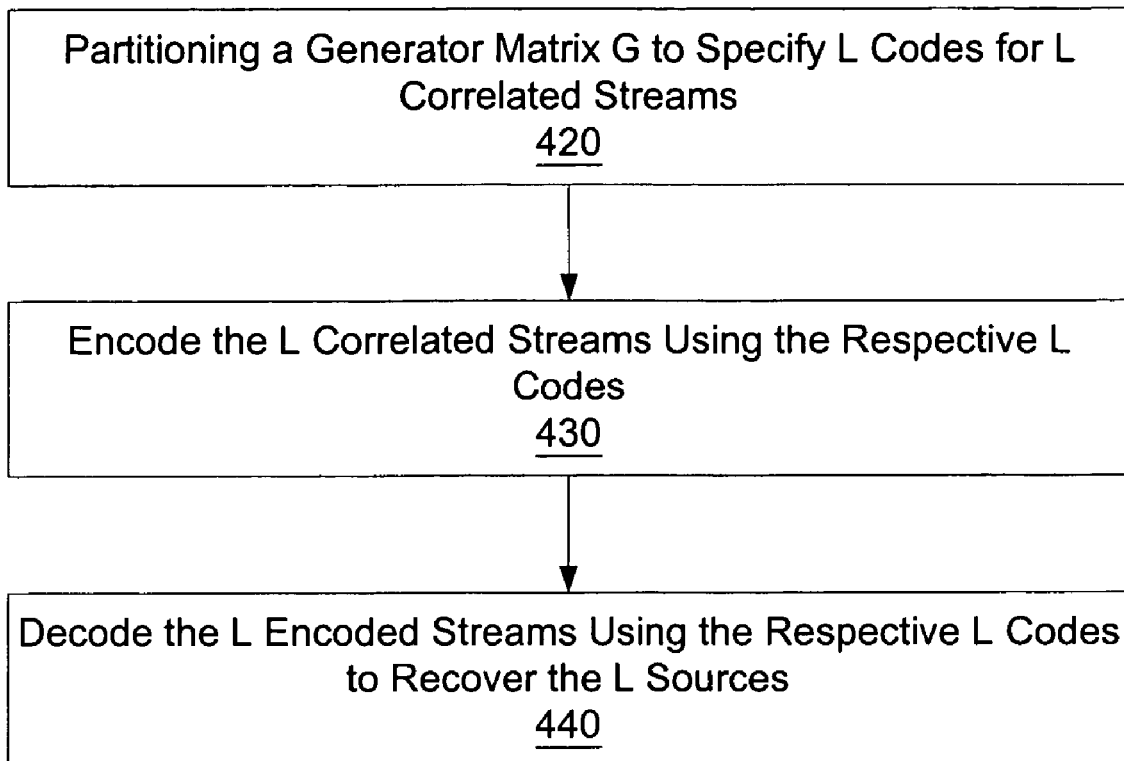


Figure 4

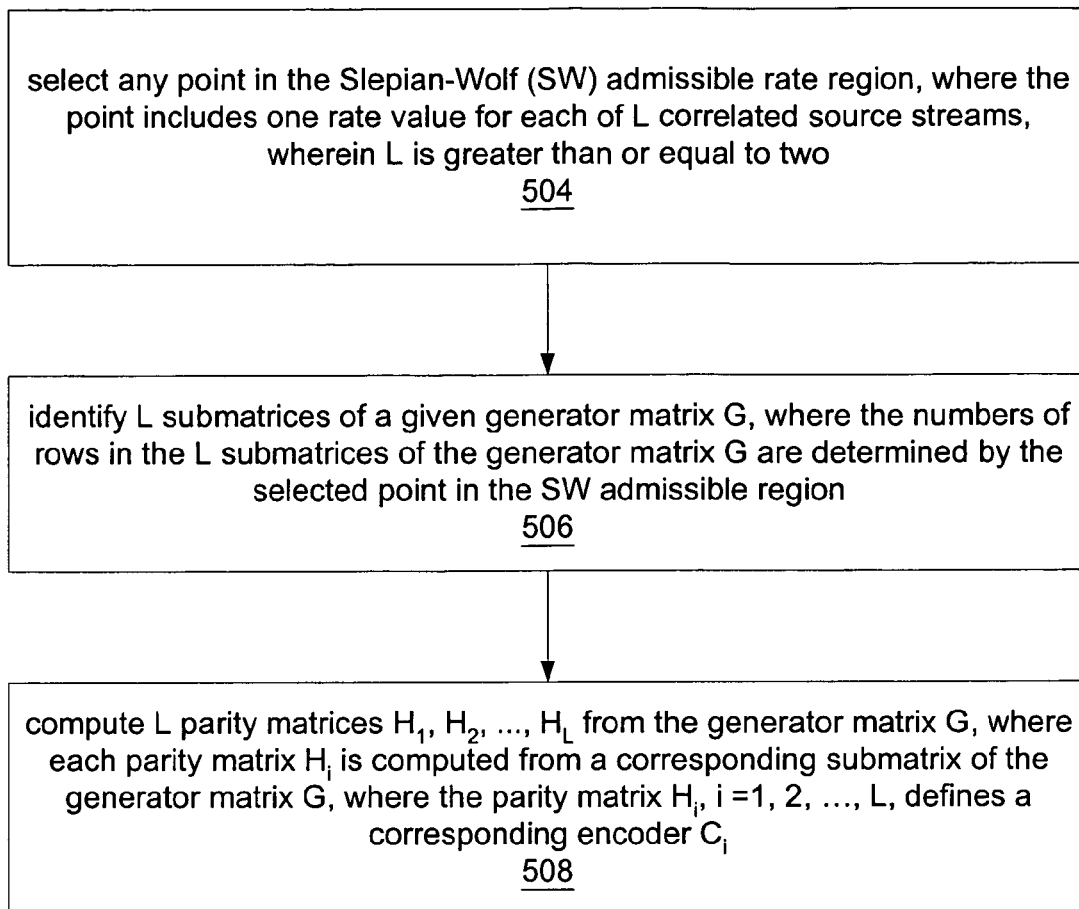


Figure 5A

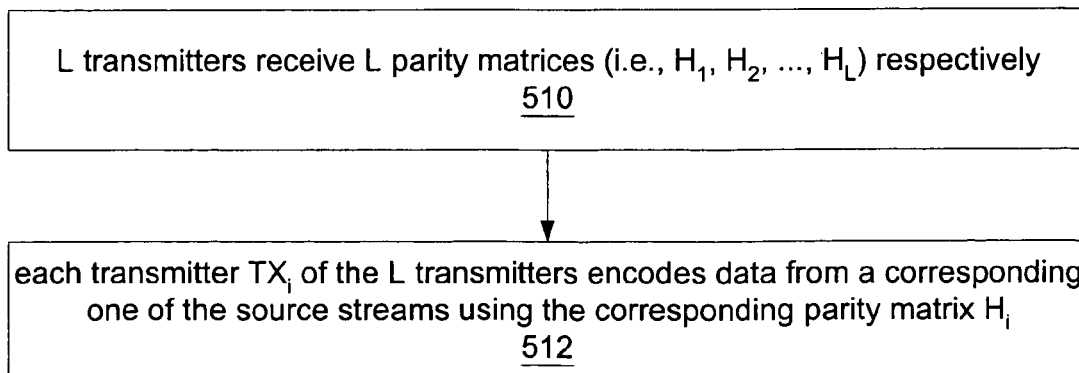


Figure 5B

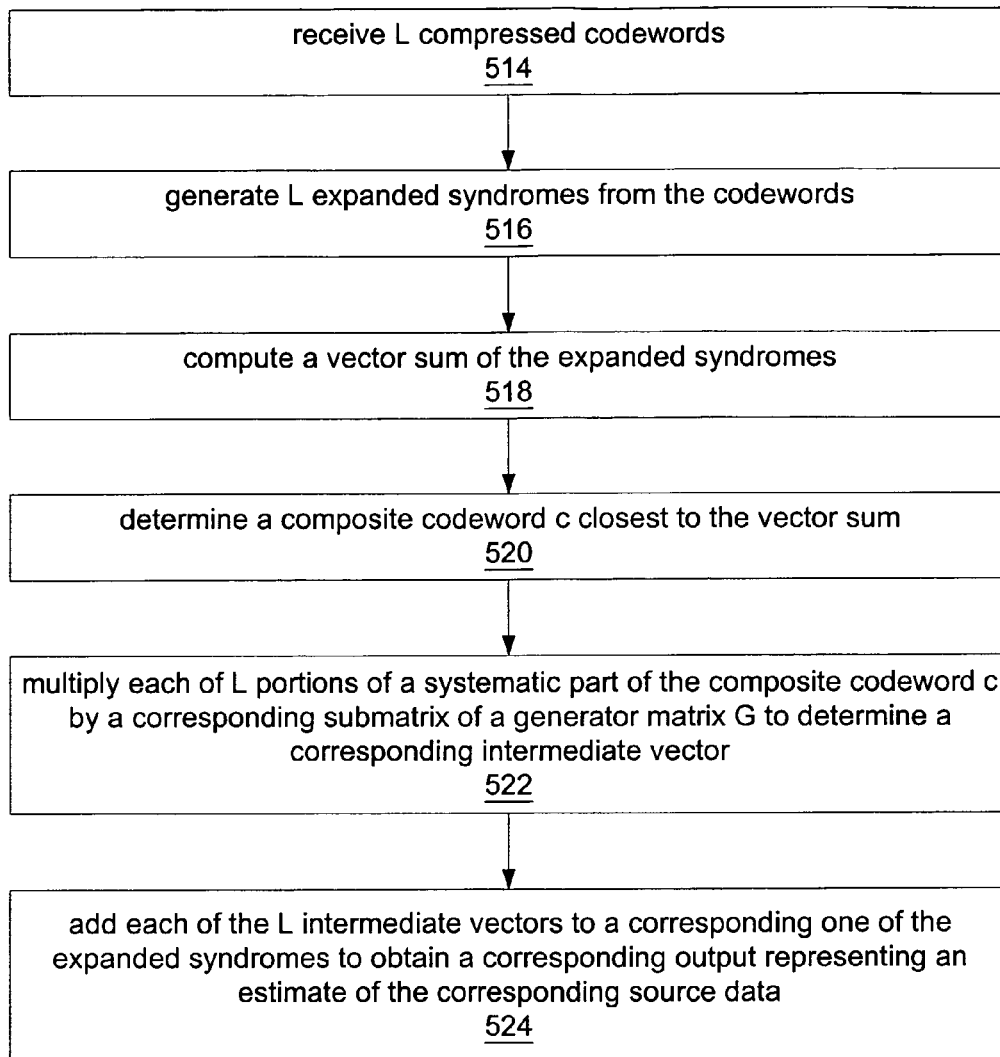


Figure 5C

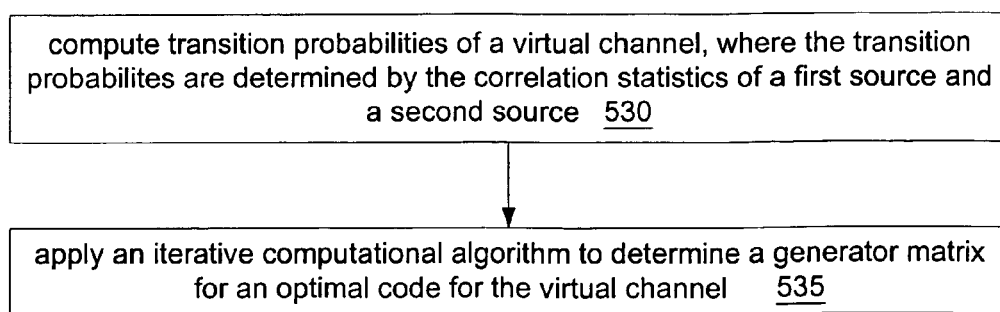


Figure 5D

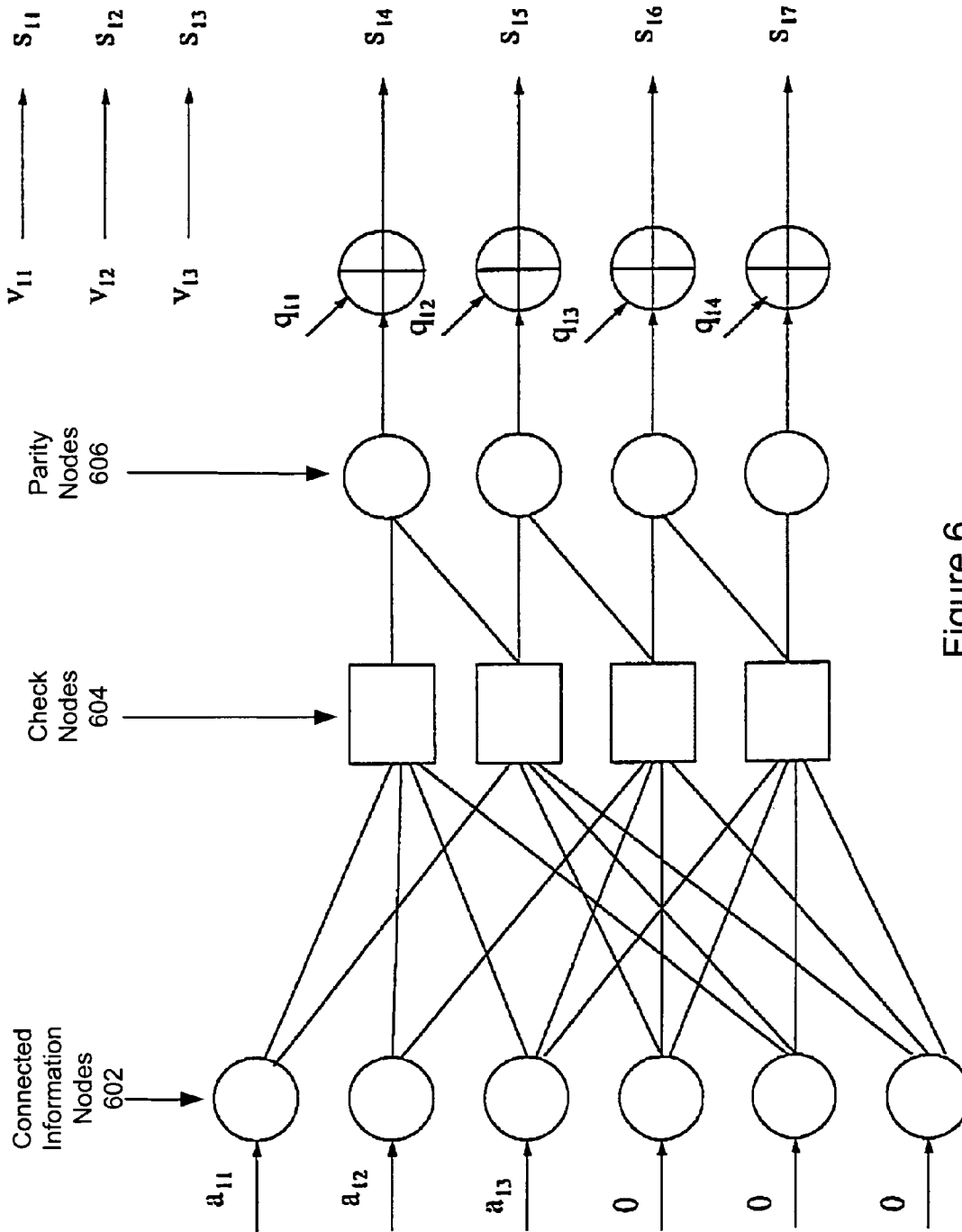


Figure 6

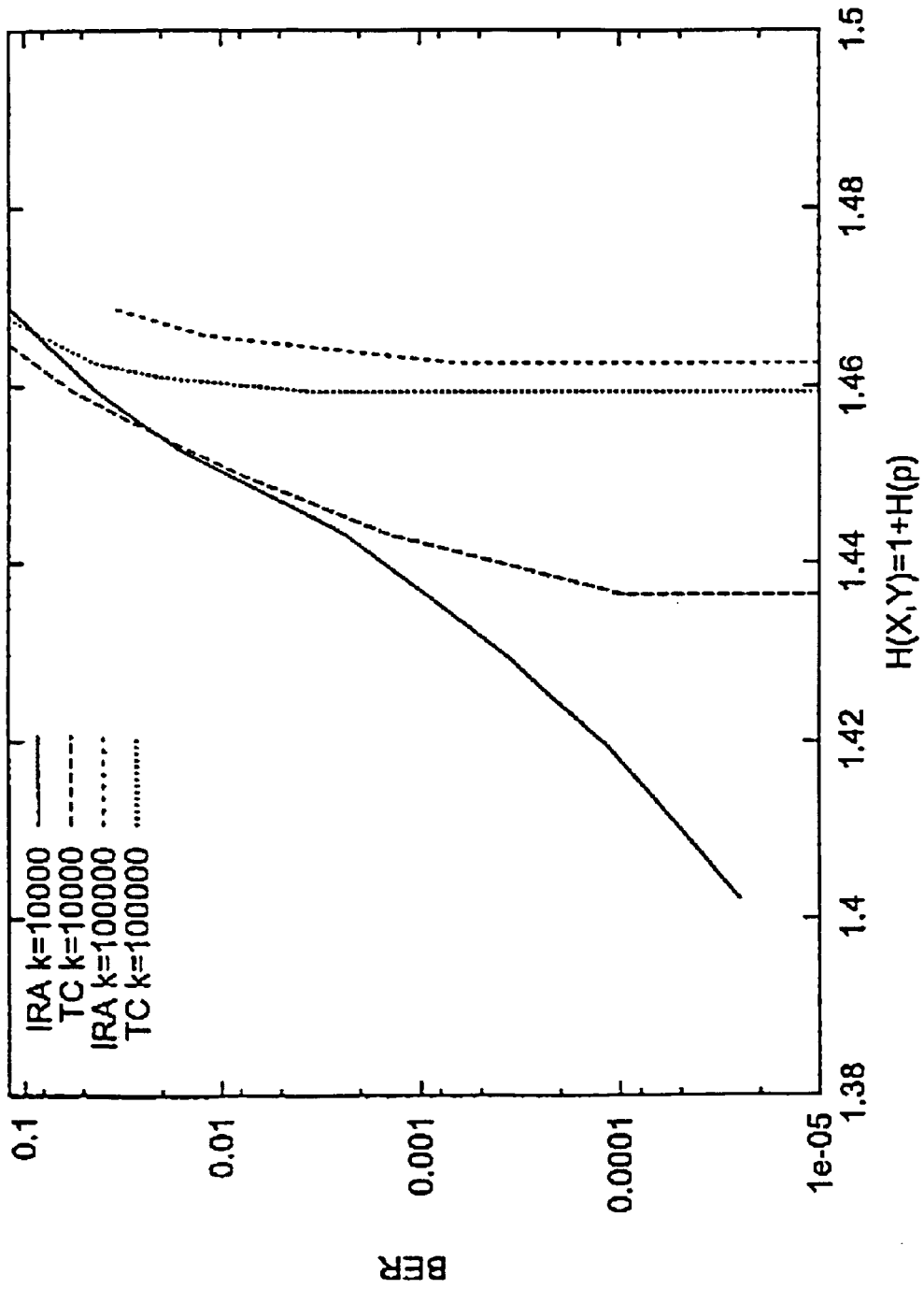


Figure 7

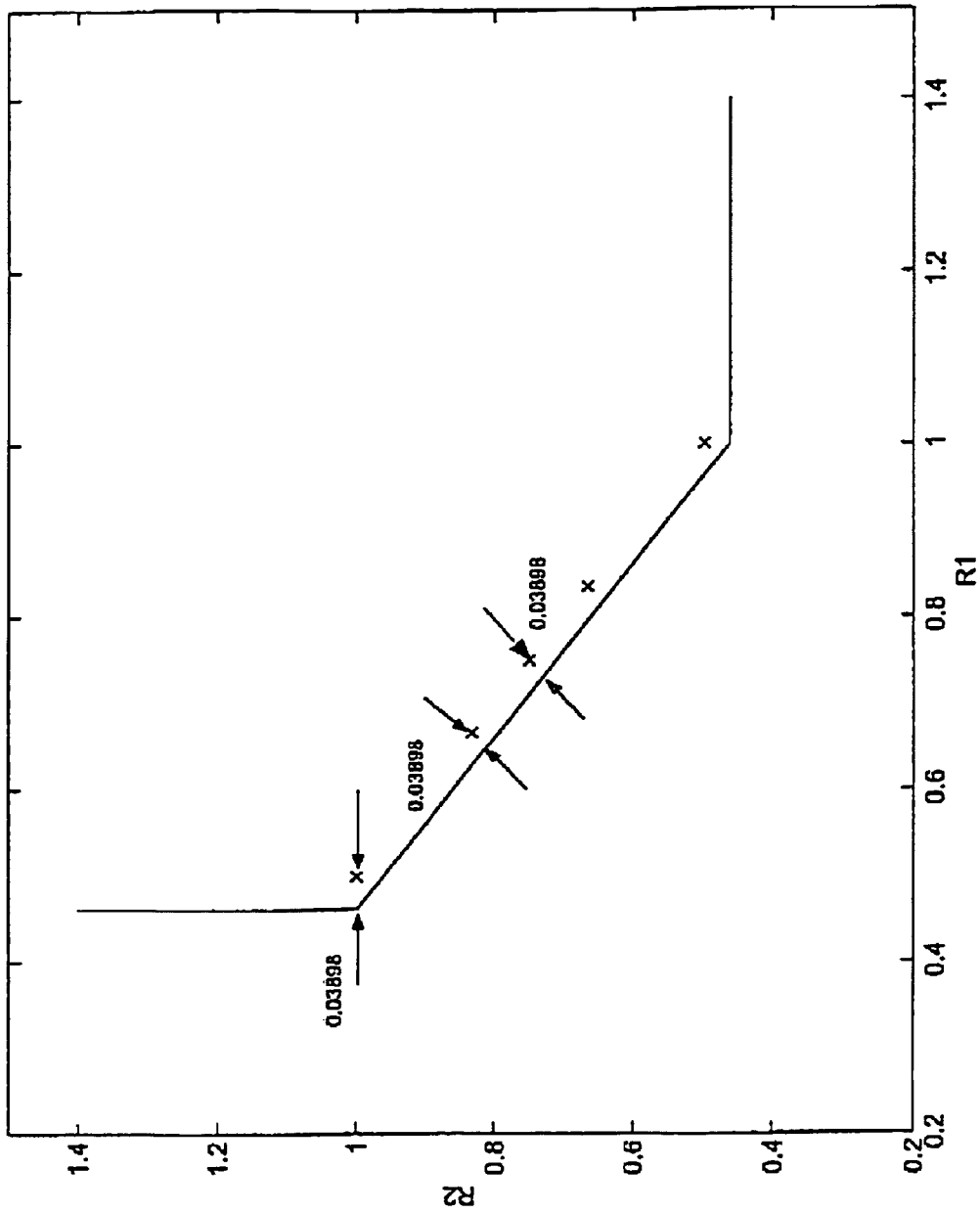


Figure 8

**MULTI-SOURCE DATA ENCODING,
TRANSMISSION AND DECODING USING
SLEPIAN-WOLF CODES BASED ON
CHANNEL CODE PARTITIONING**

The U.S. Government has a paid-up license in this invention and the right in limited circumstances to require the patent owner to license others on reasonable terms as provided for by the terms of grant number CCR-01-04834 awarded by the National Science Foundation (NSF).

FIELD OF THE INVENTION

The present invention relates to the field of information coding/decoding, and more particularly to a system and method for designing Slepian-Wolf codes for distributed source encoding/decoding.

DESCRIPTION OF THE RELATED ART

Issues related to distributed lossless compression of correlated sources are relevant for a wide variety of applications, such as distributed sensor networks and multi-source video distribution, both wired and wireless, coding for relay channels, and digital communications, among others. Distributed source coding (DSC), whose theoretical foundation was laid by Slepian and Wolf as early as 1973 (see D. Slepian and J. K. Wolf, "Noiseless coding of correlated information sources," *IEEE Trans. On Information Theory*, vol. IT-19, pp. 471-480, July 1973, incorporated by reference herein.), refers to the compression of the outputs of two or more physically separated sources that do not communicate with each other (hence distributed coding). These sources send their compressed outputs to a central point (e.g., the base station) for joint decoding. DSC is related to the well-known "CEO problem" (in which a source is observed by several agents, who send independent messages to another agent (the chief executive officer (CEO)), who attempts to recover the source to meet a fidelity constraint, where it is usually assumed that the agents observe noisy versions of the source, with the observation noise being independent from agent to agent), and is part of network information theory.

Compressing two distinct signals by exploiting their correlation can certainly provide a benefit in total rate cost. Moreover, Slepian and Wolf showed that lossless compression of two separate sources can be as efficient as if they are compressed together as long as joint decoding is done at the receiver. Several successful attempts of constructing practical coding schemes that exploit the potential of the Slepian-Wolf (SW) theorem have been developed. See, e.g., S. S. Pradhan and K. Ramchandran, "Distributed source coding using syndromes (DISCUS): design and construction," *Proc. DCC-1999, Data Compression Conference*, pp. 158-167, Snowbird, Utah, March 1999; A. Liveris, Z. Xiong, and C. Georghiadis, "Compression of binary sources with side information at the decoder using LDPC codes," *IEEE Communications Letters*, vol. 6, pp. 440-442, October 2002; A. Liveris, Z. Xiong, and C. Georghiadis, "Distributed compression of binary sources using convolutional parallel and serial concatenated convolutional codes," *Proc. DCC-2003, Data Compression Conference*, pp. 193-202, Snowbird, Utah, March 2003; A. Aaron and B. Girod, "Compression of side information using turbo codes," *Proc. DCC-2002, Data Compression Conference*, pp. 252-261, Snowbird, Utah, April 2002; J. Garcia-Frias and Y. Zhao, "Compression of correlated binary sources using turbo codes," *IEEE Communications Letters*, vol. 5, pp. 417-419, October 2001; and J.

Bajcy and P. Mitran, "Coding for the Slepian-Wolf problem with turbo codes," *Proc. IEEE Globecom-2001*, vol. 2 pp. 1400-1404, San Antonio, Tex., November 2001, all of which are incorporated by reference herein. All these schemes, with the exception of that of Garcia-Frias and Zhao, are based on asymmetric codes (see, e.g., S. S. Pradhan and K. Ramchandran, "Generalized coset codes for symmetric distributed source coding," included herewith as Appendix G); that is, they losslessly compress one source, while the other source is assumed to be perfectly known at the decoder side and is used as side information.

Thus, for two discrete, memoryless, identically distributed sources X and Y encoded separately at rates R_1 and R_2 , respectively, these codes attempt to reach the two corner points on the Slepian-Wolf (SW) bound: $(R_1, R_2) = (H(X), H(Y|X))$ and $(R_1, R_2) = (H(Y), H(X|Y))$. However, often it is desirable to vary the rates of individual encoders while keeping the total sum-rate constant. One technique for achieving this is time sharing. However, time sharing might not be practical because it requires exact synchronization among encoders.

A second technique is the source-splitting approach of Rimoldi and Urbanke (see B. Rimoldi and R. Urbanke, "Asynchronous Slepian-Wolf coding via source-splitting", *Proc. ISIT-1997 IEEE Int. Symp. Information Theory*, pp. 271, Ulm, Germany, June, 1997, incorporated by reference herein), which potentially reaches all points on the SW bound by splitting two sources into three subsources of lower entropy. Garcia-Frias and Zhao, in the reference cited above, proposed a system consisting of two different turbo codes which form a large turbo code with four component codes. In the symmetric scenario suggested (where the rates of both encoders are the same), half of the systematic bits from one encoder and half from the other are sent. Further, instead of syndrome bits, parity bits are sent.

Pradhan and Ramchandran have outlined a method for constructing a single code based on the syndrome technique, which achieves arbitrary rate allocation among the two encoders (see S. S. Pradhan and K. Ramchandran, "Generalized coset codes for symmetric distributed source coding," included herewith as Appendix G; S. S. Pradhan and K. Ramchandran, "Distributed source coding: symmetric rates and applications to sensor networks," *Proc. DCC-2000, Data Compression Conference*, pp. 363-372, Snowbird, Utah, March 2000; and S. S. Pradhan and K. Ramchandran, "Distributed source coding using syndromes (DISCUS): design and construction," *Proc. DCC-1999, Data Compression Conference*, pp. 158-167, Snowbird, Utah, March 1999, incorporated by reference herein.). The method constructs independent subcodes of the main code and assigns them to different encoders. Each encoder sends only partial information about the source; by combining two received bitstreams, a joint decoder should perfectly reconstruct the sources. Since joint decoding is performed only on a single code, if this code approaches the capacity of a channel that models the correlation among the sources, the system will approach the SW limit. Thus, an advantage of this approach is the need of only one good channel code. Pradhan and Ramchandran also showed that this code does not suffer from any performance loss compared to the corresponding asymmetric code. Moreover, any point on the SW bound can be potentially reached without increasing the encoding/decoding complexity. Further, Pradhan and Ramchandran applied the method to coding of two noisy observations of a source with scalar quantizer and trellis codes.

While the theoretical limits and bounds of SW coding are well understood, practical implementations and their actual performance and limits of have not heretofore been determined.

SUMMARY OF THE INVENTION

One embodiment of the present invention comprises a system and method for implementing Slepian-Wolf codes by channel code partitioning.

In one embodiment, a generator matrix is partitioned to generate a plurality of sub-matrices corresponding respectively to a plurality of correlated data sources. The partitioning may be performed in accordance with a rate allocation among the plurality of correlated data sources. A corresponding plurality of parity matrices may then be generated based respectively on the sub-matrices, where each parity matrix is useable to encode correlated data for a respective correlated data source.

BRIEF DESCRIPTION OF THE DRAWINGS

A better understanding of the present invention can be obtained when the following detailed description of the preferred embodiment is considered in conjunction with the following drawings, in which:

FIG. 1A illustrates a computer system suitable for implementing various embodiments of the present invention;

FIG. 1B illustrates a network system comprising two or more computer systems that may implement an embodiment of the present invention;

FIG. 2 is an exemplary block diagram of the computer systems of FIGS. 1A and 1B;

FIGS. 3A and 3B illustrate exemplary applications of the present invention, according to various embodiments;

FIG. 4 is a flowchart diagram illustrating one embodiment of a method for Slepian-Wolf coding;

FIGS. 5A-5D flowchart more detailed embodiments of the method of FIG. 4;

FIG. 6 illustrates Slepian-Wolf encoding, according to one embodiment; and

FIGS. 7 and 8 illustrate simulation results with IRA codes and turbo codes together with the SW bound, according to one embodiment.

While the invention is susceptible to various modifications and alternative forms, specific embodiments thereof are shown by way of example in the drawings and are herein described in detail. It should be understood, however, that the drawings and detailed description thereto are not intended to limit the invention to the particular form disclosed, but on the contrary, the intention is to cover all modifications, equivalents and alternatives falling within the spirit and scope of the present invention as defined by the appended claims.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Incorporation By Reference

The following references are hereby incorporated by reference in their entirety as though fully and completely set forth herein:

U.S. Provisional Application Ser. No. 60/657,520, titled "Multi-Source Data Encoding, Transmission and Decoding", filed Mar. 1, 2005;

U.S. patent application Ser. No. 11/068,737, titled "Data Encoding and Decoding Using Slepian-Wolf Coded Nested

Quantization to Achieve Wyner-Ziv Coding", filed Mar. 1, 2005, whose inventors are Zhixin Liu, Samuel S. Cheng, Angelos D. Liveris, and Zixiang Xiong.

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APPENDICES

This application includes eight appendices labeled A-H.

Appendix A comprises a paper titled: "Design of Slepian-Wolf Codes by Channel Code Partitioning" by Vladimir M. Stankovic, Angelos D. Liveris, Zixiang Xiong, and Costas N. Georghiadis.

Appendix B comprises a paper titled: "On Code Design for the Slepian-Wolf Problem and Lossless Multiterminal Networks" by Vladimir M. Stankovic, Angelos D. Liveris, Zixiang Xiong, and Costas N. Georghiadis.

Appendix C comprises a paper titled: "Slepian-Wolf Coded Nest Quantization (SWC-NQ) for Wyner-Ziv Coding: Performance Analysis and Code Design" by Zhixin Liu, Samuel S. Cheng, Angelos D. Liveris & Zixiang Xiong.

Appendix D comprises a paper titled: "Slepian-Wolf Coded Nested Lattice Quantization for Wyner-Ziv Coding: High Rate Performance Analysis and Code Design" by Zhixin Liu, Samuel S. Cheng, Angelos D. Liveris & Zixiang Xiong.

Appendix E comprises a paper titled: "Layered Wyner-Ziv Video Coding" by Qian Xu and Zixiang Xiong.

Appendix F comprises a paper titled: "A Turbo Code Tutorial" by William E. Ryan.

Appendix G comprises a paper titled: "Generalized Coset Codes for Symmetric Distributed Source Coding" by S. Sandeep Pradhan and Kannan Ramchandran.

Appendix H comprises a paper titled: "Compression of Binary Sources with Side Information at the Decoder Using LDPC Codes" by Angelos D. Liveris, Zixiang Xiong and Costas N. Georghiadis.

Terms

The following is a glossary of terms used in the present application:

Memory Medium—Any of various types of memory devices or storage devices. The term "memory medium" is intended to include an installation medium, e.g., a CD-ROM, floppy disks **104**, or tape device; a computer system memory or random access memory such as DRAM, DDR RAM, SRAM, EDO RAM, Rambus RAM, etc.; or a non-volatile memory such as a magnetic media, e.g., a hard drive, or optical storage. The memory medium may comprise other types of memory as well, or combinations thereof. In addition, the memory medium may be located in a first computer in which the programs are executed, or may be located in a second different computer which connects to the first computer over a network, such as the Internet. In the latter instance, the second computer may provide program instructions to the first computer for execution. The term "memory medium" may include two or more memory mediums which may reside in different locations, e.g., in different computers that are connected over a network.

Carrier Medium—a memory medium as described above, as well as signals such as electrical, electromagnetic, or digital signals, conveyed via a communication medium such as a bus, network and/or a wireless link.

Programmable Hardware Element—includes various types of programmable hardware, reconfigurable hardware, programmable logic, or field-programmable devices (FPDs), such as one or more FPGAs (Field Programmable Gate Arrays), or one or more PLDs (Programmable Logic Devices), such as one or more Simple PLDs (SPLDs) or one or more Complex PLDs (CPLDs), or other types of program-

mable hardware. A programmable hardware element may also be referred to as "reconfigurable logic".

Medium—includes one or more of a memory medium, carrier medium, and/or programmable hardware element; encompasses various types of mediums that can either store program instructions/data structures or can be configured with a hardware configuration program. For example, a medium that is "configured to perform a function or implement a software object" may be 1) a memory medium or carrier medium that stores program instructions, such that the program instructions are executable by a processor to perform the function or implement the software object; 2) a medium carrying signals that are involved with performing the function or implementing the software object; and/or 3) a programmable hardware element configured with a hardware configuration program to perform the function or implement the software object.

Program—the term "program" is intended to have the full breadth of its ordinary meaning. The term "program" includes 1) a software program which may be stored in a memory and is executable by a processor or 2) a hardware configuration program useable for configuring a programmable hardware element.

Software Program—the term "software program" is intended to have the full breadth of its ordinary meaning, and includes any type of program instructions, code, script and/or data, or combinations thereof, that may be stored in a memory medium and executed by a processor. Exemplary software programs include programs written in text-based programming languages, such as C, C++, Pascal, Fortran, Cobol, Java, assembly language, etc.; graphical programs (programs written in graphical programming languages); assembly language programs; programs that have been compiled to machine language; scripts; and other types of executable software. A software program may comprise two or more software programs that interoperate in some manner.

Hardware Configuration Program—a program, e.g., a netlist or bit file, that can be used to program or configure a programmable hardware element.

Graphical User Interface—this term is intended to have the full breadth of its ordinary meaning. The term "Graphical User Interface" is often abbreviated to "GUI". A GUI may comprise only one or more input GUI elements, only one or more output GUI elements, or both input and output GUI elements.

The following provides examples of various aspects of GUIs. The following examples and discussion are not intended to limit the ordinary meaning of GUI, but rather provide examples of what the term "graphical user interface" encompasses:

A GUI may comprise a single window having one or more GUI Elements, or may comprise a plurality of individual GUI Elements (or individual windows each having one or more GUI Elements), wherein the individual GUI Elements or windows may optionally be tiled together.

A GUI may be associated with a graphical program. In this instance, various mechanisms may be used to connect GUI Elements in the GUI with nodes in the graphical program. For example, when Input Controls and Output Indicators are created in the GUI, corresponding nodes (e.g., terminals) may be automatically created in the graphical program or block diagram. Alternatively, the user can place terminal nodes in the block diagram which may cause the display of corresponding GUI Elements front panel objects in the GUI, either at edit time or later at run time. As another example, the GUI may comprise GUI Elements embedded in the block diagram portion of the graphical program.

Computer System—any of various types of computing or processing systems, including a personal computer system (PC), mainframe computer system, workstation, network appliance, Internet appliance, personal digital assistant (PDA), television system, grid computing system, or other device or combinations of devices. In general, the term “computer system” can be broadly defined to encompass any device (or combination of devices) having at least one processor that executes instructions from a memory medium.

FIG. 1A—Computer System

FIG. 1A illustrates a computer system **82** operable to execute a program configured to implement various embodiments of the present invention. As shown in FIG. 1A, the computer system **82** may include input devices such as a mouse and keyboard, output devices (such as a display device and speakers). The computer system **82** may also include a network interface (e.g., an Ethernet card) for communicating with other computers over a network.

The computer system **82** may include a memory medium(s) on which one or more computer programs or software components according to any of various embodiments of the present invention may be stored. For example, the memory medium may store one or more programs which are executable to perform any or all of the methods described herein. The memory medium may also store operating system software, as well as other software for operation of the computer system. Various embodiments further include receiving or storing instructions and/or data implemented in accordance with the foregoing description upon a carrier medium.

FIG. 1B—Computer Network

FIG. 1B illustrates a system including a first computer system **82** that is coupled to a second computer system **90**. The computer system **82** may be connected through a network **84** (or a computer bus) to the second computer system **90**. The computer systems **82** and **90** may each be any of various types, as desired. The network **84** can also be any of various types, including a LAN (local area network), WAN (wide area network), the Internet, or an Intranet, among others. The computer systems **82** and **90** may execute a program in a distributed fashion. For example, computer **82** may execute a first portion of the program and computer system **90** may execute a second portion of the program.

As another example, computer **82** may display the graphical user interface of a program and computer system **90** may execute a portion of the program implementing the main functionality (i.e., the non-user interface portion) of the program.

In one embodiment, the graphical user interface of the program may be displayed on a display device of the computer system **82**, and the remaining portion of the program may execute on a device **190** connected to the computer system **82**. The device **190** may include a programmable hardware element and/or may include a processor and memory medium which may execute a real time operating system. In one embodiment, the program may be downloaded and executed on the device **190**. For example, an application development environment with which the program is associated may provide support for downloading a program for execution on the device in a real time system.

FIG. 2—Computer System Block Diagram

FIG. 2 is a block diagram representing one embodiment of the computer system **82** and/or **90** illustrated in FIGS. 1A and 1B. It is noted that any type of computer system configuration or architecture can be used as desired, and FIG. 2 illustrates a representative PC embodiment. It is also noted that the com-

puter system may be a general purpose computer system, a computer implemented on a card installed in a chassis, or other types of embodiments. Elements of a computer not necessary to understand the present description have been omitted for simplicity.

The computer may include at least one central processing unit or CPU (processor) **160** which is coupled to a processor or host bus **162**. The CPU **160** may be any of various types, including an x86 processor, e.g., a Pentium class, a PowerPC processor, a CPU from the SPARC family of RISC processors, as well as others. A memory medium, typically comprising RAM and referred to as main memory, **166** is coupled to the host bus **162** by means of memory controller **164**. The main memory **166** may store programs operable to implement Slepian-Wolf coding according to various embodiments of the present invention. The main memory may also store operating system software, as well as other software for operation of the computer system.

The host bus **162** may be coupled to an expansion or input/output bus **170** by means of a bus controller **168** or bus bridge logic. The expansion bus **170** may be the PCI (Peripheral Component Interconnect) expansion bus, although other bus types can be used. The expansion bus **170** includes slots for various devices such as described above. As shown, the computer comprises a network card **122** for communication with other devices, e.g., distributed sensor or video distribution systems, other computer systems, etc. The computer **82** further comprises a video display subsystem **180** and hard drive **182** coupled to the expansion bus **170**.

As shown, a device **190** may also be connected to the computer. The device **190** may include a processor and memory which may execute a real time operating system. The device **190** may also or instead comprise a programmable hardware element. The computer system may be operable to deploy programs according to various embodiments of the present invention to the device **190** for execution of the program on the device **190**.

FIGS. 3A and 3B—Exemplary Systems

Various embodiments of the present invention may be directed to distributed sensor systems, wireless or wired distributed video systems, or any other type of information processing or distribution systems utilizing information coding, e.g., Slepian-Wolf coding.

For example, FIG. 3A illustrates one embodiment of a distributed sensor system. As FIG. 3A shows, a receiver **308** may be operable to receive signals, e.g., correlated signals, from a plurality of sources, specifically from a plurality of sensors **306**.

However, it is noted that the present invention can be used for a plethora of applications and is not limited to the above applications. In other words, applications discussed in the present description are exemplary only, and the present invention may be used in any of various types of systems. Thus, the system and method of the present invention is operable to be used in any of various types of applications, including the control of other types of devices such as multimedia devices, video devices, audio devices, telephony devices, Internet devices, etc., as well as network control, network monitoring, financial applications, entertainment, games, etc.

FIG. 4—Method for Slepian-Wolf Coding for Multiple Data Sources

FIG. 4 illustrates a method for realizing a system of L encoders and a joint decoder for L correlated sources, where L is an integer greater than or equal to two, according to one set of embodiments. In various embodiments, some of the method elements shown may be performed concurrently, in a

different order than shown, or may be omitted. Additional method elements may also be performed as desired. As shown, this method may operate as follows.

In 420, L codes (including L encoders and L corresponding decoders) are specified given a generator matrix G. Embodiments of a method for specifying the L codes, given the generator matrix G, are described more fully below.

In 430, data from the L correlated sources are encoded using the L encoders, respectively. Embodiments of a method for performing the encoding are described more fully below.

In 440, the L encoded streams are decoded to recover information generated by the L sources. Embodiments of a method for performing the decoding are described more fully below.

FIG. 5A—Method for Specifying Slepian-Wolf Codes for Multiple Data Sources

FIG. 5A illustrates one embodiment of a method for specifying L codes for L correlated source streams. In 504, any point in the Slepian-Wolf (SW) admissible rate region may be selected. The point includes one rate value for each of the L sources streams. L is an integer greater than or equal to one (further, any point in the Slepian-Wolf (SW) admissible rate region may be selected, where the point includes one rate value for each of L correlated source streams, wherein L is greater than or equal to two). For example, a point arbitrary close to the SW sum rate limit may be selected. In various embodiments, some of the method elements shown may be performed concurrently, in a different order than shown, or may be omitted. Additional method elements may also be performed as desired. As shown, this method may operate as follows.

In 506, L submatrices of a given generator matrix G may be identified. The L submatrices may be disjoint submatrices each having the same number of columns as the matrix G. The numbers of rows in the L submatrices of the generator matrix G are determined by the selected point in the SW admissible rate region. This process of identifying L submatrices of the generator matrix G is also referred to as partitioning the generator matrix G. See below for further description of how these submatrices are identified.

In 508, L parity matrices H_1, H_2, \dots, H_L may be computed from the generator matrix G. Each parity matrix H_i is computed from a corresponding submatrix of the generator matrix G. The parity matrix $H_i, i=1, 2, \dots, L$, defines a corresponding encoder C_i , according to the relation: $(s_i)^T = H_i(x_i)^T$, wherein x_i represents a block of samples from the corresponding source stream, wherein s_i represents a result of the encoder C_i .

FIG. 5B—Method for Slepian-Wolf Encoding of Multiple Data Sources

FIG. 5B illustrates one embodiment of a method for operating L transmitters in order to encode L respective source streams, where L is an integer greater than or equal to two. In various embodiments, some of the method elements shown may be performed concurrently, in a different order than shown, or may be omitted. Additional method elements may also be performed as desired. As shown, this method may operate as follows.

In 510, each of the transmitters $TX_i, i=1, 2, \dots, L$, receives a corresponding parity matrix H_i (computed as described above). See description below for more definition of the parity matrices.

In 512, each transmitter of the L transmitters encodes data from a corresponding one of the source streams using the corresponding parity matrix H_i . For example, each transmitter may encode data of a corresponding source stream according to the relation: $(s_i)^T = H_i(x_i)^T$ wherein x_i represents a block

of samples from the corresponding source stream, wherein s_i represents a result of the encoding.

FIG. 5C—Method for Decoding Slepian-Wolf Encoded Data from Multiple Data Sources

FIG. 5C illustrates one embodiment of a method for decoding L compressed streams of information, where L is greater than or equal to two. In various embodiments, some of the method elements shown may be performed concurrently, in a different order than shown, or may be omitted. Additional method elements may also be performed as desired. As shown, this method may operate as follows.

In 514, a receiver may receive L codewords s_1, s_2, \dots, s_L (e.g., from L respective transmitters). The L codewords represent data from L information sources respectively.

In 516, the receiver generates L expanded syndromes (also referred to herein as t_1, t_2, \dots, t_L) from the codewords s_1, s_2, \dots, s_L by inserting zero or more zero values at appropriate locations (see discussion below) into each codeword, so that each of the expanded syndromes have the same length.

In 518, the receiver computes a vector sum of the expanded syndromes.

In 520, the receiver determines a composite codeword c closest to the vector sum (e.g., in the sense of Hamming distance).

In 522, the receiver multiplies each of L portions of a systematic part of the composite codeword c by a corresponding submatrix of a generator matrix G to obtain a corresponding intermediate vector; thus, L intermediate vectors are obtained altogether.

In 524, the receiver adds each of the L intermediate vectors to a corresponding one of the expanded syndromes to obtain a corresponding output representing an estimate of the corresponding source data.

FIG. 5D illustrates an embodiment of a method. In 530, the transition probabilities of a virtual channel are computed, where the transition probabilities are determined by the correlation statistics of a first source and a second source. In 535, an iterative computational algorithm is applied to determine a generator matrix for an optimal code for the virtual channel.

Slepian-Wolf Coding

Various embodiments of the present invention provide a clear and detailed solution to the problem of practical implementation of Slepian-Wolf codes. More specifically, the approach is based on systematic codes so that advanced channel codes can be employed to yield Slepian-Wolf (SW) codes that can approach any point on the theoretical bound. Additionally, practical low-complexity code designs based on powerful systematic channel codes are described. In A. Liveris, Z. Xiong, and C. Georgiades, "Compression of binary sources with side information at the decoder using LDPC codes," *IEEE Communications Letters*, vol. 6, pp. 440-442, October 2002, it was shown that with low-density parity-check (LDPC) codes it is possible to approach the theoretical limits in the SW asymmetric scenario. Irregular repeat-accumulate (IRA) codes (see H. Jin, A. Khandekar, and R McEliece, "Irregular repeat-accumulate codes," *Proc. of 2nd International Symposium on Turbo codes and related topics*, pp. 1-8, September 2000, incorporated by reference above.) are a special form of LDPC codes which suffer very small performance loss, but can easily be coded in systematic form and have low encoding complexity which make them suitable for multiterminal coding (see T. Berger, "Multiterminal source coding", *The Information Theory Approach to Communications*, G. Longo, Ed., New York: Springer-Verlag,

1977, incorporated by reference above.). Accordingly, IRA codes have been used in experiments described herein.

Additionally, to illustrate an exemplary implementation of the present scheme with convolutional codes, powerful turbo codes (see C. Berrou, A. Glavieux, and P. Thitimajshima, "Near Shannon limit error-correcting coding and decoding: Turbo codes," *Proc. ICC'93, IEEE Int. Conf. on Comm.*, pp. 1064-1070, Geneva, 1993, incorporated by reference above.) are also treated. Turbo codes have already been successfully applied to asymmetric SW and Wyner-Ziv (see A. D. Wyner and J. Ziv, "The rate-distortion function for source coding with side information at the decoder", *IEEE Trans. on Information Theory*, vol. IT-22, pp. 1-10, January 1976, incorporated by reference above.) coding of two sources. Good results are obtained with both conventional (see, e.g., A. Liveris, Z. Xiong, and C. Georghiades, "Distributed compression of binary sources using convolutional parallel and serial concatenated convolutional codes," *Proc. DCC-2003, Data Compression Conference*, pp. 193-205, Snowbird, Utah, March 2003; and J. Chou, S. S. Pradhan and K. Ramchandran, "Turbo and trellis-based constructions for source coding with side information," *Proc. DCC-2003, Data Compression Conference*, pp. 33-42, Snowbird, Utah, March 2003, both of which were incorporated by reference above.) and nonconventional turbo schemes (see, e.g., A. Aaron and B. Girod, "Compression of side information using turbo codes," *Proc. DCC-2002, Data Compression Conference*, pp. 252-261, Snowbird, Utah, April 2002; J. Garcia-Frias and Y. Zhao, "Compression of correlated binary sources using turbo codes," *IEEE Communications Letters*, vol. 5, pp. 417-419, October 2001; and J. Bajcy and P. Mitran, "Coding for the Slepian-Wolf problem with turbo codes," *Proc. IEEE Globecom-2001*, vol. 2 pp. 1400-1404, San Antonio, Tex., November 2001, each of which were incorporated by reference above.) Various embodiments of the present invention implement symmetric SW coding using conventional punctured turbo codes.

Also presented herein is an extension of the method (see S. S. Pradhan and K. Ramchandran, "Generalized coset codes for symmetric distributed source coding," included herewith as Appendix G; and B. Rimoldi and R. Urbanke, "Asynchronous Slepian-Wolf coding via source-splitting", *Proc. ISIT-1997 IEEE Int. Symp. Information Theory*, pp. 271, Ulm, Germany, June, 1997, incorporated by reference above.) to SW coding of multiple sources (see, e.g., T. Cover, "A proof of the data compression theorem of Slepian and Wolf for ergodic sources", *IEEE Trans. on Information Theory*, vol. IT-21, pp. 226-228, March 1975, incorporated by reference above.), which is of special importance in sensor networks (and wireless video distribution, among other application domains). For example, after quantization of an observed corrupted version of the source, each distinct sensor may encode its observation by exploiting the correlation between the observations and the source (see Y. Oohama, "The Rate-Distortion Function for the Quadratic Gaussian CEO Problem," *IEEE Trans. on Information Theory*, vol. 44, pp. 1057-1070, May 1998, incorporated by reference above.).

Thus, to reach the theoretical limits (see, Y. Oohama, cited above), a code for lossless compression capable of trading-off transmission rates among sensors is needed. It is shown herein that as long as the correlation among the sources is

such that their sum is a Bernoulli-p process, a single channel code can be used to approach the joint entropy limit. In addition, the complexity of encoding/decoding does not exceed that of the asymmetric codes. Furthermore, in contrast to the asymmetric codes, the obtained code has additional error detection capability.

Below, a method for designing a single code for SW coding of multiple sources is first described, then how this theoretical approach can be applied to practical code constructions using systematic IRA and turbo codes. Finally, experimental results for two sources and conclusions are provided.

Multiple Source Slepian-Wolf Coding

Consider an SW coding system which consists of L encoders and a joint decoder. Let X_1, \dots, X_L be discrete, memoryless, uniformly distributed correlated random sources and let x_1, \dots, x_L denote their realizations. The i-th encoder compresses X_i at rate R_i independently from the information available at other encoders. The decoder receives the bitstreams from all the encoders and jointly decodes them. It should reconstruct all received source messages with arbitrarily small probability of error. The achievable rate region is then (see T. Cover, "A proof of the data compression theorem of Slepian and Wolf for ergodic sources", *IEEE Trans. on Information Theory*, vol. IT-21, pp. 226-228, March 1975.):

$$R_{i_1} + \dots + R_{i_k} \leq H(X_{i_1}, \dots, X_{i_k} | X_{j_1}, \dots, X_{j_{L-k}})$$

where for $k \leq L$, $\{i_1, \dots, i_k\} \subseteq \{1, \dots, L\}$, and $\{j_1, \dots, j_{L-k}\} = \{1, \dots, L\} \setminus \{i_1, \dots, i_k\}$.

A practical code may be constructed that can potentially approach the above bound for any achievable rate allocation among the encoders. The binary case is treated, where it is assumed that all X_i 's are of length n bits.

Definition 1 A general SW code is a pair (C, M), where C is an (n, k) linear binary channel code given by generator matrix $G_{k \times n}$, and M is an ordered set of integers $\{m_1, \dots, m_L\}$ such that $\sum_{j=1}^L m_j = k$.

For each $i=1, \dots, L$, code C_i may be formed as a subcode of C with generator matrix G_{i, m_i} which consists of m_i rows of G starting from row $m_1 + \dots + m_{i-1} + 1$. Without loss of generality suppose that the code C is systematic. Let $m_{i-} = m_1 + \dots + m_{i-1}$ and $m_{i+} = m_{i+1} + \dots + m_L$. I_k denotes the kxk identity matrix, and $O_{k_1 \times k_2}$ is the $k_1 \times k_2$ all-zero matrix. Then, for $G = [I_k \ P_{k \times (n-k)}]$, the generator matrix of subcode C_i is

$$G_i = [O_{m_i \times m_i} \ I_{m_i} \ O_{m_i \times m_{i-}} \ P_{i, m_i \times (n-k)}] \quad (1)$$

where $P^T = [P_1^T \ \dots \ P_L^T]$.

One choice for the $(n-m_i) \times n$ parity matrix H_i of C_i is

$$H_i = \begin{bmatrix} I_{m_i} & O_{m_i \times m_i} & O_{m_i \times m_{i+}} & O_{m_i \times (n-k)} \\ O_{m_{i+} \times m_i} & O_{m_{i+} \times m_i} & I_{m_{i+}} & O_{m_{i+} \times (n-k)} \\ O_{(n-k) \times m_i} & P_i^T & O_{(n-k) \times m_{i+}} & I_{n-k} \end{bmatrix} \quad (2)$$

Encoding may be performed by multiplication of the incoming n-length vector $x_i = [u_i \ a_i \ v_i \ q_i]$ (vectors u_i , a_i , v_i , and q_i are of length m_{i-} , m_i , m_{i+} , and $n-k$, respectively) with the parity matrix H_i . In this way the syndrome vector $s_i^T = H_i x_i^T$ of length $n-m_i$ may be formed as:

$$s_i^T = \begin{bmatrix} u_i^T \\ v_i^T \\ q_i^T \oplus P_i^T a_i^T \end{bmatrix}, \quad (3)$$

where \oplus denotes addition in GF(2).

Let a length n row-vector t_i be defined as

$$t_i^T = \begin{bmatrix} u_i^T \\ 0_{m_i \times 1} \\ v_i^T \\ q_i^T \oplus P_i^T a_i^T \end{bmatrix}. \quad (4)$$

Then, $x_i \oplus t_i = a_i G_i$ is a valid codeword of C_i , and thus also of C . The decoder collects all syndromes s_1, \dots, s_L and forms the sum $t_1 \oplus \dots \oplus t_L$. From linearity, it follows that $x_1 \oplus t_1 \oplus \dots \oplus x_L \oplus t_L$ is a valid codeword of C . The task of the decoder is then to find a codeword c that is closest (in Hamming distance) to the vector $t_1 \oplus \dots \oplus t_L$. Let the vector $[\hat{a}_1 \dots \hat{a}_L]$ be the systematic part of the codeword c . The sources may be recovered as: $\hat{x}_i = \hat{a}_i G_i \oplus t_i$.

Given the length of the messages n , the number of encoders L , and the set of desirable transmission rates R_1, \dots, R_L (that are achievable; see T. Cover, "A proof of the data compression theorem of Slepian and Wolf for ergodic sources", *IEEE Trans. on Information Theory*, vol. IT-21, pp. 226-228, March 1975.), parameters of the SW code may be selected in the following way:

For $i=1, \dots, L$, $m_i = n - R_i$, $k = \sum_{j=1}^L m_j$. If the joint distribution of random variables X_1, \dots, X_L is such that $w(x_1 \oplus \dots \oplus x_L) \leq t$, where $w(\cdot)$ denotes the Hamming weight, then the code C should be an (n, k, d_H) code that can correct at least t errors; thus, the Hamming distance of the code is $d_H \geq 2t + 1$, and from the sphere packing bound $n - k \geq \log \sum_{j=0}^t \binom{n}{j}$ must hold.

Proposition 1 If the parameters of a general SW code (C, M) are selected as above and the correlation of the sources is such that $w(x_1 \oplus \dots \oplus x_L) \leq t$, then the decoding error equals zero.

Proof: The proof follows directly from S. S. Pradhan and K. Ramchandran, "Distributed source coding: symmetric rates and applications to sensor networks," *Proc. DCC-2000, Data Compression Conference*, pp. 363-372, Snowbird, Utah, March 2000, incorporated by reference above, and the discussion above.

An advantage of this technique is that only one good channel code is needed. Indeed, for $L=2$, if the binary code C is approaching the capacity of a binary symmetric channel (BSC), then the general SW code (C, A) will approach the SW limit as long as the joint correlation between X_1 and X_2 can be modeled with the same BSC. However, in the case $L > 2$, finding a channel that models the correlation among sources is more involved. As long as this correlation is such that $X_1 \oplus \dots \oplus X_L$ is a Bernoulli- p process, a single channel code C can be efficiently designed. This can be the case in the remote multiterminal setting (T. Berger, "Multiterminal

source coding", *The Information Theory Approach to Communications*, G. Longo, Ed., New York: Springer-Verlag, 1977, incorporated by reference above.) where an encoder observes only a noisy version of the source. Indeed, for the source S , an observation can be often modeled as $X_i = S + N_i$, ($i=1, \dots, L$), where N_i is an independent and identically distributed (i.i.d.) discrete random variable independent of S .

The method may also apply to the case when C is a convolutional code, as will be shown below in an example using punctured turbo codes. For clarity, an example of the code construction for the case $L=2$ using a systematic channel code (a similar example but with a non-systematic code is hinted in S. S. Pradhan and K. Ramchandran, "Generalized coset codes for symmetric distributed source coding," included herewith as Appendix G; and S. S. Pradhan and K. Ramchandran, "Distributed source coding: symmetric rates and applications to sensor networks," *Proc. DCC-2000, Data Compression Conference*, pp. 363-372, Snowbird, Utah, March 2000, incorporated by reference above) is presented. Let X and Y be two discrete memoryless uniformly distributed variables of length seven bits such that the Hamming distance between them is at most one. The source messages are separately encoded and sent to a joint decoder. The decoder then attempts to losslessly reconstruct both sources.

The SW bound for this case is 10 bits (see D. Slepian and J. K. Wolf, "Noiseless coding of correlated information sources," *IEEE Trans. On Information Theory*, vol. IT-19, pp. 471-480, July 1973, incorporated by reference above). This bound can be achieved in the asymmetric scenario by transmitting one source, e.g., X , at rate $R_1 = H(X) = 7$ bits and by coding the second source, Y , at $R_2 = H(Y|X) = 3$ bits. It is shown how the same total rate can be achieved with the symmetric approach by using $R_1 = R_2 = 5$ bits. Since $n=7$ bits, and a code is desired that can correct at least one bit error, for an SW code C the systematic (7,4) Hamming code is selected, defined by the generator matrix:

$$G_{k \times n} = [I_4 P] = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}.$$

Its parity matrix is:

$$H = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix}.$$

Further two subcodes of C , C_1 and C_2 , may be constructed by splitting G into two generator matrices, G_1 that contains the first $m=2$ rows of G , and G_2 that contains the last two rows. X may be coded using C , and Y using C_2 . Let $P^T = [P_1^T P_2^T]$. Then for the $(n-m) \times n$ parity-check matrices H_1 and H_2 of C_1 and C_2 , respectively, the following may be obtained from (2):

$$\begin{aligned}
 H_1 &= \begin{bmatrix} O_{m \times m} & I_m & O_{m \times (n-k)} \\ P_1^T & O_{(n-k) \times m} & I_{n-k} \end{bmatrix} \\
 &= \begin{bmatrix} O_{m \times m} & I_{n-m} \end{bmatrix} \\
 &= \begin{bmatrix} 0010000 \\ 0001000 \\ 1100100 \\ 0100010 \\ 1000001 \end{bmatrix},
 \end{aligned}$$

$$\begin{aligned}
 H_2 &= \begin{bmatrix} I_m & O_{m \times m} & O_{m \times (n-k)} \\ O_{(n-k) \times m} & P_2^T & I_{n-k} \end{bmatrix} \\
 &= \begin{bmatrix} 1000000 \\ 0100000 \\ 0010000 \\ 0011010 \\ 0011001 \end{bmatrix}
 \end{aligned}$$

since both H_1 and H_2 have rank $n-m$ and $H_1 G_1^T = H_2 G_2^T = O_{(n-m) \times m}$.

Let realizations of the sources be $x=[0010110]$ and $y=[0110110]$. Since the Hamming distance between x and y is one, it should be possible to decode the messages correctly.

Syndromes for both x and y may be formed. To do so, x and y may be written in the form

$$x=[a_1 \ v_1 \ q_1]=[00 \ 10 \ 110],$$

$$y=[u_2 \ a_2 \ q_2]=[01 \ 10 \ 110].$$

The length $n-m$ syndromes, s_1 and s_2 , formed by the two subcodes are

$$\begin{aligned}
 s_1^T &= H_1 x^T \\
 &= \begin{bmatrix} v_1^T \\ P_1^T a_1^T \oplus q_1^T \end{bmatrix} \\
 &= [10110]^T
 \end{aligned}$$

$$\begin{aligned}
 s_2^T &= H_2 y^T \\
 &= \begin{bmatrix} u_2^T \\ P_2^T a_2^T \oplus q_2^T \end{bmatrix} \\
 &= [01001]^T.
 \end{aligned}$$

The length n row-vectors t_1 and t_2 may then be given by

$$\begin{aligned}
 t_1^T &= \begin{bmatrix} O_{m \times 1} \\ v_1^T \\ P_1^T a_1^T \oplus q_1^T \end{bmatrix} \\
 &= [0010110]^T
 \end{aligned}$$

-continued

$$\begin{aligned}
 t_2^T &= \begin{bmatrix} u_2^T \\ O_{m \times 1} \\ P_2^T a_2^T \oplus q_2^T \end{bmatrix} \\
 &= [0100001]^T.
 \end{aligned}$$

Then the row-vectors $x \oplus t_1$ and $y \oplus t_2$ are codewords of the codes C_1 and C_2 , respectively.

Thus, by sending s_1 and s_2 from the two encoders to the joint decoder, the decoder may find the codeword in C that is closest to $t_1 \oplus t_2 = [0110111]$. Since there is no error in decoding, this codeword may be $x \oplus t_1 \oplus y \oplus t_2 = [0010111]$ because the Hamming distance between x and y is one and the minimal Hamming distance of the code C is three. The corresponding reconstructions $\hat{a}_1 = a_1$ and $\hat{a}_2 = a_2$ may then be obtained as the systematic part of the codeword. Since $a_1 G_1 = x \oplus t_1$ and $a_2 G_2 = y \oplus t_2$, the sources may be reconstructed as $\hat{x} = \hat{a}_1 G_1 \oplus t_1 = [0010110] = a_1 G_1 \oplus t_1$, $\hat{y} = \hat{a}_2 G_2 \oplus t_2 = [0110110] = a_2 G_2 \oplus t_2$. It may thus be seen that x and y are indeed recovered error-free.

25 Practical Code Design

Practical SW codes using systematic IRA and turbo codes may be designed as described below using the notation established above.

Systematic IRA Codes

The present methods may be applied to systematic IRA codes (see H. Jin, A. Khandekar, and R McEliece, "Irregular repeat-accumulate codes," *Proc. of 2nd International Symposium on Turbo codes and related topics*, pp. 1-8, September 2000, incorporated by reference above.). Systematic IRA codes are powerful channel codes that combine the advantages of LDPC codes (message passing iterative decoding, simple analysis and code design) and turbo codes (linear time encoding). Their performance is comparable to that of irregular LDPC codes of the same codeword length. For simplicity, symmetric SW coding of two binary sources X and Y are considered. Code construction for the general case is essentially the same.

FIG. 6—Encoding Multiple Data Sources

FIG. 6 illustrates one embodiment of encoding of a source x . As FIG. 6 shows, in this example, at each check (square) node **604** all the connected information nodes **602** (cycles on the left) are modulo-2 added and corresponding values of the parity nodes **606** (cycles on the right) are determined. Then, q_1 is modulo-2 added. Here $n=10$, $k=6$, $m=3$, $\lambda(x)=0.25x+0.75x^2$, and $\rho(x)=x^3$.

At the first encoder, the length n source output x is split into three parts in the form

$$x=[a_1 \ v_1 \ q_1] \tag{5}$$

where a_1 , v_1 are row-vectors of length $m=k/2$ and q_1 is a row-vector of length $n-k=n-2m$.

First, $a_1 P_1$ may be determined by setting the values of the systematic IRA variable nodes to $[a_1 \ O_{1 \times m}]$, that is, half of the systematic part may be set to zero.

Next, the length $n-m$ syndrome s_1 that is formed by the first encoder may be obtained by appending v_1 to $u_1 P_1 \oplus q_1$. The encoding procedure is represented in FIG. 6.

In a similar way, s_2 may be formed at the second encoder from $y=[u_2 \ a_2 \ q_2]$. At the joint decoder, first, vectors t_1 and t_2 may be formed as explained above; then, a common IRA decoding of $t_1 \oplus t_2$ may be performed, and \hat{a}_1 and \hat{a}_2 obtained

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as the systematic part of the recovered codeword; finally, \hat{x} and \hat{y} may be reconstructed as:

$$\hat{x} = [\hat{a}_1 \ O_{1 \times m}] G \oplus t_1 \quad (6)$$

$$\hat{y} = [O_{1 \times m} \ \hat{a}_3] G \oplus t_2 \quad (7)$$

As a result, if the used systematic IRA code can approach the capacity of a channel, then if the same channel models the statistics of $x \oplus y$, the resulting IRA coding scheme based on the above setup will also approach the SW limit for any rate allocation between the encoders. The procedure can be generalized to any asymmetric scenario with any number of sources. However, when more than two sources are used, modeling the exact correlation with a channel is more involved and hence more challenging.

Turbo Codes

The SW code construction with systematic turbo codes (see C. Berrou, A. Glavieux, and P. Thitimajshima, "Near Shannon limit error-correcting coding and decoding: Turbo codes," *Proc. ICC'93, IEEE Int. Conf. on Comm.*, pp. 1064-1070, Geneva, 1993, incorporated by reference above.) is now briefly explained. Although turbo codes consist of two convolutional coders, they can be treated as linear block codes. Thus, the technique described above may be applied without modification. Indeed, assuming again the symmetric scenario, for the source realization x given by (5), $a_1 P_1$ may be determined by coding the k -length vector $[a_1 \ O_{1 \times m}]$ with the first convolutional encoder. The vector $[a_1 \ O_{1 \times m}]$ may also be interleaved and fed into the second encoder. The syndrome may be formed then as:

$$s_1 = [v_1 a_1 P_1 \oplus q_1]^T.$$

To get \hat{a}_1 and \hat{a}_2 at the decoder, iterative maximum a posteriori decoding may be applied to the vector $t_1 \oplus t_2$ from (4). Then, \hat{x} and \hat{y} may be obtained from (6) and (7), respectively.

FIGS. 7 & 8—Results

A simulation of SW coding of two i.i.d. binary discrete sources X and Y whose correlation is modeled as a BSC with crossover probability p was conducted. Experimental results for IRA and turbo codes are provided below.

In these experiments, the used systematic (n, k) IRA code is with rate 0.50227 and the degree distribution polynomials are (see H. Jin, A. Khandekar, and R. McEliece, "Irregular repeat-accumulate codes," *Proc. of 2nd International Symposium on Turbo codes and related topics*, pp. 1-8, September 2000, incorporated by reference above.): $\lambda(x) = 0.252744x^2 + 0.081476x^{11} + 0.327162x^{12} + 0.184589x^{46} + 0.154029x^{48}$, $\rho(x) = x^8$. The number of iterations in the decoder was limited to 20.

The turbo encoder includes two identical recursive systematic convolutional encoders (from W. E. Ryan, "A Turbo Code Tutorial," included herewith as Appendix F) with memory length 4, generators (31, 27) octal, and code rate 1/3. The parity bits of both encoders were punctured to achieve the code rate of 1/2. A maximum a posteriori algorithm was used for decoding, with the number of iterations limited to 20.

Obtained results are shown in FIG. 7. The SW bound is 1.5 bits. The information block length was $k=104$ and $k=105$ bits. For each point at least 10^8 codeword bits were simulated. The results are given as residual bit error rate (BER) averaged over the two sources as a function of the joint entropy $H(X, Y) = H(X) + H(X|Y) = 1 + H(p)$.

FIG. 7 illustrates BER averaged over the two sources as a function of the joint entropy $H(X, Y) = 1 + H(p)$ for two different information block lengths k and two different channel coders. It can be seen that similar performances were

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obtained with both coders. With the length of $k=10$ the gap to the SW limit was about 0.04 bits, which is comparable to the results of the asymmetric approach with LDPC reported in A. Liveris, Z. Xiong, and C. Georghiades, "Compression of binary sources with side information at the decoder using LDPC codes," *IEEE Communications Letters*, vol. 6, pp. 440-442, October 2002. Note that according to the present coding procedure, usually either both sources are recovered error-free or both are corrupted. Also, because of the additional encodings at the decoder side, the errors propagate. Thus, either the whole messages are perfectly reconstructed or they are heavily damaged. (This is the reason why the drop for $k=10$ with IRA codes was not sharp as expected.) Therefore, the decoder can detect errors with high certainty by comparing the two reconstructions.

FIG. 8 illustrates results with IRA codes and $k=105$ together with the SW bound. More specifically, three different rate allocations among the encoders were simulated by changing the number of rows (m_1 and m_2) in the generator matrices of subcodes assigned to two encoders. In addition to the symmetric scenario, where $m_1 = m_2 = k/2$, with obtained equal rates of both encoders, $R_1 = R_2 = (n-k)/n$, two asymmetric cases were also treated. In the first case, $m_1 = k/3$ and $m_2 = 2k/3$, resulting in $R_1 = (n-k/3)/n$ and $R_2 = (n-2k/3)/n$. Finally, in the totally asymmetric scenario, m_1 was set to zero, and m_2 to k , which resulted in $R_1 = H(X) = 1$ and $R_2 = H(Y|X) = (n-k)/n$. Results obtained with the IRA based scheme and $k=105$ together with the SW bound are shown in FIG. 8. Error-free transmission was assumed if BER was lower than 10^{-6} . As expected, all three cases resulted in the same gap of 0.039 bits to the bound. Thus, the different rate allocations did not affect the performance. Similar results were obtained with the punctured turbo coder.

CONCLUSIONS AND BENEFITS

Thus, based on the above precise and detailed interpretation of Pradhan and Ramchandran's outlined method for constructing a single channel code that achieves arbitrary rate allocation among two encoders in the SW coding problem (see S. S. Pradhan and K. Ramchandran, "Generalized coset codes for symmetric distributed source coding," included herewith as Appendix G; and S. S. Pradhan and K. Ramchandran, "Distributed source coding: symmetric rates and applications to sensor networks," *Proc. DCC-2000, Data Compression Conference*, pp. 363-372, Snowbird, Utah, March 2000, incorporated by reference above.), based on the systematic setup, a low-complexity coding designs using advanced systematic IRA and turbo codes that are capable of approaching any point on the SW bound has been provided.

Additionally, these results were extended to SW coding of multiple sources (see T. Cover, "A proof of the data compression theorem of Slepian and Wolf for ergodic sources," *IEEE Trans. on Information Theory*, vol. IT-21, pp. 226-228, March 1975, incorporated by reference above.). It has been shown herein that for a particular correlation model among sources, a single code can be designed, which is an important advantage of the present method, as a single code can be used to approach the joint entropy limit. Note that if the designed code approaches the capacity of the channel that models correlation, then the system will approach the theoretical limit. Thus, even when the number of sources is high, since all the sources are decoded by a single code, only one (good) code is needed. In addition, low complexity and the inherent error detection capability make the present method beneficial and desirable for both direct and remote multiterminal problems (see T. Berger, "Multiterminal source coding", *The*

Information Theory Approach to Communications, G. Longo, Ed., New York: Springer-Verlag, 1977, incorporated by reference above.)

It is noted that to approach the theoretical limits in multi-terminal coding with a fidelity criterion, after quantization of the sources, lossless coding may be needed to further decrease the rate (see S. S. Pradhan and K. Ramchandran, "Distributed source coding using syndromes (DISCUS): design and construction," *Proc. DCC-1999, Data Compression Conference*, pp. 158-167, Snowbird, Utah, March 1999; J. Chou, S. S. Pradhan and K. Ramchandran, "Turbo and trellis-based constructions for source coding with side information," *Proc. DCC-2003, Data Compression Conference*, pp. 33-42, Snowbird, Utah, March 2003; and Y. Yang, S. Chen, Z. Xiong, and W. Zhao, "Wyner-Ziv coding based on TCQ and LDPC codes," *Proc. of 37th Asilomar Conference on Signals, Systems, and Computers*, Pacific Grove, Calif., November 2003, all of which were incorporated by reference above). Hence, in some embodiments, the method proposed herein may be applied in this second compression step. Therefore, the design of a single practical code for an entire multi-source system, e.g., a whole sensor network, that can approach or even reach the theoretical limits is feasible.

Although the embodiments above have been described in considerable detail, numerous variations and modifications will become apparent to those skilled in the art once the above disclosure is fully appreciated. It is intended that the following claims be interpreted to embrace all such variations and modifications.

We claim:

1. A method implemented using a computing device, the method comprising:

(a) the computing device selecting any point in a Slepian-Wolf (SW) admissible rate region, wherein the point includes one rate value for each of L correlated source streams, wherein L is greater than or equal to two;

(b) the computing device identifying L submatrices of a given generator matrix G, wherein the numbers of rows in the L submatrices of the generator matrix G are determined by the selected point in the SW admissible region;

(c) the computing device computing L parity matrices H_1, H_2, \dots, H_L from the generator matrix G, wherein each parity matrix H_i is computed from the corresponding submatrix of the generator matrix G;

wherein the parity matrix $H_i, i=1, 2, \dots, L$, defines a corresponding encoder C_i according to the relation $(s_i)^T = H_i(x_i)^T$, wherein x_i represents a block of samples from the corresponding source stream, wherein s_i represents a result of the encoder C_i .

2. The method of claim 1 further comprising: providing the L parity matrices to L transmitters respectively,

wherein each of the L transmitters is configured to multiply the corresponding source stream block x_i by the corresponding parity matrix to determine the result s_i for the encoder C_i .

3. The method of claim 1 further comprising: providing the matrix G to a receiver; wherein the receiver is configured to:

receive the results s_1, s_2, \dots, s_L from L transmitters respectively;

generate L expanded syndromes from the results s_1, s_2, \dots, s_L by inserting zero or more zero values at appropriate positions into each result, so that each of the expanded syndromes have the same length;

compute a vector sum of the expanded syndromes; determine a codeword c closest to the vector sum;

multiply each of L portions of a systematic part of the codeword c by a corresponding submatrix of the generator matrix G to determine a corresponding intermediate vector; and

add each of the L intermediate vectors to a corresponding one of the expanded syndromes to obtain a corresponding output representing an estimate of the corresponding source data block x_i .

4. The method of claim 1, wherein each of the source streams is generated by a corresponding one of a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed.

5. The method of claim 1, wherein each of the correlated source streams is generated by a corresponding sensor in a distributed sensor network.

6. The method of claim 1, wherein each of the correlated source streams is generated by a corresponding video source in a distributed video network.

7. The method of claim 1, wherein the number of rows in each of the L submatrices of the generator matrix G is based on the rate value for the corresponding source stream.

8. The method of claim 1, further comprising: storing the parity matrices H_1, H_2, \dots, H_L on one or more memory media for distribution to L corresponding encoding systems.

9. The method of claim 1, wherein the computing device includes:

a processor configured to execute program instructions; or one or more application-specific integrated circuits (ASICs); or

a combination of the processor configured to execute program instructions and one or more ASICs.

10. A method comprising:

L encoders respectively encoding L correlated information sources using, respectively, L distinct submatrices of a parity check matrix, in order to generate L syndromes, wherein L is greater than one; and

the L encoders sending the L syndromes to a joint decoder; wherein each of the submatrices of the parity check matrix is derived from a corresponding submatrix of a generator matrix G, wherein the submatrices of the generator matrix G have row ranks determined by a point selected anywhere in a Slepian-Wolf admissible rate region.

11. The method of claim 10, wherein the joint decoder is configured to decode the L syndromes using, respectively, the submatrices of the generator matrix G.

12. The method of claim 10, wherein the information sources are memoryless information sources, wherein the information sources are spatially distributed.

13. The method of claim 10, wherein each of the information sources is a sensor in a distributed sensor network.

14. The method of claim 10, wherein each of the information sources is a video source in a distributed video network.

15. The method of claim 10, wherein each of the information sources is an audio source.

16. The method of claim 10, wherein the computing device includes:

a processor configured to execute program instructions; or one or more application-specific integrated circuits (ASICs); or

a combination of the processor configured to execute program instructions and one or more ASICs.

17. A computer-implemented method comprising:

a computer system partitioning a generator matrix to generate a plurality of sub-matrices corresponding respectively to a plurality of correlated data sources,

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wherein the partitioning is performed in accordance with a rate allocation among the plurality of correlated data sources; and
 the computer system determining a corresponding plurality of parity matrices based respectively on the sub-matrices,
 wherein each parity matrix is configured to encode correlated data for a respective one of the correlated data sources;
 computing a plurality of parity matrices from the generator matrix,
 wherein a given parity matrix is computed from a corresponding sub-matrix of the generator matrix; and
 providing the plurality of parity matrices to respective transmitters.

18. The method of claim 17, wherein the data sources are memoryless data sources, wherein the memoryless data sources are spatially distributed.

19. The method of claim 17, wherein each of the data sources is a sensor in a distributed sensor network.

20. The method of claim 17, wherein each of the data sources is a video source in a distributed video network.

21. The method of claim 17, further comprising:
 the computer system distributing the parity matrices to a plurality of encoding systems.

22. The method of claim 17, further comprising:
 the computer system sending the submatrices of the generator matrix to a decoding system.

23. The method of claim 17, wherein the sub-matrices have rows, and wherein the numbers of rows in the sub-matrices of the generator matrix are determined by a corresponding selected point in a Slepian-Wolf admissible region.

24. The method of claim 17, wherein the partitioning further comprises:

selecting a point in a Slepian-Wolf admissible region, wherein the Slepian-Wolf point includes a rate value for a given correlated data source of the plurality of correlated data sources; and

determining a sub-matrix dimension for a first sub-matrix of the plurality of sub-matrices corresponding to the generator matrix,

wherein the determination of the sub-matrix dimension is based on the selected point in a Slepian-Wolf admissible region.

25. An apparatus comprising:

one or more processors; and
 a memory storing instructions that, when executed by the one or more processors, cause the one or more processors to perform operations comprising:

(a) selecting a point in a Slepian-Wolf (SW) admissible rate region, wherein the point includes a rate value for each of L correlated source streams, wherein L is greater than or equal to two;

(b) identifying L submatrices of a given generator matrix G, wherein the numbers of rows in the L submatrices of the generator matrix G are determined by the selected point in the SW admissible region;

(c) computing L parity matrices H_1, H_2, \dots, H_L from the generator matrix G, wherein each parity matrix H_i is computed from the corresponding submatrix of the generator matrix G;

wherein the parity matrix H_i , $i=1, 2, \dots, L$, defines a corresponding encoder C_i according to the relation $(s_i)^T = H_i(x_i)^T$, wherein x_i represents a block of samples from the corresponding source stream, wherein s_i represents a result of the encoder C_i .

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26. The apparatus of claim 25, the operations further comprising:

providing the L parity matrices to L transmitters respectively,

wherein each of the L transmitters is configured to multiply the corresponding source stream block x_i by the corresponding parity matrix H_i to determine the result s_i for the encoder C_i .

27. The apparatus of claim 25, wherein the source streams are generated by at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed;

sensors in a distributed sensor network;

video sources in a distributed video network.

28. A tangible computer-readable medium having computer-executable instructions stored thereon that, if executed by a computing device, cause the computing device to perform operations comprising:

(a) selecting a point in a Slepian-Wolf (SW) admissible rate region, wherein the point includes a rate value for each of L correlated source streams, wherein L is greater than or equal to two;

(b) identifying L submatrices of a given generator matrix G, wherein the numbers of rows in the L submatrices of the generator matrix G are determined by the selected point in the SW admissible region;

(c) computing L parity matrices H_1, H_2, \dots, H_L from the generator matrix G, wherein each parity matrix H_i is computed from the corresponding submatrix of the generator matrix G;

wherein the parity matrix H_i , $i=1, 2, \dots, L$, defines a corresponding encoder C_i according to the relation $(s_i)^T = H_i(x_i)^T$, wherein x_i represents a block of samples from the corresponding source stream, wherein s_i represents a result of the encoder C_i .

29. The tangible computer-readable medium of claim 28, the operations further comprising receiving the L correlated source streams from at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed;

sensors in a distributed sensor network; or

video source in a distributed video network.

30. An apparatus comprising:

one or more processors; and

a memory storing instructions that, when executed by the one or more processors, cause the one or more processors to perform operations comprising:

using L encoders, respectively encoding L correlated information sources using, respectively, L distinct submatrices of a parity check matrix, in order to generate L syndromes, wherein L is greater than one; and
 sending the L syndromes to a joint decoder;

wherein each of the submatrices of the parity check matrix is derived from a corresponding submatrix of a generator matrix G,

wherein the submatrices of the generator matrix G have row ranks determined by a point selected anywhere in a Slepian-Wolf admissible rate region.

31. The apparatus of claim 30, the operations further comprising receiving correlated information from at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed;

sensors in a distributed sensor network; or

video sources in a distributed video network.

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32. A tangible computer-readable medium having computer-executable instructions stored thereon that, if executed by a computing device, cause the computing device to perform operations comprising:

using L encoders, respectively encoding L correlated information sources using, respectively, L distinct submatrices of a parity check matrix, in order to generate L syndromes, wherein L is greater than one; and sending the L syndromes to a joint decoder;

wherein each of the submatrices of the parity check matrix is derived from a corresponding submatrix of a generator matrix G,

wherein the submatrices of the generator matrix G have row ranks determined by a point selected anywhere in a Slepian-Wolf admissible rate region.

33. The tangible computer-readable of claim 32, the operations further comprising receiving correlated information from at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed; sensors in a distributed sensor network; or video source in a distributed video network.

34. An apparatus comprising:

one or more processors; and

a memory storing instructions that, in response to execution by the one or more processors, cause the one or more processors to perform operations comprising:

partitioning a generator matrix to generate a plurality of sub-matrices corresponding respectively to a plurality of correlated data sources,

wherein the partitioning is performed in accordance with a rate allocation among the plurality of correlated data sources;

determining a corresponding plurality of parity matrices based respectively on the sub-matrices,

wherein each parity matrix is configured to encode correlated data for a respective one of the correlated data sources;

the operations further comprising:

computing a plurality of parity matrices from the generator matrix,

wherein a given parity matrix is computed from a corresponding sub-matrix of the generator matrix; and

providing the plurality of parity matrices to respective transmitters.

35. The apparatus of claim 34, wherein the sub-matrices have rows, and wherein the numbers of rows in the sub-matrices of the generator matrix are determined by a corresponding selected point in a Slepian-Wolf admissible region.

36. The apparatus of claim 34, the operations further comprising:

selecting a point in a Slepian-Wolf admissible region, wherein the Slepian-Wolf point includes a rate value for a given correlated data source of the plurality of correlated data sources; and

determining a sub-matrix dimension for a first sub-matrix of the plurality of sub-matrices corresponding to the generator matrix,

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wherein the determination of the sub-matrix dimension is based on the selected point in a Slepian-Wolf admissible region.

37. The apparatus of claim 34, the operations further comprising receiving correlated data from at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed;

sensors in a distributed sensor network; or

video source in a distributed video network.

38. A tangible computer-readable medium having computer-executable instructions stored thereon that, if executed by a computing device, cause the computing device to perform operations comprising:

partitioning a generator matrix to generate a plurality of sub-matrices corresponding respectively to a plurality of correlated data sources,

wherein the partitioning is performed in accordance with a rate allocation among the plurality of correlated data sources;

determining a corresponding plurality of parity matrices based respectively on the sub-matrices,

wherein each parity matrix is configured to encode correlated data for a respective one of the correlated data sources,

the operations further comprising:

computing a plurality of parity matrices from the generator matrix,

wherein a given parity matrix is computed from a corresponding sub-matrix of the generator matrix; and

providing the plurality of parity matrices to respective transmitters.

39. The tangible computer-readable of claim 38, wherein the sub-matrices have rows, and wherein the numbers of rows in the sub-matrices of the generator matrix are determined by a corresponding selected point in a Slepian-Wolf admissible region.

40. The tangible computer-readable of claim 38, the operations further comprising:

selecting a point in a Slepian-Wolf admissible region, wherein the Slepian-Wolf point includes a rate value for a given correlated data source of the plurality of correlated data sources; and

determining a sub-matrix dimension for a first sub-matrix of the plurality of sub-matrices corresponding to the generator matrix,

wherein the determination of the sub-matrix dimension is based on the selected point in a Slepian-Wolf admissible region.

41. The tangible computer-readable of claim 38, the operations further comprising receiving correlated data from at least one of:

a plurality of memoryless data sources, wherein the memoryless data sources are spatially distributed;

sensors in a distributed sensor network; or

video source in a distributed video network.

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