

# Virtual MIMO and Distributed Signal Processing for Sensor Networks - An Integrated Approach

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**Abstract**— This paper proposes an effective sensor data transmission approach where virtual implementation of multiple input multiple output (V-MIMO) cooperative communication is judiciously integrated with joint distributed compression and Recursive Least Squares (RLS) based adaptive signal processing. Both space-time block codes (STBC) and Vertical Bell Laboratories Layered Space Time (V-BLAST) architecture are considered for energy efficient virtual MIMO implementations. The energy efficiency of the integrated system is analyzed for different transmission distances and channel conditions. The numerical results show that, beyond certain transmission distance thresholds, the proposed integrated scheme offers significant energy efficiency compared to previously proposed systems. We also show that this integrated approach is very effective in highly correlated multimedia data based wireless sensor networks. In particular, it can be ideal for networks based on prioritized transmission of wavelet transformed image and video data.

## I. INTRODUCTION

Large-scale, energy efficient and inexpensive wireless sensor networks are finding new applications in various fields. Some of these include, for example, industrial plant monitoring, biomedical applications, survivor detection and remote surveillance. Many of them may involve multimedia data processing and analysis under resource-constraints (for example, in video/image sensor based remote surveillance). Thus design of economically and technically feasible large-scale multimedia sensor networks on distributed platforms is an important research area. Content-rich video and audio data can be efficiently processed and communicated utilizing their characteristic properties. For example in [1], a multi-priority video partitioning scheme that enhances the multimedia capabilities of code division multiple access (CDMA) systems was proposed. Those techniques can be applied in video surveillance sensor networks allowing different sensors to transmit different prioritized video streams to a base station where high resolution video data can be retrieved after applying certain signal/image processing techniques. Some of these multimedia applications in sensor networks have been addressed, for example, in [2]. But many of these networks consist of battery-operated sensors with small physical dimensions introducing strict energy constraints into the system. Thus energy-efficiency is one of the important design objectives in such networks.

Dual antenna-array MIMO techniques have been shown to offer significant performance improvements in wireless communication systems. But their drawbacks include complex receiver circuitry and signal processing requirements as well as large physical dimensions to accommodate multiple antennas, thus increasing the power consumption at the circuit level. The recently proposed Virtual MIMO (V-MIMO) concept allows realization of MIMO communication in wireless sensor networks with single-antenna nodes via the so-called local communications among sensor nodes [3]. Still V-MIMO may require complex circuitry and augmented transmission requirements. Another approach to improve energy-efficiency is the distributed data compression. Till now, many researchers have concentrated only on demonstration of energy efficiency of

V-MIMO compared to traditional SISO systems. However, realizing full potential of V-MIMO schemes in wireless sensor networks requires efficient integration of distributed compression algorithms with V-MIMO architecture. This paper proposes such an integrated design for V-MIMO based sensor systems. In particular, it integrates distributed compression and adaptive signal processing with V-MIMO architectures and evaluates the resulting performance.

A scheme that exploits the inherent spatio-temporal correlations among sensor data in a distributed network to compress sensor data before transmission was proposed in [4]. While this can be applicable to most wireless sensor network data, this may be particularly useful in the case of image or video data based sensor networks. In this paper, we propose a modified adaptive correlation tracking technique based on Recursive Least Squares (RLS) algorithm that provides improved energy efficiency compared to the previously proposed scheme. Moreover, we propose a new method of computing encoding information based on a Gaussian approximation which seems to perform better at larger transmission distances compared to the method developed, for example, in [4]. For multimedia sensor networks, we introduce wavelet transform based prioritized data transmission.

A network model with a data gathering node (DGN) and a collection of sensing nodes is considered. The DGN is assumed to be less energy-constrained compared to the sensing nodes. Most of the complex processing are thus carried out at the DGN resulting in better energy efficiency at the energy-constrained data collection node level. Our results obtained under different channel conditions over various transmission distances, demonstrate that with a judicious integration of the proposed distributed compression techniques with V-MIMO architecture, both the number of sensor transmissions and the required signal energy per transmission can be reduced. Moreover, we demonstrate the effectiveness of our technique on real sensor data and multimedia data such as images.

The rest of this paper is organized as follows: In Section II we introduce the V-MIMO architecture and the proposed integrated design followed by an energy consumption analysis. Section III provides numerical results based on real sensor data. Conclusions and future research ideas are summarized in Section IV.

## II. PROPOSED INTEGRATED SENSOR SYSTEM DESIGN

### A. System Description

Note that, while recently many virtual MIMO schemes have been proposed for sensor networks [3], [5], here we primarily consider STBC and V-BLAST based communication. For simplicity, we will consider a 2x2 MIMO system since generalization to higher order MIMO systems is straightforward. In [3], [6] the concept of sensor cooperation was introduced to achieve *virtual MIMO communication* with single-antenna sensor nodes. In a virtual MIMO scheme, the nodes that are close to each other form a cluster. Each node associates itself with at least one pre-determined cluster. In the case of virtual

STBC (V-STBC), all sensors within a cluster need to share their information (via so-called local communication) in order for a cluster to form a virtual multiple antenna array. Once this is done, each sensor node in a cluster acts as an antenna element of a centralized array and the formed virtual antenna array (VAA) space-time block encodes the cluster data that is to be sent to the DGN. The local communication within the cluster may be implemented using time division multiple-access (TDMA). We assume that unlike sensor nodes, the DGN can accommodate multiple antennas which enables the system to achieve true MIMO capability with local communications only at transmitter side. Transmission of cluster data from a VAA to the DGN is known as the long-haul communication.

If virtual V-BLAST (VV-BLAST) is assumed for cluster data transmission, in contrast to the V-STBC, local communication step may be avoided at both ends. But, since all virtual antenna elements of a VAA requires equal length data for virtual BLAST implementation, this may not be always true (for example in case of distributed compression). However, we can overcome this problem via a variable power control strategy in which successive VV-BLAST is executed starting with the lowest sensor data length among all the sensors of the cluster. For example, if a network has 3 sensors each having 100, 200, and 300 data symbols respectively, to be sent to a DGN, then 3x3 VV-BLAST is implemented first to transmit 100 data symbols where all the sensors participate in the process, then the 2<sup>nd</sup> and 3<sup>rd</sup> sensors transmit next 100 symbols via 2x2 VV-BLAST, and finally the 3<sup>rd</sup> sensor transmits its last 100 symbols via SISO to DGN. Here all the sensor nodes and DGN are assumed to be in perfect synchronization along with data symbol length knowledge (of course we could also use 3 × 3, 2 × 3 and 1 × 3, respectively, if the DGN has a fixed number of antennas). When the system delay is a major concern, the above power control strategy is more effective compared to V-STBC based communication since delay incurred during the local communication step can be avoided. This strategy is advantageous under certain channel conditions and beyond certain long-haul transmission distances as can be seen from our results.

We employ a modified version of the adaptive correlation tracking-based distributed coding method developed in [4] to achieve data compression. Basically it is a source-coding scheme with side-information. For example, in a network with each cluster having two sensor nodes, one of the sensors (called the reference sensor) of each cluster always sends its data uncoded (or compressed only with respect to its own past data). The DGN keeps track of the inter-sensor data correlation structure and provide the other sensor with this information. Then, the second sensor can compress its data with respect to its own past readings and that of the reference sensor's readings, based on the sensor data correlation information provided by the DGN. Thus, each sensor can compress its data without any inter-sensor communication. However, once we implement this scheme in conjunction with V-STBC, the inter-sensor communication inside a cluster is required. But now the communication energy required for this is minimal since it is performed on the compressed data. Note that it is also possible to compress this shared data again at each sensor before the transmission, though we do not consider that here.

The DGN computes the required encoding information using a linear predictive model. If  $X_k^{(j)}$  is the observation of sensor  $j$  at time  $k$ , then the prediction for  $X_k^{(j)}$  computed at DGN is:

$$Y_k^{(j)} = \underline{\theta}^{(j)T}(k) \underline{z}^{(j)}(k) \quad (1)$$

where

$$\begin{aligned} \underline{\theta}^{(j)} &= \left( \alpha_1^{(j)} \alpha_2^{(j)} \dots \alpha_{j-1}^{(j)} \beta_1^{(j)} \beta_2^{(j)} \dots \beta_M^{(j)} \right)^T, \\ \underline{z}^{(j)}(k) &= \left( X_k^{(1)} X_k^{(2)} \dots X_k^{(j-1)} X_{k-1}^{(j)} X_{k-2}^{(j)} \dots X_{k-M}^{(j)} \right)^T, \end{aligned}$$

and  $\alpha_l^{(j)}$ 's and  $\beta_j^{(j)}$ 's are the weighting coefficients. We choose the filter coefficient vector in order to minimize the weighted least squares error where prediction error is given by  $e_k^{(j)} = X_k^{(j)} - Y_k^{(j)}$ . Then, it is well-known that least-squares filter coefficient vector at time  $k$  is given by

$$\underline{\theta}_{opt}^{(j)}(k) = (R^{(j)}(k))^{-1} \underline{r}_{zx}^{(j)}(k), \quad (2)$$

where  $R^{(j)}(k)$  and  $\underline{r}_{zx}^{(j)}(k)$  are the exponentially weighted deterministic autocorrelation and cross correlation of data  $\underline{z}^{(j)}(k)$ . The above filter coefficient computation can then be performed adaptively using the following recursive least-squares (RLS) algorithm:

$$\underline{\theta}_{new}^{(j)} = \underline{\theta}^{(j)}(k+1) = \underline{\theta}^{(j)}(k) + \underline{g}^{(j)}(k+1) e_{k+1}^{(j)}, \quad (3)$$

where  $\underline{g}^{(j)}(k+1)$  is the gain vector [7]. The RLS algorithm is initialized by assuming that each sensor transmits an  $N_{tr}$  uncoded data samples at the beginning.

The distributed compression is performed as in [4] assuming that there is a codebook common to all sensors and the DGN. According to this coding scheme a sensor needs only  $i(k, j)$  bits to represent an  $n$  bit reading produced by the  $n$ -bit A/D converter. Note that  $i(k, j)$  is the encoding side-information the DGN provided to the sensor  $j$  at time  $k$ , where  $i(k, j) < n$ . It can be shown that the tolerable prediction error in this scheme is given by  $2^{i-1} \Delta$  where  $\Delta$  is the quantization step of the A/D converter. In [4], the following expression for computing the encoding information was developed by bounding the probability of decoding error  $P_e = P(|e_k^{(j)}| > 2^{i(k, j)-1} \Delta)$  using the Chebyshev's inequality

$$i(k, j) = \frac{1}{2} \log_2 \left( \frac{\sigma_{e_k^{(j)}}^2}{\Delta^2 P_e} \right) + 1. \quad (4)$$

However, (4) can be very loose leading to over estimating  $i(k, j)$ . In this paper, we propose a tighter expression by assuming that the prediction error  $e_k^{(j)}$  is Gaussian distributed with mean zero and variance  $\sigma_{e_k^{(j)}}^2$ . This error model leads to the following new expression for the encoding side-information:

$$i(k, j) = \log_2 \left( \frac{\sigma_{e_k^{(j)}} Q^{-1}(P_e/2)}{\Delta} \right) + 1. \quad (5)$$

As we will see in numerical results, the above Gaussian approximation performs better than (4) in most situations. The DGN decodes the actual sensor reading by using the  $i(k, j)$  bits transmitted by a sensor in conjunction with knowledge of the common codebook structure [4]. Note that, at the end of the training period, the DGN initializes the prediction error variance as  $\sigma_{e^{(j)}}^2 = \frac{1}{N_{tr}-1} \sum_{k=1}^{N_{tr}} |e_k^{(j)}|^2$ . In order to keep up with the time-varying nature of the sensor data it then adaptively updates the prediction error variance in a decision-driven mode.

In integrating the above distributed compression algorithm with virtual MIMO communications, we assume that the DGN broadcasts the encoding information periodically every  $T_{Rec}$  seconds. Each sensor then compresses all  $N_{Rec}$  samples within a time block of  $T_{Rec}$  and combines them into a single stream. Thus, in the case of V-STBC, the local communications are performed periodically once every  $T_{Rec}$ . Note that, since DGN broadcasts the encoding information every node knows the encoding information  $i(k, j)$  of all the other nodes in its cluster. After the local communications, each sensor demodulates the received data symbols and re-combines them into a single

stream of data ensuring same symbol streams at all sensors. Now the nodes in a cluster are ready to perform space-time block coding as elements in an antenna array. In practice, however, channel errors during the local communications may result in unequal data streams at sensors leading to error propagation during the long-haul communication. However, this can be minimized by ensuring a sufficiently small error rate for local communication.

Throughout this paper, we assume M-QAM modulation for both local and long-haul communications. In practice, M-QAM implementation may require few extra tail bits to be added to the sensor data bit stream (so that the total number of bits is divisible by  $b (= \log_2 M)$ ). The number of tail bits ( $N_{DC}$ ) added at each sensor can be determined by its corresponding encoding information. It should be noted that the proposed block local communication of once every  $T_{Rec}$  seconds helps reduce the number of required tail bits thereby reducing the extra energy spent on  $N_{DC}$  tail bits. For improved performance, we also consider variable-rate MIMO communication in which the M-QAM constellation size is optimized with respect to long-haul transmission distance [3].

In a virtual V-BLAST based system, each sensor compresses its data and variable power control strategy explained above is implemented with the M-QAM modulated symbols. Since cluster radii are supposed to be small, we assume that the local communication in a V-STBC based system is over an AWGN channel. The long-haul communication, however, is assumed to be over a Rayleigh fading channel in case of both V-STBC and VV-BLAST.

### B. Energy consumption analysis

Generally speaking, the two main power consumption components along a signal path are the power consumed by all power amplifiers ( $P_{PA}$ ) and the power consumed by the circuit blocks of sensors ( $P_C$ ) [3], [5]. The  $P_{PA}$  term can be approximated as in [3]

$$P_{PA} = (1 + \alpha) P_{out} \quad (6)$$

where  $\alpha = \xi/\eta - 1$  with  $\eta$  being the drain efficiency of the RF power amplifier and  $\xi$ -peak-to-average ratio (PAR). If M-QAM is used, then  $\xi = 3 \frac{M-2\sqrt{M}+1}{M-1}$  [5]. The transmit power  $P_{out}$  can be determined as:

$$P_{out} = C_1 d^\kappa \bar{E}_b R_b, \quad (7)$$

where  $d, \kappa, \bar{E}_b$  and  $R_b$  are the transmission distance, the signal path loss parameter, average energy per bit required for a given bit-error-rate (BER) specification and the system bit rate, respectively. For details of the constant  $C_1$  we refer the reader to [5]. We may compute  $\bar{E}_b$  using the standard expressions given, in the case of V-STBC, in [3], [5] and, in the case of VV-BLAST, in [6].

For V-STBC, sensor circuit power consumption to broadcast its data during local communications within the cluster is:  $P_C^{(LocTx)} \approx P_{DAC} + P_{mix} + P_{filt} + P_{synth}$  where the terms are the power consumption values for the D/A converter (DAC), the mixer, the active filters at the transmitter side and the frequency synthesizer, respectively. Similarly, sensor circuit power consumption in receiving the broadcasted data from other sensors of the cluster is given by  $P_C^{(LocRx)} \approx P_{synth} + P_{LNA} + P_{mix} + P_{IFA} + P_{filr} + P_{ADC}$  where the terms are the powers consumed by low noise amplifier (LNA), the intermediate frequency amplifier (IFA), the active filters at the receiver side and the A/D converter (ADC), respectively.

The total energy consumption per bit (at a node) for local communication in V-STBC can then be estimated as:  $E_t^{Local} = \frac{P_{PA} + P_C^{(LocTx)} + (N_s - 1) \times P_C^{(LocRx)}}{R_b}$  where  $R_b$  is the system bit rate and  $N_s$  is the number of sensor nodes in a cluster. In this case,  $P_{PA}$  is computed assuming that  $d = d_{Loc}$ , where  $d_{Loc}$  is the distance between any pair of sensors in a cluster.

For both V-STBC and VV-BLAST, the total circuit energy consumption of a cluster during long-haul communication can be given as  $P_C^{(Long)} \approx (P_{DAC} + P_{mix} + P_{filt} + P_{synth}) \times N_s$ . The total energy consumption per bit for a cluster during the long-haul communication is then approximated as  $E_t^{Long} = \frac{P_{PA} + P_C^{(Long)}}{R_b}$ . Here  $P_{PA}$  is computed assuming that  $d = d_{Long}$ , where  $d_{Long}$  is the distance between the cluster and the DGN. Note that, throughout this paper, we assume that the DGN has perfect knowledge of fading channel coefficients. It should be noted that, in the case of VV-BLAST with power-control  $\bar{E}_b$  changes with the number of data samples to be transmitted. We will use the notation  $E_t^{Long} = E_t^{LS}$  for V-STBC and  $E_t^{LB,p}$  for  $p \times p$  VV-BLAST.

During the system training all  $N_{tr}$  samples of each sensor are sent to the DGN uncompressed either using V-STBC along with local communications or using VV-BLAST. Thus, the total energy required for training by all  $N_s$  sensor nodes of a cluster is  $E^{Tr} = (E_t^{Local} + E_t^{LS}) \times n \times N_s \times N_{tr}$  in the case of for V-STBC and  $E^{Tr} = (E_t^{LB,N_s}) \times n \times N_s \times N_{tr}$  in the case of VV-BLAST, where  $n$  is the bits per sample without compression.

At each sample instant  $k$  the DGN broadcasts encoding information  $i(k, j)$  of all nodes within a cluster. Since  $i(k, j) \leq n$ , this requires a maximum of  $N_s \times \log_2(n)$  bits. Let  $L$  be the total number of samples collected from each sensor of a cluster. If  $r$  is the number of times a cluster receives encoding information updates from the DGN during correlation tracking, then the total number of samples  $L = N_{tr} + r \times N_{Rec}$  since after each update the sensors accumulate  $N_{Rec}$  data samples before transmission. The total energy consumption of all sensors of a cluster in receiving the encoding information can be computed as  $E^{Re} = r \times E_t^{re} \times \log_2(n) \times N_s^2$ . Since we are only concerned with the energy spent by the data collection sensors, in this case  $E_t^{re}$  is computed as  $\frac{P_C^{(LocRx)}}{R_b}$ .

We assume that, during correlation tracking, local and long-haul communications for V-STBC and long-haul communications for VV-BLAST are also performed  $r$  times, once in every  $T_{Rec}$ . In case of V-STBC, the total energy consumption for transmission of compressed readings by all the sensors of a cluster to the DGN can show to be  $E^{Comp} = (E_t^{Local} + E_t^{LS}) \sum_{j=1}^{N_s} \sum_{k=N_{tr}+1}^L i(k, j)$ . Note that according to our implementation of VV-BLAST, the order of the BLAST scheme decreases as sensors with less number of bits to send exhaust theirs. As a result initially a cluster transmits with an  $N_s \times N_s$  BLAST, then with an  $N_s - 1 \times N_s - 1$  BLAST and so on. Finally the sensor with the largest amount of data may have to send its remaining data via SISO. Let us denote by  $S_j^m = N_{Rec} i(N_{tr} + (m-1)N_{Rec} + 1, j)$  the total number of bits  $j$ -th sensor has at the beginning of the  $m$ -th transmission block for  $m = 1, \dots, r$ . Assuming that sensor indices are ordered in increasing order of number of bits, then  $E^{Comp}$  for VV-BLAST is given by  $E^{Comp} = \sum_{m=1}^r \sum_{j=1}^{N_s} j E_t^{LB,j} (S_{N_s+1-j}^m - S_{N_s-j}^m)$  where we have defined  $S_0^m = 0$  for all  $m$ .

We also need to consider the energy spent on tail bits included in mapping to M-QAM. For V-STBC, tail bits added during local and long-haul communications are  $N_{DC}^{local} = \sum_{j=1}^{N_s} \sum_{p=0}^{r-1} [N_{Rec} i(p N_{Rec} + N_{tr} + 1, j)] \bmod \log_2 M$  and  $N_{DC}^{long} = \sum_{p=0}^{r-1} ([N_{Rec} \sum_{j=1}^{N_s} i(p N_{Rec} + N_{tr} + 1, j)] \bmod \log_2 M)$ , respectively. Hence, the total energy spent on tail bits in the case of V-STBC is given by  $E^{Extra} = E_t^{Local} \times N_{DC}^{local} + E_t^{LS} \times N_{DC}^{long}$ . For VV-BLAST, this is computed as in the previous paragraph.

### C. Integrated System Efficiency Analysis

The total energy consumed by the proposed virtual MIMO-based system in collecting all  $L$  samples from all  $N_s$  sensors of a cluster is  $E^{Total} = E^{Tr} + E^{Re} + E^{Comp} + E^{Extra}$ . We evaluate

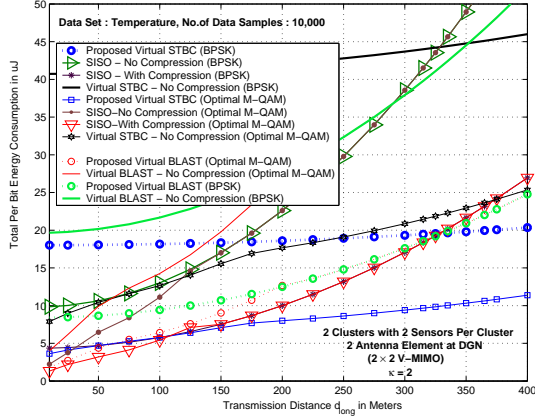


Fig. 1. Total Per Bit Energy Consumption With BPSK and Optimal M-QAM modulations

the energy efficiency of the proposed system with respect to three different reference systems. First is a system where all sensors send their readings to the DGN uncompressed (i.e., SISO with no compression). In this case, the total energy consumption of the system is given by,  $E^{Ref1} = L \times E_t^{SISO} \times N_s \times (n + n \bmod \log_2 M)$  where  $E_t^{SISO}$  is the per bit energy of SISO in Rayleigh fading. Note that, in this case  $P_C = P_C^{(LocTx)}$  and  $P_{PA}$  is computed with  $d = d_{Long}$ .

The second reference system is one in which all sensors encode their readings using the proposed RLS-based distributed compression algorithm but has no virtual transmitter or receiver diversity (i.e., SISO with compression). In this case the overall energy consumption of the system can be given as  $E^{Ref2} = E^{Comp} + E_t^{SISO} \times (N_{tr} \times n \times N_s + N_{DC}^{SISO})$ , where  $E^{Comp} = E_t^{SISO} \times \sum_{k=N_{tr}+1}^L \sum_{j=1}^{N_s} i(k, j)$ . Note that, here we also assume that the sensors combine  $N_{Rec}$  samples after each time they receive encoding information from the DGN.

The third reference system is one having virtual multiple antenna clusters but no distributed source coding (i.e., V-MIMO without compression). The total energy consumption of this system is given by  $E^{Ref3} = (E_t^{Local} + E_t^{Long}) \times N_s \times L \times (n + n \bmod \log_2 M)$ .

We define the energy efficiency  $\eta_E$  of the proposed integrated system with respect to any of the above reference schemes as  $\eta_E = \frac{E^{Ref} - E^{Total}}{E^{Ref}} \times 100\%$ .

### III. EXPERIMENTAL RESULTS

A network with a single DGN and two clusters, each with a pair of equi-distant sensors, is considered as the simulation test-bed. One of the 4 sensors is assumed to always acts as a reference sensor. For V-STBC, local communication distance  $d_{Loc}$  is set to 10 meters. Simulations are performed on the temperature data set used in [4] with over 10,000 samples for each sensor. A 12-bit A/D converter with a dynamic range of [-128,128] is assumed. We also assume that  $N_{tr} = 65$ ,  $N_{Rec} = 20$  and perfect feedback of encoding information from DGN to the sensor nodes. All power-consumption parameter values are the same as in [5].

Figure 1 shows the per bit energy consumption of the proposed and reference schemes as a function of the transmission distance  $d_{Long}$  for  $\kappa = 2$  with both BPSK and optimal M-QAM constellations. If minimization of per bit energy consumption is considered as the performance criterion then, the BPSK modulated proposed V-STBC-based integrated design has better performance beyond  $\approx 165m$  and  $\approx 325m$  compared to that of SISO with no compression and SISO with

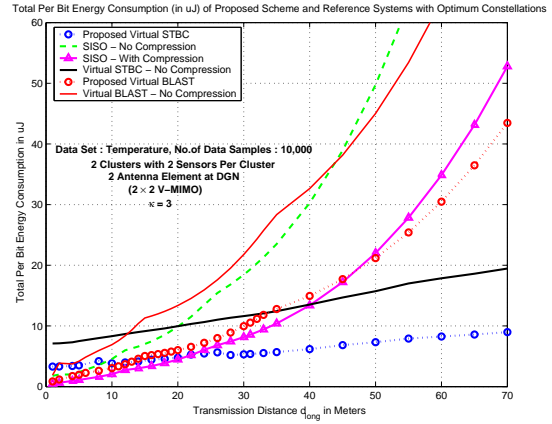


Fig. 2. Total Per Bit Energy Consumption With Optimal Constellations

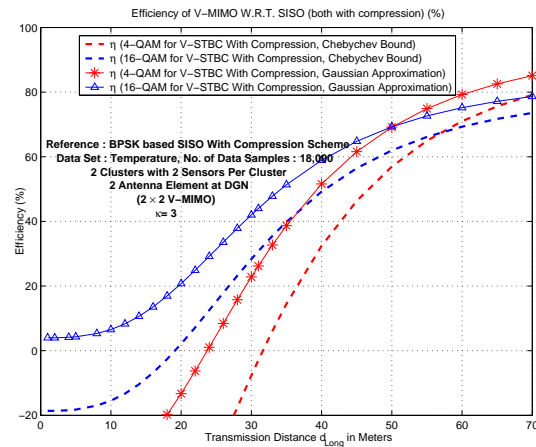


Fig. 3. Energy Efficiency

compression schemes, respectively. Moreover, VV-BLAST-based proposed design also has better performance compared to both SISO with and without compression schemes for relatively large  $d_{Long}$  transmission distances. For example, VV-BLAST outperforms SISO with compression for  $d > 330m$  (both with optimal M-QAM). It can also be shown that, if  $\kappa > 2$  these critical transmission distances at which the proposed schemes outperforms the reference schemes reduces drastically (for example, with  $\kappa = 3.5$  and BPSK modulation, both V-STBC-based and VV-BLAST-based schemes seen to outperform SISO with compression scheme for about 27m). Since  $\kappa > 2$  values are more realistic for typical wireless communications (near-earth propagation) channels, the proposed virtual MIMO-based integrated schemes can offer great energy savings for reasonable transmission distances. Note also that, the V-STBC-based proposed scheme with optimal M-QAM performs better than VV-BLAST-based design unless  $d_{Long}$  is very low. However, it can be shown that when the transmission delay is a major concern the VV-BLAST may be a better choice even for large long-haul distances [6].

In Fig. 2 we have shown the per bit energy consumption comparisons based on rate-optimized systems in a channel with  $\kappa = 3$ . Figure 2 shows that, although at very small transmission distances the SISO with compression scheme is better than both proposed integrated designs, for reasonably large distances they significantly outperform the SISO-based designs. Moreover, despite being slightly inferior to VV-

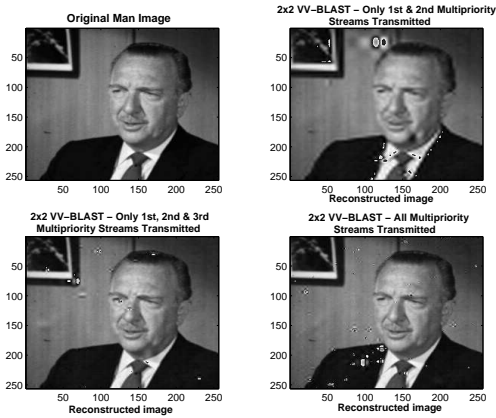


Fig. 4. Man Images at the DGN with Wavelet Based Transmission

BLAST-based scheme at very low transmission distances, V-STBC-based proposed integrated design has the best performance out of all the schemes beyond about 21m. Similarly, in the case of no compression systems also V-STBC-based design has the best performance out of the three considered systems. However, it should be mentioned that variable-rate QAM systems as in Fig. 2 require complex circuitry at sensor nodes. One way to reduce node design complexity is to opt a sub-optimal fixed-rate modulation. For instance, numerical results have shown that in a channel with  $\kappa = 3$ , 4-QAM modulation may provide reasonably improved performance over a SISO system with both V-STBC-based and VV-BLAST-based proposed schemes.

Figure 3 shows the energy efficiency performance of such fixed-rate,  $2 \times 2$  V-STBC-based proposed integrated systems with respect to a fixed-rate BPSK system. In Fig. 3 we have shown the efficiencies achieved with previously proposed Chebyshev bound based and our proposed Gaussian approximation based methods for computing the encoding information. As can be seen from Fig. 3, the proposed Gaussian approximation seems to provide somewhat improved performance over the Chebyshev bound based method. This performance gain is more profound particularly for larger distances. Of course, the reason for the inferiority of the Chebyshev bound is that it can be very loose for small error probabilities.

Finally to test the performance of the V-STBC and VV-BLAST in multi-media applications, we considered a  $256 \times 256$  man.bin image as the sensor data. Assuming perfect registration and restoration process at the DGN, the original image can be rebuilt using the sensor image data from different sensors. At sensors, the image data are wavelet transformed and divided into multi-priority streams. In our simulations we assumed a 4-level multi-priority division. In a traditional implementation each sensor will be required to transmit all its streams to the DGN. However, in our energy-efficient design only the specific prioritized streams, that are chosen based on the quality requirement at the DGN, are allowed to be transmitted from each sensor. In our proposed prioritizing scheme each sensor in a cluster of  $N_s$  sensors is asked to transmit only a  $1/N_s$  fraction of a chosen stream.

Note that here we have assumed a network with a single cluster and a DGN. As before two sensors per cluster and two antennas at the DGN are assumed ( $2 \times 2$  MIMO). The bit-error-rate is fixed to  $10^{-3}$ . The efficiency of the proposed integrated system with wavelet-transform based prioritizing and V-MIMO, is evaluated with respect to a reference system in which all the sensors of a cluster transmit the full image

data without any prioritization. Our comparison of achieved energy efficiency values of V-STBC and VV-BLAST based multi-priority wavelet transmission schemes with respect to this SISO-based reference system revealed that at lower long-haul transmission distances the VV-BLAST based prioritized-wavelet coefficient transmission scheme has better energy-efficiency compared to that of a V-STBC based corresponding scheme whereas as distance increases the gain of V-STBC becomes better. In Fig. 4 we have shown the simulated man images reconstructed at the DGN by combining different multi-priority wavelet streams received from different sensors.

#### IV. CONCLUSIONS

In this paper, we proposed energy efficient, integrated sensor network designs based on virtual MIMO and distributed source coding with RLS-based adaptive signal processing. By developing a detailed energy analysis method and using real sensor data, we showed that the proposed integrated designs can offer significant energy savings beyond certain long-haul transmission distances. We also proposed a new side encoding information computation method based on a Gaussian error approximation. This new method was shown to further improve the achieved energy efficiencies of the integrated system designs, particularly at large transmission distances. The proposed distributed compression scheme assisted by the RLS-based adaptive correlation tracking is effective in exploiting high data correlations present in sensor networks. Moreover, we have verified (this fact was shown before, for example, in [6]) that the energy gains of virtual MIMO-based schemes becomes more pronounced as channel path loss exponent increases. Overall, our results show that the proposed integrated designs based on virtual MIMO communication is a viable choice for cooperative networks with single-antenna sensor nodes. Finally, we proposed a wavelet-coefficient based multi-priority image transmission scheme for a sensor network designed with our proposed integrated virtual MIMO and distributed compression. Numerical results showed that this priority-based transmission scheme can offer significant energy efficiencies with reasonable image re-construction performance in low-power, multimedia sensor networks.

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#### REFERENCES

- [1] K. Ramakrishnan, K. Namuduri, and S. K. Jayaweera, "Multi-priority video partitioning for cdma based communication systems," in *IEEE Veh. Tech. Conf.*, Orlando, FL, Oct. 2003.
- [2] M. Gerla and K. Xu, "Multimedia streaming in large-scale sensor networks with mobile swarms," *SPECIAL ISSUE: Special section on sensor network technology and sensor data management*, vol. 32, no. 4, pp. 72–76, December 2003.
- [3] S. K. Jayaweera, "Energy efficient virtual mimo-based cooperative communications for wireless sensor networks," in *2nd International Conf. on Intelligent Sensing and Information Processing (ICISIP 05)*, Chennai, India, Jan 2005.
- [4] J. Chou, D. Petrovic, and K. Ramchandran, "A distributed and adaptive signal processing approach to reducing energy consumption in sensor networks," in *IEEE INFOCOM*, San Francisco, CA, Mar. 2003.
- [5] S. Cui, A. J. Goldsmith, and A. Bahai, "Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 22, no. 6, pp. 1089–1098, October 2004.
- [6] S. K. Jayaweera, "An energy-efficient virtual mimo communications architecture based on v-blast processing for distributed wireless sensor networks," in *1st IEEE International Conf. on Sensor and Ad-hoc Communications and Networks (SECON)*, Santa Clara, CA, oct 2004.
- [7] M. Chebolu and S. K. Jayaweera, "Energy efficiency analysis of an RLS-based adaptive signal processing algorithm for energy aware sensor networks," in *2nd International Conf. on Intelligent Sensing and Information Processing (ICISIP 05)*, Chennai, India, Jan 2005.