An Efficient Resource Utilization Scheme for Video Transmission over Wireless Sensor Networks

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Abstract— In this paper we propose an energy efficient video transmission strategy for wireless sensor networks, which combines wavelet-based image decomposition and cooperative communication. The proposed scheme uses the selective decode and forward (SDF) cooperation, so that a relay node collaborates with the source by forwarding only a lower-resolution version of the original video, obtained via discrete wavelet transform (DWT). We show that the proposed SDF-DWT strategy is more energy efficient than non-cooperative single-hop and multi-hop, also outperforming the regular SDF scheme. In addition, we show that our method can achieve the energy efficiency of incremental DF (IDF), without the need of a feedback channel.

Keywords: Cooperative communication, video transmission, wireless sensor networks, DWT.

I. INTRODUCTION

The advancement in wireless communications and electronics has enabled the development of low power sensor networks. The sensor networks can be used for various application areas (e.g., health, military, home). For different application areas, there are different technical issues that researchers are currently resolving. Wireless Sensor Networks (WSNs) are a collection of tiny nodes, consisting of sensing, data processing and communicating components, often connected in an ad hoc manner. These nodes are typically battery-operated and their recharge or replacement may be undesirable or not possible [1]. Thus, energy consumption is a key issue in the design of WSNs. An important WSN class, the Visual Sensor Networks (VSNs), has a camera as the sensor component and thus deal with images and videos. A video has an amount of data many orders greater than typical sensors data, like temperature, pressure, and humidity. Video data transmission consumes much more energy than for other typical WSN applications [2].

The large amount of data traffic for video transmissions over a WSN can rapidly shorten the lifetime of the network, so a strategy to mitigate this problem is to promote some sort of image data compression. Recent works have investigated transmission in WSNs, and many of them employ wavelet-based image compression. The [3] authors consider a non-cooperative multi-hop scenario and propose two schemes based on discrete wavelet transform (DWT). Semi-reliable transmission is employed, enabling priority based packet discarding by intermediate nodes according to their battery charge. A source node responds to a video query by the destination node, which specifies the desired video quality. Videos coming from different paths are combined at cluster heads, and then multiple copies of the combined videos are retransmitted. In [5] an energy efficient point-to-Point transmission scheme is discussed. The DWT is used in order to obtain different quality layers, and an algorithm adaptively determines the coding and transmission parameters.

Considering that network nodes are frequently single antenna devices, due to cost and size constraints, one technique to achieve energy savings is cooperative communications [6], [7]. In this technique a relay node overhears the communication between the source and destination nodes and collaborates forwarding the source information to the destination. One of the most employed cooperative protocols is known as selective decode-and-forward (SDF), where the relay only forwards the messages it can correctly decode. Another cooperative protocol, incremental decode-and-forward (IDF), is similar to SDF, but the relay forwards the messages correctly decoded only when required by the destination node.

Cooperative communications can save energy by reducing the required transmit power, but the additional RF circuitry consumption of the relay nodes must be taken into account [8]. It is important to note that in cooperative schemes the communication takes place in two time slots, while in case of non-cooperative single-hop transmission it usually occurs in a single time slot. So, the transmit power reduction obtained in cooperative schemes comes at the expense of the spectral efficiency seen at the receiver. A fair energy consumption comparison between cooperative and non-cooperative schemes should consider the same target packet loss rate and end-to-end throughput. The results in [9] show that, when these two constraints are considered, the cooperative schemes can be considerably more energy efficient than multi-hop and single hop, even for short transmission distances. The most energy efficient scheme is IDF [9], but it requires a feedback channel.

In this paper we propose an efficient video transmission strategy exploiting the multi-resolution characteristic of DWT. Differently than [3]-[5] , we consider the SDF cooperative transmission scheme, in which the relay sends a lower resolution version of the video originally transmitted from the source to the destination node. Thus, even if the destination does not receive the video from the source, there is a probability that it receives it from the relay. As we assume that transmissions are orthogonal in time and that the relay transmits less data than the source, the main contribution of this paper is to show that the overall energy consumption can be considerably reduced, with a negligible decrease on the average video quality. Moreover, we show that the proposed DWT-based SDF scheme can achieve the energy efficiency of IDF, with the advantage that in our proposed scheme a return channel is not required. The rest of this paper is organized as follows. Section II describes the

DWT and a video quality assessment metric. Section III analyzes the energy consumption of some transmission schemes, while the proposed SDF-DWT is presented in Section IV. Numerical results are shown in Section V and finally, Section VI concludes the paper.

II. IMAGEQUALITY METRIC FOR DWT CODED VIDEOS

The wavelet transform has been frequently used in signal processing applications. Its inherent capacity for multi resolution representation motivated a quick adoption and widespread use of wavelets in image-processing applications [10]. DWT is a process which can be roughly described as the decomposition of a digital signal by passing it through two filters, a low-pass filter (L) and a high-pass filter (H). This process generates two sub-bands, the low-pass sub-band representing a down sampled low-resolution version of the original signal, and the high-pass sub-band representing the residual information of the original signal, needed for the perfect reconstruction of the original set from the low-resolution version. Since image is a bi-dimensional signal, a 2D-DWT is performed. This is achieved by first applying the L and H filters to the image row by row, then re-filtering the output column by column by the same filters. As a result, the image is divided into four sub-bands, the LLsub-band, containing the image low-resolution version, and three sub-bands HL, $LH$and HH, containing horizontal, vertical and diagonal residual information, respectively [3]. The decomposition procedure can be repeated recursively to obtain multiple levels of decomposition. The most commonly used multidimensional 2D-DWT structure consists of a recursive decomposition of the LLsub-band, illustrated in Figure 1, where 2D-DWT was applied twice. In this paper we adopt the Le Gall 5-tap/3-tap wavelet filters [3], which are an energy efficient DWT implementation for image compression, requiring only fixed point operations.

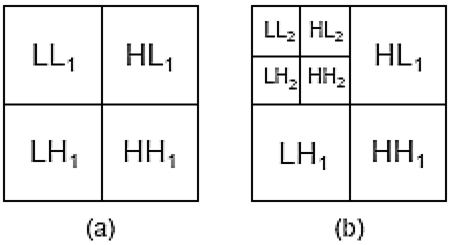

Fig. 1: 2D-DWT applied (a) once and (b) twice.

For a long time, the Mean-Squared Error (MSE), and the equivalent Peak-to-Signal Noise Ratio (PSNR), have been the dominant quantitative performance metrics in the field of signal processing [11]. Even though MSE and PSNR are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization, they are not very well matched to perceived visual quality [12]. The main reason is that distinct kind of image distortions can produce very similar MSE/PSNR values, although their perceived visual quality be quite different. Due to this, great efforts have gone into the development of quality assessment metrics that take advantage of known characteristics of the human visual system (HVS). Some of these metrics take into account the structural similarity of the original and the reconstructed images, rather than an error measurement. One of such a metric is the Structural Similarity Index (SSIM), based on the assumption that HVS is highly adapted to extract structural information from the viewing field. Thus, a measure of structural information change can provide a good approximation to perceived image distortion. Like MSE/PSNR, SSIM is a full-reference metric, in the sense that it compares a distorted version of an image with its original one. The similarity between both videos ranges from 0 (none) to 1 (identical). Assuming that x and y are local image patches taken from the same location of two videos that are being compared, the local SSIM index measures the similarities of three elements of the image patches: the similarity l(x, y) of the local patch luminance (brightness values), the similarity c(x, y) of the local patch contrast, and the similarity s(x, y) of the local patch structure. These local similarities are expressed using simple, easily computed statistics, and are combined together to form local SSIM [12] as:

$$\mathrm{SSIM}(\mathrm{x},\mathrm{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \quad (1)$$

Where μ_x and $\mu_y$are, respectively, the local sample means of x and y, σ_x and σ_y are, respectively, the local sample standard deviations of x and y, and $\sigma_{xy}$is the sample cross correlation of x and y after removing their means. The parameters C_1 and C_2 are small positive constants based on the dynamic range of the pixel values that stabilize each term, so that near-zero sample means, variances, or correlations do not lead to numerical instability. According to, it is useful to apply the SSIM index locally rather than globally. So, the statistics above are computed locally within a sliding window that moves pixel-by-pixel across the image, resulting in a SSIM map. This window has size 11 ×11 pixels, which is weighted by a circular-symmetric Gaussian function w = {w_i /1, 2, ..., N}, with standard deviation of 1.5 samples, normalized to unit sum ($\sum_{i=1}^{N} w_i = 1$). The estimates of local statisticsμ_x , σ_X and σ_{xy} are then computed as:

$$\mu_x = \sum_{i=1}^{N} w_i x_i, \quad (2)$$

$$\sigma_x = \left(\sum_{i=1}^{N} w_i (x_i - \mu_x)^2\right)^{\frac{1}{2}}, \quad (3)$$

$$\sigma_{xy} = \sum_{i=1}^{N} w_i (x_i - \mu_x)(y_i - \mu_y). \quad (4)$$

In practice, a single overall quality measure of the entire image is calculated by considering the mean SSIM (MSSIM) index:

$$\mathrm{MSSIM}(\mathrm{X},\mathrm{Y}) = \frac{1}{M}\sum_{j=1}^{M} \mathrm{SSIM}(\mathrm{x}_j,\mathrm{y}_j), \quad (5)$$

Where X and Y are the reference and the distorted images, respectively, $x_j$and $y_j$are the image contents at the j-th local window, and Miss the number of local windows in the image.

III. ENERGY CONSUMPTION ANALYSIS

We consider three relevant nodes in a WSN – source (S), relay (R) and destination (D) – where the source tries to communicate with the destination, and the relay is at an intermediate position. In addition, we assume that transmissions are orthogonal in time and that the nodes are half-duplex. The methods are characterized in terms of outage probability, and the Nakagami-$m$distribution [13] is employed to model the wireless propagation environment. Moreover, we assume that the channel is in long-term quasi-static fading.

For any given node i, transmitting a frame s, the received signal r_{ij}at node j is given by:

$$\mathrm{r}_{ij} = \sqrt{P\,\gamma_{ij}}\,h_{ij}\,\mathrm{s} + \mathrm{n}_{ij}, \qquad (6)$$

where P is the transmit power, h_{ij} is a scalar that represents the unity variance Nakagami-$m$quasi-static fading and nijrepresents the AWGN vector, with variance $N_0/2$ per dimension, where N_0 is the thermal noise power spectral density per Hertz. The path loss between $i$and $j$is given by [14]:

$$\gamma_{ij} = \frac{G\lambda^2}{(4\pi)^2 d_{ij}^{\alpha} M_l N_f}, \qquad (7)$$

Where$G$is the total gain of the transmit and receive antennas, $\lambda$is the wavelength and d_{ij}corresponds to the distance between nodes $i$and j. Parameter $\alpha$is the path loss exponent, $M_l$is the link margin and $N_f$is the noise figure at the receiver.

In the following we analyze the energy consumption in terms of the total energy consumption per bit, where we also include the power consumed by the RF circuitry for transmitting and receiving, which impacts the overall energy consumption especially at short distances. Two non-cooperative strategies are considered (single-hop and multi-hop), and two cooperative strategies (SDF and IDF), while a novel cooperative scheme, called SDF-DWT, is proposed in Section IV.

A. Single-hop Transmission (SH)

According to the model introduced in [8], the total consumed energy per bit in a transmission from $S$to $D$is:

$$E_{SH} = \frac{P_{PA,SH} + P_{TX} + P_{RX}}{R_b}, \qquad (8)$$

Where P_{PA}, represents the power consumed by the power amplifier in SH transmission, P_{TX} and P_{RX}, which are respectively the energy consumed by the transmitting and the receiving circuitry and $R_b$corresponds to the bit rate in bits/s.The energy efficiency analysis is performed under the constraint of an outage probability. In the transmission of a frame from node $i$to node j, an outage occurs when the Signal-to-Noise Ratio (SNR) at node $j$falls below a threshold β= 2^{Δ} −1 [14], where Δ = $R_b/B$is the spectral efficiency and $B$is the system bandwidth. In Nakagami-$m$fading, the outage probability of the SH transmission is given by [15]:

$$\mathcal{O}_{SH} = \frac{\Psi\left(m, \frac{mN\beta}{\gamma_{ij}P}\right)}{\Gamma(m)}, \qquad (9)$$

Where $\Gamma(a)$ and $\Psi(a, b)$ are the complete and incomplete gamma functions, respectively, and N= $N_0 \cdot B$is the noise power. At high SNR (low outage region), the outage probability can be approximated by [15]:

$$\mathcal{O}_{SH} \simeq \frac{1}{\Gamma(m+1)}\left(\frac{mN\beta}{\gamma_{ij}P}\right)^m. \qquad (10)$$

The minimal transmit power for SH is constrained by a target end-to-end spectral efficiency Δ and a target outage probability $\mathcal{O}*$at the receiver. Thus, by replacing o_{SH} by $\mathcal{O}*$, such that$o_{SH} \leq \mathcal{O}*$, the minimal transmit power P_{SH}^* is the power that minimizes (10) [9].

B. Multi-hop Transmission (MH)

In MH, S sends a packet to R which then forwards it to D. The S-Dlink is not utilized. Moreover, we assume that R is able to detect if the packet was received correctly or not, and Rforwards it to D only if the packet was correctly received. Otherwise, the packet is considered lost.

As mentioned before, the loss in spectral efficiency inherent to MH (which takes two time slots) reduces the Maximum end-to-end throughput to half that of SH [9]. Thus, in order to obtain the same end-to-end throughput, each transmission requires twice the spectral efficiency of SH. Consequently, an outage occurs when the received SNR is below a threshold $\beta' = 2^{2\Delta} - 1$. Thus, the outage probability for each i-$j$link is:

$$p_{ij} \simeq \frac{1}{\Gamma(m+1)}\left(\frac{mN\beta'}{\gamma_{ij}P}\right)^m. \qquad (11)$$

The overall outage probability for MH is given by the combination of the outages in the S-R and R-Dlinks:

$$\mathcal{O}_{MH} = p_{SR} + (1 - p_{SR}) \cdot p_{RD}, \qquad (12)$$

And, similar to SH, the minimal transmit power for MH, P_{MH}^* can be obtained from (12) by replacing o_{MH} by $\mathcal{O}*$. Then, the total consumed energy per bit in MH is:

$$E_{MH} = \frac{P_{PA,MH} + P_{TX} + P_{RX}}{2R_b} + (1 - p_{SR}) \cdot \frac{P_{PA,MH} + P_{TX} + P_{RX}}{2R_b}. \qquad (13)$$

The first term in (13) corresponds to the energy consumed by the first transmission, while second term, which occurs with probability $(1-p_{SR})$, corresponds to the energy consumed by the retransmission. In addition, note that all terms are divided by $2R_b$, because with the spectral efficiency multiplied by two, each single transmission is two times faster.

C. Decode-and-Forward Cooperative Transmission

As in MH, DF schemes also require two time slots to perform the communication: a broadcast from Sin the first time slot followed by a retransmission from Rin the second time slot. Considering that selection combining [14] is used at D, the end-to-end outage probability for the DF protocol, which includes the outage probabilities of the three links involved in the transmission, S-D,S–$R$and R-D, obtained from (11), is:

$$\mathcal{O}_{DF} = p_{SD} \cdot [p_{SR} + (1 - p_{SR}) \cdot p_{RD}], \qquad (14)$$

Which is the same for both SDF and IDF schemes, and from which we can obtain the minimal transmit power P^*_{DR}, given an outage target of $\mathcal{O}*$.

D. Selective DF (SDF)

In the SDF protocol, R cooperates whenever it successfully decodes the message from S. Then, the total consumed energy per bit is:

$$E_{SDF} = \frac{P_{PA,DF} + P_{TX} + 2P_{RX}}{2R_b} + (1 - p_{SR}) \cdot \frac{P_{PA,DF} + P_{TX} + P_{RX}}{2R_b}, \quad (15)$$

Where the first term in (15) represents the energy consumed in the broadcast phase, and the second term represents the case where $R$is successful in decoding the message from R, which is retransmitted to D. Note that the total energy consumption of SDF has one additional $P_{RX}$when compared to MH. That is because in the first time slot both $D$and Rhave to decode the transmission from S.

D. *Incremental DF (IDF)*

The IDF cooperative protocol takes advantage of the availability of a feedback channel. Through this channel, D is able to request a retransmission from Rif the previous transmission from S was not successful. Thus, Ronly retransmits if required by D. Then, total consumed energy per bit is:

$$E_{IDF} = \frac{P_{PA,DF} + P_{TX} + 2P_{RX}}{2R_b} + p_{SD} \cdot (1 - p_{SR}) \cdot \frac{P_{PA,DF} + P_{TX} + P_{RX}}{2R_b}, \quad (16)$$

Which only differs from (15) by an additional pSD in the second term of the equation, indicating that Rretransmits only if the message from the source could be perfectly recovered, and only if the transmission from Sfails.

IV. PROPOSED SCHEME: SDF-DWT

We consider applications where, although high quality videos are preferred, videos with lower quality are tolerable. This way, we proposed an SDF-DWT scheme, based on the classical SDF protocol; however, instead of retransmitting the entire video, the relay forwards only a lower-resolution version of it. As mentioned in Section II, when the 2D-DWT is applied to an image, four sub-bands are produced, with $LL1$ sub-band corresponding to a quarter-size version of the original image. Applying the 2D-DWT again over $LL1$ sub band produces the $LL2$ sub-band which is, by its turn, a quarter-size version of the $LL1$ sub-band image, corresponding to an image which is 1/16 times smaller than the original one. This decomposition procedure could be done many times as desired, but at the expense of a lower image quality. The resulting total consumed energy per bit in the proposed SDFDWT is:

$$E_{DWT} = \frac{P_{PA,DF} + P_{TX} + 2P_{RX}}{2R_b} + \frac{(1 - p_{SR})}{4^{N_{DWT}}} \cdot \frac{P_{PA,DF} + P_{TX} + P_{RX}}{2R_b}, \quad (17)$$

Where N_{DWT} corresponds to the number of times the 2D-DWT is applied to the original video. The first term in (17) represents the consumed energy when the entire video sent by $S$is received at $R$and D, while the second term represents the case where the lower-resolution video is forwarded by R. Note that, since the time spent during the second time slot is smaller than in the other schemes by a factor of $4^{N_{DWT}}$, a reduction on the overall energy consumption is expected.

In order to quantify the quality of the retransmitted video, since Ralways forwards a lower-resolution version of the original video sent by S, we define an video overall mean quality index, $Q_{N_{DWT}}$. We consider "mean quality" in the sense that we compute a mean value between the number of times that Dreceives the entire video from S, and the number of times that Dreceives the lower-resolution Video from R, weighted by their respective MSSIM values. So, the overall mean quality index for the N_{DWT} -th 2D-DWT level is:

$$Q_{N_{DWT}} = MSSIM_{MAX} \,.\, (1 - p_{SD}) + MSSIM_{N_{DWT}} . p_{SD}(1- p_{SR})(1- p_{RD}) \qquad (18)$$

Where $MSSIM_{MAX}$is the MSSIM value for the entire video (equal to 1), and $MSSIM_{N_{DWT}}$is the MSSIM value when the N_{DWT} -th 2D-DWT level is applied to the video. Therefore, the first term in (18) represents the case when Dhas successfully decoded the entire video from S, and the second term represents the case when the transmission from S to D failed, but Dcould successfully decodes the video from R.

V. NUMERICAL RESULTS

In this section we numerically compare the energy efficiency of the presented transmission schemes. We assume typical parameters used in literature and the simple WSN scenario mentioned on section III, with three nodes – source (S), relay (R) and destination (D). We assume that the link margin and the noise figure are M_l= 40 dB and N_f= 10 dB, respectively, the total antenna gain is G= 5 dBi, the carrier frequency is fc= 2.5 GHz and $N0$ = −174 dBm/Hz. Moreover, we consider a bandwidth of B= 10 kHz and the path loss exponent α= 2.5. Figure 2 shows the total energy consumed per bit for SH, MH, SDF, IDF, and the proposed SDF-DWT scheme, for N_{DWT} = 1, N_{DWT} = 2 and N_{DWT} = 3 in the case of NLOS. We assume a maximum packet loss rate of $\mathcal{O}$*= 10−2 and spectral efficiency of Δ = 2 bits/s/Hz. We also assume that $R$is at the midpoint in a straight line between $S$and D. As we observe, the proposed SDF-DWT scheme performs much better than single-hop, multi-hop schemes and, as expected, overcomes SDF in the whole distance range. The performance almost achieves the IDF one when 2D-DWT is applied once, and outperforms it when 2D-DWT is applied two and three times. We show a similar LOS scenario in Figure 3. Although SH presents a general improvement compared to the NLOS scenario, SDF-DWT outperforms all the other schemes when 2D-DWT is applied one, two and three times.

However, the gains in Figures 2 and 3 come at a potential loss in video quality. In order to determine the video quality loss we utilize a 512×512 bitmap gray-scale Yogitha video as the original test video.

We first apply the 2D-DWT to an image of video generating the $LL1$ sub-band.

Then we perform it recursively two more times, generating $LL2$ and $LL3$ sub-bands.

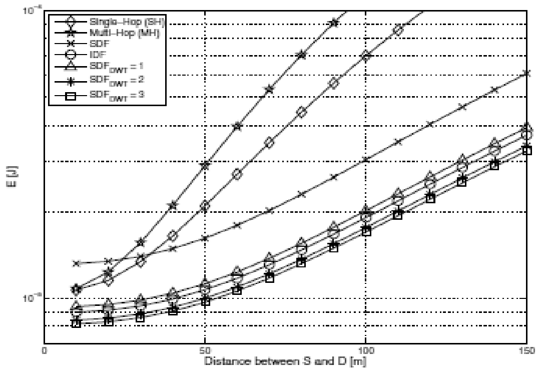

Fig. 2: Energy consumption in a NLOS scenario, for O*= 10 −2 and Δ = 2 bits/s/Hz.

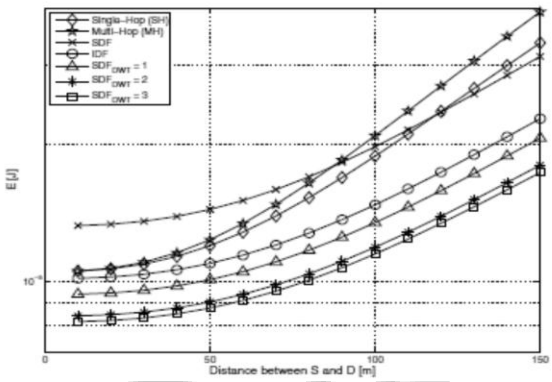

Fig. 3: Energy consumption in a LOS scenario, for O*= 10− 2 and Δ = 2 bits/s/Hz.

Each of these sub-bands is compared to the original image using a Matlab implementation of MSSIM index algorithm available online at [16]. In fact, as the images must be equal in size to be compared by MSSIM, the inverse 2D-DWT is applied to LLisub-bands until the original size is obtained. In this case, residual information sub-bands HLi, $LHi$and $HHi$are all made equal to zero. The obtained MSSIM values are 0.9301, 0.8324, for $LL1$, $LL2$ and respectively, which are very consistent with perceived visual quality of the images, as can be seen in Figure 4. It is worth to point out that even though applying 2D-DWT several times produces smaller images, visual quality also degrades. Besides, the overall energy consumption does not decrease at the same ratio, since energy consumption reduction occurs only in the second transmission time slot. For example, the application of the third 2D-DWT causes a substantial decrease in the image quality, from 0.8324 in MSSIM values, as shown in image (c) of Figure 4.However the energy savings per bit are very small, as shown in Figures 2 and 3. Hence, a trade-off between energy savings and video quality must be considered, depending on the available energy of the nodes and the video quality application constraints.

In terms of the video overall mean quality index, we show in Table I the results for $Q_{N_{DWT}}$considering three maximum packet loss constraints, O*= 10−2, O*= 10−3, and O*= 10−4. The more restrictive the packet loss is, the greater the contribution from $S$is in the $Q_{N_{DWT}}$index. Also, the contribution from $S$is more significant in an NLOS Environment than when some LOS is present.

Fig. 4: (a) Original image, MSSIM = 1 (b) $LL1$, MSSIM = 0.9301 (c) $LL2$, MSSIM = 0.8324 .

	NLOS scenario, m = 1					
	Outage Probabilities			Quality Index Q_{NDWT}		
O*	(1-O*)	(1-PSD)	(1-PRD)	Q1 (1-DWT)	Q2 (2-DWT)	Q3 (3-DWT)
10^{-2}	0.9900	0.8305	0.9700	0.9789	0.9633	0.9271
10^{-3}	0.9990	0.9467	0.9906	0.9953	0.9902	0.9784
10^{-4}	0.9999	0.9941	0.9970	0.9987	0.9971	0.9933
	NLOS scenario, m = 2					
	Outage Probabilities			Quality Index Q_{NDWT}		
O*	(1-O*)	(1-PSD)	(1-PRD)	Q1 (1-DWT)	Q2 (2-DWT)	Q3 (3-DWT)
10^{-2}	0.9900	0.5987	0.9875	0.9627	0.9244	0.8356
10^{-3}	0.9990	0.8734	0.9960	0.9902	0.9779	0.9494
10^{-4}	0.9999	0.9600	0.9987	0.9971	0.9932	0.9842

Table 1: Overall Video Quality Index

VI. CONCLUSION

In this paper we investigate the energy efficiency of a video transmission in a simple WSN scenario combining wavelet multilevel decomposition with an SDF cooperative scheme. The energy consumption for a video transmission is less in Wireless Sensor Networks by combining the Wavelet multilevel decomposition with an SDF cooperative operation. Hence the proposed scheme is more energy efficient than the Single Hop and the Multi Hop technique.

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