HS-EM Based Blind MIMO Channel Estimation for Dynamically Scalable JPEG Transmission

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***Abstract*—An Expectation-Maximization (EM) based scheme is presented in the context of compressed image transmission for blind Multiple-Input Multiple-Output (MIMO) wireless channel estimation. This cross-layer content-aware algorithm employs a combination of hard and soft (HS) symbol information from the header blocks of the scalable JPEG compressed image to estimate the complex baseband MIMO wireless channel. The proposed HS-EM scheme can significantly reduce the overhead for communication by avoiding the transmission of dedicated pilot symbols which constitute a considerable overhead in a MIMO wireless system. Further, the unique blend of HS information makes the algorithm ideally suited for scalable image transmission in the fast-fading wireless environment, while it simultaneously avoids the convergence problems typically associated with conventional blind estimation algorithms. Simulation results are presented in the end which demonstrate the performance of the proposed estimation scheme in terms of mean-squared error (MSE), BER, block error rate and PSNR in a MIMO wireless system.**

I. Introduction

Multiple-Input Multiple-Output communication has gained widespread attention in recent years as a key wireless technology. Such systems offer the dual advantages of link throughput enhancement through spatial multiplexing and wireless channel fading mitigation through diversity reception [?] which make them particularly attractive for implementation over wireless channels. Hence, MIMO has naturally been included as a key technology enabler in the major cellular and wireless local area network (WLAN) standards such as LTE/LTE-A, WiMAX, UMTS/HSPA+, 802.11n and so on. Such future systems are also envisaged to support a variety of rich data services with high speed transfer of images and video. Hence, cross-layer and content-aware MIMO techniques optimized for the delivery of such multimedia content through utilization of the structure of the underlying data are generating significant research interest [?].

Channel estimation is a key module in MIMO communication systems as the performance of the detection schemes and QoS for multimedia delivery depend critically on the accuracy and precision of the channel knowledge. Typically, the wireless channel is estimated by transmitting a known sequence of pilot symbols on the wireless link which constitutes an overhead in the system as the pilot symbols do not carry information. This already high overhead increases drastically in MIMO systems, since the total number of parameters to be estimated scales with the product of the number of receive and transmit antennas, resulting in a much higher pilot overhead. Hence, one is motivated to develop schemes to compute robust MIMO channel estimates without pilot transmissions. Conventional blind schemes in literature [?] do not utilize information available in the underlying data structure such as in the context of JPEG image transmission and are frequently prone to convergence problems and unidentifiability issues [?]. Such aspects are of great concern for multimedia transmission in practical wireless systems, where computational complexity and reliability are important design aspects along with support for high rate data transfer.

Motivated by the above factors, a novel blind HS-EM (hard-soft EM) algorithm is presented in the context of MIMO channel estimation for JPEG compressed image transmission. This scheme computes the maximum-likelihood (ML) estimate of the MIMO channel matrix by employing an Expectation-Maximization (EM) based algorithm. The MIMO channel is estimated from the header blocks of the compressed scalable JPEG stream, which belong to structured data sets, without the need to rely on pilot symbols. The size and quality parameters of the JPEG image are dynamically scalable depending on the fading wireless environment and scheduler load. The combination of hard and soft information makes the scheme robust against the variations in the transmitted header information arising out of such scalability, while at the same time it avoids both the pilot symbol overhead and ill-convergence problems associated with blind estimation algorithms [?]. Simulation results demonstrate that the proposed scheme achieves the Cramer-Rao Bound (CRB) for MIMO channel estimation and is hence mean-squared error (MSE) optimal. Further, it can be readily extended to include any transmitted pilot symbols to further enhance the accuracy of the MIMO channel estimate.

The rest of the paper is organized as follows. The next section presents the MIMO wireless system model, followed by the HS-EM algorithm and Cramer-Rao Bound for MIMO channel estimation in section **??**. Simulation results for mean-squared error, bit/packet error rates and PSNR for MIMO based JPEG transmission are presented in section **??** and conclusions are given in the end. Finally, it needs to be emphasized that JPEG is employed in the context of this work since it is a significantly popular compression format for image storage and distribution. However, the proposed scheme has widespread applicability and can be readily extended to other multimedia formats such as MPEG-2, MPEG-4, H.264 etc.

II. System Model

The flat-fading MIMO channel can be modeled as the complex matrix $\mathbf{H} \in \mathbb{C}^{r \times t}$, where r, t denote the number of receive and transmit antennas in the system. At time index k, the baseband wireless system model can be represented as,

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) + \eta(k)$$

where $\mathbf{y} \in \mathbb{C}^{r \times 1}, \mathbf{x} \in \mathbb{C}^{t \times 1}$ are the r and t dimensional complex receive and transmit symbol vectors respectively. The spatio-temporally white Gaussian noise is represented by $\eta(k) \in \mathbb{C}^{r \times 1}$ and has the covariance $\mathbf{R}_\eta \triangleq \mathrm{E}\left\{\eta(k)\eta^H(k)\right\} = \sigma_n^2 \mathbf{I}_r$. The channel matrix $\mathbf{H}$ arises from the random Rayleigh nature of the underlying MIMO wireless channel and has to be estimated at the receiver for the purposes of symbol detection. Once, the channel estimate $\hat{\mathbf{H}}$ is obtained, the symbol vectors $\mathbf{x}(k)$ of per symbol power P_d can be detected using the MMSE receiver $\mathbf{F} \triangleq P_d \hat{\mathbf{H}}^H \left(P_d \hat{\mathbf{H}}\hat{\mathbf{H}}^H + \sigma_n^2 \mathbf{I}_r\right)^{-1}$ as,

$$\hat{\mathbf{x}}(k) = \mathbf{F}\mathbf{y}(k), \tag{1}$$

where $\hat{\mathbf{H}}$ represents the estimate of the channel matrix $\mathbf{H}$ obtained from the channel estimation procedure. Let $\mathbf{X}_h \triangleq [\mathbf{x}_h(1), \mathbf{x}_h(2), ..., \mathbf{x}_h(N_h)] \in \mathbb{C}^{t \times N_h}$ be the N_h transmitted header symbol vectors classified as hard symbol vectors and $\mathbf{Y}_h \triangleq [\mathbf{y}_h(1), \mathbf{y}_h(2), ..., \mathbf{y}_h(N_h)] \in \mathbb{C}^{r \times N_h}$ be the corresponding received hard outputs. The input-output relation for the transmitted hard symbol vectors can be expressed as,

$$\mathbf{Y}_h = \mathbf{H}\mathbf{X}_h + \mathbf{V}_h, \tag{2}$$

where $\mathbf{V}_h$ is a stacking of the noise vectors. Let N_s soft information vectors be transmitted, with each vector $\mathbf{x}_s(i) \in \mathcal{U}_i, 1 \leq i \leq N_s$, where $\mathcal{U}_i$ is an indexed symbol vector set defined as,

$$\mathcal{U}_i = \left\{\mathbf{u}_i^1, \mathbf{u}_i^2, \ldots, \mathbf{u}_i^{L_i}\right\}, \mathbf{u}_i^j \in \mathbb{C}^{t \times 1}$$

and $L_i \triangleq |\mathcal{U}_i|$ is the cardinality of $\mathcal{U}_i$. Let $\mathbf{y}_s(i)$ denote the corresponding received soft symbol vector. The soft information reflects the scalable nature of the image transmission scheme. For instance, when the i^{th} vector corresponds to the JPEG quality header information block, $\mathcal{U}_i$ denotes the set of possible quantization tables such as shown in Table **??**. This is the basis of the HS-EM algorithm for MIMO estimation described next.

III. HS-EM for ML MIMO Estimation

The Expectation-Maximization (EM) framework can be conveniently employed to compute the MIMO channel estimate $\hat{\mathbf{H}}$ from the otherwise intractable likelihood cost function that is derived from the above system model. The EM algorithm originally proposed in [**?**] is very attractive from a practical implementation perspective since it asymptotically converges to the optimal maximum-likelihood (ML) estimate. Further, it is ideally suited in the context of JPEG image transmission, since the transmitted image parameters belong to a specified set depending on the image capture device specifications, feedback about the wireless fading environment etc. For instance, parameters such as image size, Quantization Table (QT) are examples of structured data elements which can be used to garner soft information, while the different markers etc. such as SOI, JFIF, can be employed as hard information. A sample partitioning of a few of the JPEG header blocks into HS components is give in Table **??**. The HS-EM algorithm for $\hat{\mathbf{H}}$ computation is described below.

The complete information for the above system can be represented by $\mathcal{D}$ defined as, $\mathcal{D} \triangleq \{\mathbf{Y}_h, \mathbf{X}_h, \mathbf{Y}_s, \mathbf{X}_s\}$, where the soft information is the hidden data. Let $\hat{\mathbf{H}}^{(k)}$ denote the estimate of the MIMO channel matrix after the k^{th} M-step of the EM algorithm. Substituting the above components of the complete information $\mathcal{D}$, one can obtain the expected log-likelihood $\mathcal{G}\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right)$ for the E-step as,

$$\mathcal{G}\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right) \triangleq \mathcal{L}_h(\mathbf{H}) + \mathcal{L}_s\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right), \tag{3}$$

where the quantities $\mathcal{L}_h(\mathbf{H})$ and $\mathcal{L}_s\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right)$ represent the loglikelihood components for the hard and soft information respectively. The expression for $\mathcal{L}_h(\mathbf{H})$ can be obtained as,

$$\mathcal{L}_h(\mathbf{H}) = \|\mathbf{Y}_h - \mathbf{H}\mathbf{X}_h\|^2. \tag{4}$$

It can be readily noticed that the expression defined above for $\mathcal{L}_h(\mathbf{H})$ does not involve $\hat{\mathbf{H}}^{(k)}$, the k^{th} M-step estimate. Hence, it can be conveniently employed to obtain the estimate $\hat{\mathbf{H}}^{(0)}$ to initiate the HS-EM algorithm. Thus, the information from the hard likelihood significantly helps avoid the initial point problems otherwise associated with ill-convergence issues in conventional blind MIMO channel estimation algorithms. The soft likelihood component $\mathcal{L}_s\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right)$ can similarly be deduced as,

$$\mathcal{L}_s\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right) = \sum_{i=1}^{N_s} \sum_{j=1}^{L_i} p\left(\mathbf{u}_i^j | \mathbf{y}_s(i); \hat{\mathbf{H}}^{(k)}\right) \left\|\mathbf{y}_s(i) - \mathbf{H}\mathbf{u}_i^j\right\|^2. \tag{5}$$

The estimate $\hat{\mathbf{H}}^{(k+1)}$ from the $(k+1)^{th}$ M-step of the HS-EM algorithm can be obtained by the maximization of the log likelihood function in (**??**) as,

$$\hat{\mathbf{H}}^{(k+1)} = \arg\max \mathcal{G}\left(\mathbf{H}, \hat{\mathbf{H}}^{(k)}\right).$$

The above maximization is carried out by considering the matrix derivative of the cost function above. Substituting the expressions for the soft and hard likelihood functions from (**??**),(**??**) one can further simplify the above expression. The simplification for the soft information symbols is similar to the one in [**?**]. Due to a lack of space, the elaborate derivation of these expressions is avoided here and the closed form expression for the MIMO channel estimate $\hat{\mathbf{H}}^{(k+1)}$ can be obtained as,

$$\hat{\mathbf{H}}^{(k+1)} = \mathbf{R}_{\{(\mathbf{Y}_h, \mathbf{X}_h), (\mathbf{Y}_s, \mathbf{X}_s)\}} \left(\mathbf{R}_{\{(\mathbf{X}_h, \mathbf{X}_h), (\mathbf{X}_s, \mathbf{X}_s)\}}\right)^{-1}, \tag{6}$$

TABLE I: Table for Sample HS Classification of JPEG Header Bytes.

Type	Name	# of Bytes	Bytes
Hard	SOI Marker	2	0xFF, 0xD8
Hard	JFIF Marker	2	0xFF, 0xE0
Hard	JFIF Identifier	5	0x4A, 0x46, 0x49, 0x46, 0x00
Hard	QT Marker	2	0xFF, 0xDB
Soft	Q Table	64	0x08, 0x06, 0x06,...
Soft	Number of Lines	2	0x20, 0x00
Soft	Number of Samples/Line	2	0x20, 0x00

$$\hat{\mathbf{H}}^{(k+1)} = \mathbf{R}_{\{(\mathbf{Y}_h,\mathbf{X}_h),(\mathbf{Y}_s,\mathbf{X}_s),(\mathbf{Y}_p,\mathbf{X}_p)\}} \left(\mathbf{R}_{\{(\mathbf{X}_h,\mathbf{X}_h),(\mathbf{X}_s,\mathbf{X}_s),(\mathbf{X}_p,\mathbf{X}_p)\}}\right)^{-1}$$

$$\mathbf{R}_{\{(\mathbf{Y}_h,\mathbf{X}_h),(\mathbf{Y}_s,\mathbf{X}_s),(\mathbf{Y}_p,\mathbf{X}_p)\}} = \sum_{l=1}^{N_h} \mathbf{y}_h(l)\mathbf{x}_h^H(l) + \sum_{i=1}^{N_s}\sum_{j=1}^{L_i} p\left(\mathbf{u}_i^j|\mathbf{y}_s(i);\hat{\mathbf{H}}^{(k)}\right)\mathbf{y}_s(i)\left(\mathbf{u}_i^j\right)^H + \sum_{q=1}^{N_p}\mathbf{y}_p(q)\mathbf{x}_p^H(q)$$

$$\mathbf{R}_{\{(\mathbf{X}_h,\mathbf{X}_h),(\mathbf{X}_s,\mathbf{X}_s),(\mathbf{X}_p,\mathbf{X}_p)\}} = \sum_{l=1}^{N_h} \mathbf{x}_h(l)\mathbf{x}_h^H(l) + \sum_{i=1}^{N_s}\sum_{j=1}^{L_i} p\left(\mathbf{u}_i^j|\mathbf{y}_s(i);\hat{\mathbf{H}}^{(k)}\right)\left(\mathbf{u}_i^j\right)\left(\mathbf{u}_i^j\right)^H + \sum_{q=1}^{N_p}\mathbf{x}_p(q)\mathbf{x}_p^H(q)$$

TABLE II: Conventional Pilots Inclusion for $\hat{\mathbf{H}}$ Estimation Accuracy Enhancement.

where the hard-soft cross-covariance matrix between the received and transmitted information $\mathbf{R}_{\{(\mathbf{Y}_h,\mathbf{X}_h),(\mathbf{Y}_s,\mathbf{X}_s)\}}$ is,

$$\sum_{l=1}^{N_h}\mathbf{y}_h(l)\mathbf{x}_h^H(l) + \sum_{i=1}^{N_s}\sum_{j=1}^{L_i} p\left(\mathbf{u}_i^j|\mathbf{y}_s(i);\hat{\mathbf{H}}^{(k)}\right)\mathbf{y}_s(i)\left(\mathbf{u}_i^j\right)^H$$

and the hard-soft covariance for the transmit information $\mathbf{X}_h, \mathbf{X}_s$ denoted by $\mathbf{R}_{\{(\mathbf{X}_h,\mathbf{X}_h),(\mathbf{X}_s,\mathbf{X}_s)\}}$ is defined as,

$$\sum_{l=1}^{N_h}\mathbf{x}_h(l)\mathbf{x}_h^H(l) + \sum_{i=1}^{N_s}\sum_{j=1}^{L_i} p\left(\mathbf{u}_i^j|\mathbf{y}_s(i);\hat{\mathbf{H}}^{(k)}\right)\left(\mathbf{u}_i^j\right)\left(\mathbf{u}_i^j\right)^H$$

The posterior probabilities assuming equally likely soft symbol vectors are given as,

$$p\left(\mathbf{u}_i^j|\mathbf{y}_s(i);\hat{\mathbf{H}}^{(k)}\right) = \frac{p\left(\mathbf{y}_s(i)|\mathbf{u}_i^j;\hat{\mathbf{H}}^{(k)}\right)}{\sum_{l=1}^{L_i} p\left(\mathbf{y}_s(i)|\mathbf{u}_i^l;\hat{\mathbf{H}}^{(k)}\right)}.$$

The quantity $p\left(\mathbf{y}_s(i)|\mathbf{u}_i^j;\hat{\mathbf{H}}^{(k)}\right)$ is given by the Gaussian likelihood function,

$$\frac{1}{\sqrt{(2\pi)^r|\mathbf{R}_\eta|}}\exp\left\{-\frac{1}{\sigma_n^2}\left\|\mathbf{y}_s(i)-\hat{\mathbf{H}}^{(k)}\mathbf{u}_i^j\right\|^2\right\}.$$

Thus, the HS-EM algorithm computes a reliable MIMO channel estimate using (**??**) in very few M-steps. Further, as already discussed above, the initial estimate $\hat{\mathbf{H}}^{(0)}$ can be computed from the hard information vectors as,

$$\hat{\mathbf{H}}^{(0)} = \left(\sum_{l=1}^{N_h}\mathbf{y}_h(l)\mathbf{x}_h^H(l)\right)\left(\sum_{l=1}^{N_h}\mathbf{x}_h(l)\mathbf{x}_h^H(l)\right)^{-1}$$

The cross-layer nature of the algorithm suggests that the accuracy of the channel estimate can be significantly enhanced by making the header symbols available for channel estimation. Further, any conventional pilot symbols $\mathbf{X}_p$ and corresponding outputs $\mathbf{Y}_p$ can be readily incorporated in the above scheme to enhance the accuracy of the HS-EM estimate as illustrated by expressions in Table **??**.

A. *Cramer-Rao Bound for* $\mathbf{H}$ *Estimation*

As suggested in [**?**] for the construction of CRBs of complex parameters, let the complex parameter vector $\bar{\theta} \in \mathbb{C}^{2rt\times 1}$ be constructed by stacking the parameter vector $\text{vec}(\mathbf{H})$ ($\text{vec}(\cdot)$ denotes standard vectorization) and its conjugate as,

$$\bar{\theta} \triangleq \begin{bmatrix} \text{vec}(\mathbf{H}) \\ \text{vec}(\mathbf{H}^*) \end{bmatrix}$$

The Cramer-Rao Bound (CRB) for the estimation of $\bar{\theta}$ is given by the matrix $\mathbf{J}_{\bar{\theta}}^{-1}$, where $\mathbf{J}_{\bar{\theta}} \in \mathbb{C}^{2r\times 2r}$ is the complex Fisher information matrix (FIM) for the parameter vector $\bar{\theta} \in \mathbb{C}^{2r\times 1}$ and is given as,

$$\mathbf{J}_{\bar{\theta}} = -\text{E}\left\{\frac{\partial^2\mathcal{L}\left([\mathbf{Y}_h,\mathbf{Y}_s]\,|[\mathbf{X}_h,\mathbf{X}_s]\,;\bar{\theta}\right)}{\partial\bar{\theta}\,\partial\bar{\theta}^H}\right\}$$

The CRB for the MSE of the MIMO channel matrix estimate in the above system can be derived as,

$$\text{E}\left\{\left\|\hat{\mathbf{H}}-\mathbf{H}\right\|^2\right\} \geq r\sigma_n^2\text{tr}\left(\left(\mathbf{X}_h\mathbf{X}_h^H+\mathbf{X}_s\mathbf{X}_s^H\right)^{-1}\right), \quad (7)$$

where $\text{tr}(\cdot)$ denotes the trace of the matrix. It can be seen from the simulation study in the next section that the HSEM scheme for MIMO estimation achieves this CRB and is MSE optimal for unbiased estimation of the channel matrix $\mathbf{H}$.

IV. Simulation Results

A 4×4 Rayleigh flat-fading MIMO wireless system i.e. with $r=4$ receive antennas and $t=4$ transmit antennas was simulated. The reference image set of 4 images in Table **??** was considered for JPEG transmission over the MIMO wireless fading channel. Further, by scaling the size and quantization parameters dynamically as per the parameter set in Table **??**, a total of 64 images of varying sizes and JPEG compression quality were considered for transmission, from which the image to be transmitted was chosen randomly. Hence, the

TABLE III: Image Set for MIMO JPEG Transmission. The size and quality (QT) of each image can be scaled dynamically to effectively create a set of 64 images from which the image transmitted over the MIMO channel is selected randomly.

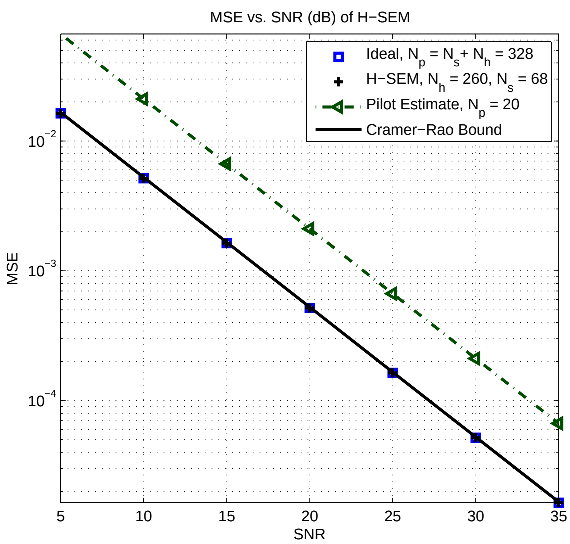

Fig. 1: MSE Comparison of using HS-EM ($N_h = 260, N_s = 68$) for the 4×4 MIMO wireless channel $\mathbf{H}$ estimation.

transmitted image size and the quantization table (QT) header symbols constitute soft information blocks as illustrated in Table **??**. The QT is assumed to belong to one of a set of $L_{\mathrm{QT}} = 4$ possible QTs for $35\%, 55\%, 75\%, 95\%$ JPEG image quality and the corresponding quantization step sizes in the JPEG standard *zig-zag* scan order are given in Table **??**. The rest of the header is partitioned as hard information and results in $N_s = 68, N_h = 260$ symbols for the image set

Size	64×64	128×128	256×256	512×512
Quality	35%	55%	75%	95%

TABLE IV: Image Parameter Set

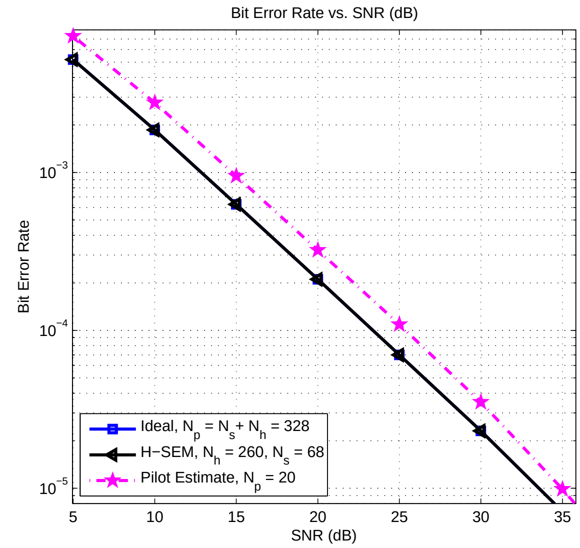

Fig. 2: BER comparison of HS-EM with pilot only estimation for JPEG Transmission over the 4×4 MIMO channel.

described above. Such a partitioning also allows for flexibility in algorithm implementation making the system robust for scalability of image size, QT aspects. The QPSK modulated JPEG stream packets are appended with the 8 bit CRC, $\mathrm{CRC}-8 = \mathrm{x}^8 + \mathrm{x}^7 + \mathrm{x}^6 + \mathrm{x}^4 + \mathrm{x}^2 + 1$, to detect packet errors. The symbols are demultiplexed spatially across the t transmit antennas. At the receiver, each receive vector is passed through the MMSE symbol detector in (**??**) constructed from the MIMO estimate $\hat{\mathbf{H}}$ followed by multiplexing of the spatial streams. The stopping criterion $\mathrm{MAX\_ITER} = 10$ yields good performance for the HS-EM. After the CRC check, the bits are input to the JPEG decoder.

The mean-squared error (MSE) of MIMO channel estimation for the simulated system is shown in Fig.**??** from which it can be observed that the HS-EM scheme ($N_s = 68, N_h = 260$) achieves an estimation accuracy close to the ideal $N_p = N_s + N_h = 328$ pilot symbol based estimation. In other words, this blind scheme is equivalent to the transmission of $N_p = 328$ pilot symbols, suggesting that the HS-EM is very robust. Further, it can be seen that the HS-EM estimate achieves the CRB for $\mathbf{H}$ estimation given in (**??**) and is hence the ML optimal estimator. The MSE of an estimator employing a pilot overhead of $N_p = 20$ is plotted for comparison, which illustrates that the blind HS-EM scheme achieves a significantly lower MSE while eliminating the pilot overhead. Fig.**??** and Fig.**??** demonstrate the bit error rate (BER) and block error rate (BLER) performance respectively of the MIMO system for HS-EM based $\mathbf{H}$ estimation. HS-EM achieves a performance close to the ideal scheme. They can also be seen to yield a 2 dB improvement in performance compared to exclusively pilots based conventional least-squares estimation with $N_p = 20$. Fig.**??** demonstrates a 2 dB improvement in peak SNR (PSNR) performance of the blind HS-EM scheme for images of varying size $64, 128$ and quality $75\%, 35\%$.

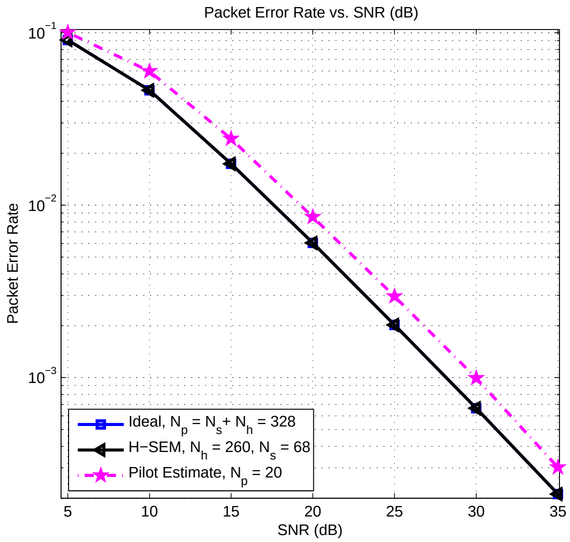

Fig. 3: Block Error Rate (BLER) vs. SNR (dB) for HS-EM estimation employing CRC-8 based block error detection.

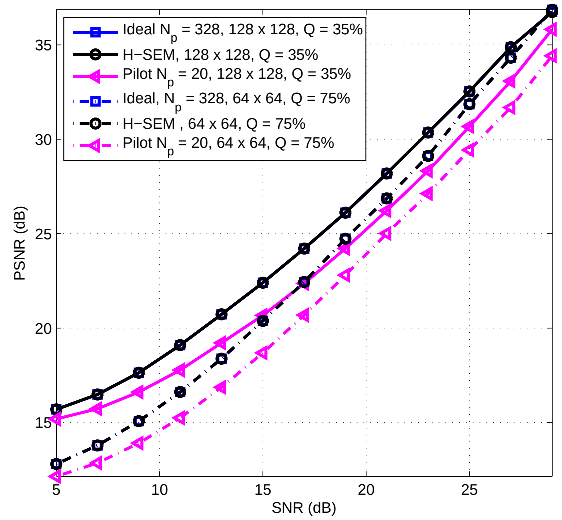

Fig. 4: PSNR vs. SNR for sample 128×128 and 64×64 JPEG images after reconstruction at the receiver JPEG decoder.

V. Conclusion

The HS-EM algorithm for MIMO channel estimation in the context of JPEG image transmission elaborated above intelligently employs the structure of the underlying image content to compute an accurate MIMO channel estimate. Thus, it not only avoids pilot overheads but also the unique combination of hard-soft information makes it robust for practical implementation and helps avoid convergence and complexity issues associated with conventional blind estimation algorithms. Simulation results demonstrate good MSE, bit error-rate and block error-rate performance for the proposed scheme in a MIMO wireless system. This scheme can be readily extended to several other multimedia transmission schemes based on MPEG-2/4, H.263, H.264 etc.

35%	55%	75%	95%	35%	55%	75%	95%
23	14	8	2	80	50	28	6
16	10	6	1	78	50	28	6
17	11	6	1	91	58	32	6
20	13	7	1	102	65	36	7
17	11	6	1	131	83	46	9
14	9	5	1	111	70	39	8
23	14	8	2	91	58	32	6
20	13	7	1	97	61	34	7
18	12	7	1	124	78	44	9
20	13	7	1	98	62	35	7
26	16	9	2	78	50	28	6
24	15	9	2	80	50	28	6
23	14	8	2	114	72	40	8
27	17	10	2	155	98	55	11
34	22	12	2	115	73	41	8
57	36	20	4	124	78	44	9
37	23	13	3	135	86	48	10
34	22	12	2	139	88	49	10
31	20	11	2	146	93	52	10
31	20	11	2	148	94	52	10
34	22	12	2	146	93	52	10
70	44	25	5	88	56	31	6
50	32	18	4	109	69	39	8
53	33	19	4	160	102	57	11
41	26	15	3	172	109	61	12
57	36	20	4	159	101	56	11
82	52	29	6	142	90	50	10
72	46	26	5	170	108	60	12
87	55	31	6	131	83	46	9
85	54	30	6	143	91	51	10
81	51	29	6	146	93	52	10
72	46	26	5	141	89	50	10

TABLE V: Quantization Tables for JPEG in zig-zag Scan Order with Coefficient numbers $1-32$ on left and $33-34$ on the right. $35, 55, 75, 95$ correspond to the JPEG Quality Factor.