Optimal Viterbi Based Total Variation Sequence Detection (TVSD) For Robust Image/Video Decoding In Wireless Sensor Networks

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***Abstract*—In this letter, we propose a novel scheme for robust reconstruction, based on total variation regularization, towards image/video communication in multimedia wireless sensor networks. We derive the optimal joint source channel decoder as the combination of a maximum likelihood cost function and an anisotropic total variation norm based regularization factor. The proposed scheme exploits the bounded variation (BV) property of images and is thus ideally suited for reconstruction. Subsequently, it is demonstrated that the trellis based Viterbi decoder can be employed for robust image reconstruction using modified total variation state and branch metrics. Simulation results for BTC and JPEG encoded image transmission demonstrate a superior reconstruction performance for the proposed scheme in comparison to conventional methods.**

***Index Terms*—Image/video reconstruction, total variation regularization, Viterbi decoder, wireless sensor networks.**

I. Introduction

THE advent of wireless sensor networks (WSN) has enabled several new applications such as target tracking, remote environment monitoring etc. A typical WSN [1] consists of clusters of sensor nodes which communicate with the cluster head. Further, image and video communication is a key component of multimedia sensor networks, which have attracted significant attention for surveillance and defense applications. However, in wireless scenarios, transmission of multimedia content comprising of images and video frames is challenging due to the highly error prone nature of communication over the fading wireless channel. This has necessitated the development of robust error resilient schemes for image and video reconstruction in fading WSNs. In this context, several schemes have been suggested in existing literature, which improve the performance of image recovery by exploiting the fading channel diversity properties, such as parallel channel coding at the physical layer and multiple description (MD) source coding at the application layer [2]. MD coding enhances the error resilience of the multimedia stream transmitted over the wireless link by using a correlating block transform which adds controlled redundancy [3]. Although this procedure mitigates the effect of packet erasures which occur during communication, it leads to an overall reduction of the compression efficiency. The sensor nodes in a typical WSN are small battery operated wireless devices. Thus, they are severely limited in terms of the number of antennas that can be employed to exploit spatial diversity. Further, the stringent bandwidth and energy constraints, coupled with the lower computational resources, discourage the employment of redundancy increasing schemes such as MD codes, which lead to higher processing and transmission overheads. It is therefore necessary to design low complexity schemes for WSNs, which limit the transmit pre-processing at the miniature sensor nodes. The work in [1] describes an interesting scheme which employs the temporal correlation of the sensor data for error correction at the cluster head, leading to robust data reconstruction. Further, this scheme is implemented at the cluster head, thereby significantly decreasing the computational complexity at the sensor nodes. Also, total variation regularization schemes have been demonstrated to yield superior image/video reconstruction performance as shown in works such as [4]. The work in [4] demonstrates an application of TV based image reconstruction in the context of image/video blur removal. However, none of the schemes above consider image reconstruction for digitally modulated coded image transmission over a fading wireless channel. Therefore, in this work, we present a novel scheme based on total variation regularization in multimedia wireless sensor networks. Specifically, we motivate the robust image decoding problem as the maximum likelihood symbol decoder in conjunction with an L_1 regularization component which is based on the principle of bounded total variation of the decoded image stream. It is demonstrated that the optimal total variation sequence decoder can be derived employing the Viterbi algorithm with appropriate state and path metrics, thereby making it very attractive and efficient for implementation in WSNs. To demonstrate the performance of the proposed scheme, we employ BTC, JPEG encoding for wireless image transmission. This demonstrates that the presented algorithm is general in nature and can be extended to other compression schemes in a relatively straightforward fashion. Simulation results are presented to demonstrate the reconstruction performance of the proposed scheme. The organization of the letter is as follows: Section II describes the wireless system model for coded image transmission and introduces the notation used in the rest of the discussion. Section III details the proposed Viterbi algorithm based TVSD (Total Variation Sequence Detection) scheme for image reconstruction along with the expressions

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for the regularized trellis state and branch metrics. In Section IV, we demonstrate the performance of the proposed scheme with the aid of simulations and conclude with Section V.

II. System Model for Coded Image Communication

Consider an $M \times N$ digital image $\mathbf{P}$, with the individual elements of $\mathbf{P}$ represented by $p_{i,j}$ for $1 \leq i \leq M, 1 \leq j \leq N$. Each element $p_{i,j}$ gives the gray scale intensity level corresponding to pixel location (i, j), also known as the pixel value. Prior to being transmitted to the WSN cluster head, the image may be encoded at the sensor node employing an appropriate image coding scheme such as BTC, JPEG etc to achieve an appropriate level of compression, which is necessary due to the limited bandwidth available for wireless transmission. The various components of the system for wireless coded image transmission and reconstruction are discussed in the following subsections. We begin with a brief outline of the wireless system model next.

A. Wireless System Model

Let the encoded image comprise of m and n coded blocks in each column and row respectively. Hence there are a total of $L = mn$ coded blocks where the lth block has K_l coded components and the kth coded component of the lth block contains K_l^k symbols. Let the ith modulated symbol of the kth coded component in the lth block be represented by $x_l^k(i) \in \mathcal{S} \subset \mathbb{C}$, where $\mathcal{S}$ denotes an R-ary digital modulation constellation such as BPSK ($R = 2$), QPSK ($R = 4$) etc and $\mathbb{C}$ denotes the set of complex numbers. Let $y_l^k(i) \in \mathbb{C}$ denote the received signal corresponding to the transmission of symbol $x_l^k(i)$ over the wireless channel. The model for the input-output system above can be expressed as,

$$y_l^k(i) = h x_l^k(i) + \eta_l^k(i), \tag{1}$$

where $h \in \mathbb{C}$ is the complex valued Rayleigh fading coefficient characterizing the wireless channel between the transmitter and receiver and $\eta_l^k(i)$ is the complex zero mean additive white Gaussian noise of variance σ_η^2 at the receiver.

B. Conventional Maximum Likelihood (ML) Decoder

Let $\mathbf{x}_l^k = [x_l^k(1), x_l^k(2), \ldots, x_l^k(K_l^k)]^T$ and $\mathbf{y}_l^k = [y_l^k(1), y_l^k(2), \ldots, y_l^k(K_l^k)]^T$ denote the transmit and receive symbol vectors respectively corresponding to the kth coded component of the lth block. Let $\mathbb{S}_b$ denote the set of valid symbol vectors of dimension b with $\mathbb{S}_b \subseteq \mathcal{S}^b \triangleq \prod_{i=1}^{b} \mathcal{S}$, where $\mathcal{S}^b$ consists of all possible b dimensional symbol vectors $\mathbf{s}_i \in \mathcal{S}^b$, $1 \leq i \leq R^b$. Conventionally, the transmitted b dimensional symbol vector $\mathbf{x}_l^k \in \mathbb{S}_b$ is recovered from the received b dimensional signal vector $\mathbf{y}_l^k \in \mathbb{C}^b \triangleq \prod_{i=1}^{b} \mathbb{C}$ at the receiver employing the least squares cost function based optimization rule described as given in [5],

$$\hat{\mathbf{x}}_l^k = \underset{\mathbf{x}_l^k \in \mathbb{S}_b}{\arg\min} \|\mathbf{y}_l^k - \mathbf{H}_l^k \mathbf{x}_l^k\|_2^2. \tag{2}$$

Here $\mathbf{H}_l^k \in \mathbb{C}^{b_l^k \times b_l^k}$ is the effective fading channel coefficient matrix, where b_l^k is the number of symbols in the kth coded symbol vector of the lth block and is defined as,

$$\mathbf{H}_l^k = \begin{bmatrix} h & 0 & 0 & \cdots & 0 \\ 0 & h & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & h \end{bmatrix}.$$

However, in practical image communication scenarios, the simplistic ML decoder above does not exploit the spatial (spatio-temporal in context of videos) bounded variation structure of the coded image. This leads to a significantly high residual error in the image reconstructed from the received symbols, which arises due to the high probability of symbol error corresponding to communication over the fading wireless channel. For such scenarios, specifically related to the context of image reconstruction, Total Variation (TV) cost based regularization approaches have been demonstrated to yield significantly superior quality of image recovery. It has been shown that the L_1 regularization factor based TV optimization framework, which enforces smoothness of the computed solution, is ideally suited for a wide variety of image processing applications such as deblurring, denoising, turbulence effect reduction etc. Thus, the optimal algorithm for image decoding can be formulated as the paradigm of TVSD, which jointly decodes the entire transmit stream, unlike the decoupled decoder in (2). In the next section, we describe the L_1 regularization based TV likelihood cost function and the modified TV metric based Viterbi algorithm for image reconstruction.

III. Viterbi Algorithm Based TV Sequence Detection

The optimal decoding rule corresponds to estimating the transmit symbol vector sequence $\mathcal{X} = [\mathbf{x}_1^k, \mathbf{x}_2^k, \ldots, \mathbf{x}_L^k]$ given the received signal vector time series $\mathcal{Y} = [\mathbf{y}_1^k, \mathbf{y}_2^k, \ldots, \mathbf{y}_L^k]$ where $\mathcal{X} \in \mathbb{S}_k^L \triangleq \prod_{l=1}^{L} \mathbb{S}_{b_l^k}$ and $\mathcal{Y} \in \prod_{l=1}^{L} \mathbb{C}^{b_l^k}$. It is well known that the optimal decoded sequence $\hat{\mathcal{X}}$ maximizes the *a posteriori* probability density, derived using Bayes' rule as,

$$\begin{aligned}\hat{\mathcal{X}} &= \underset{\mathcal{X} \in \mathbb{S}_k^L}{\arg\max}\, P(\mathcal{X}/\mathcal{Y}) = \underset{\mathcal{X} \in \mathbb{S}_k^L}{\arg\max}\, P(\mathcal{Y}/\mathcal{X}) \times P(\mathcal{X}) \\ &= \underset{\mathcal{X} \in \mathbb{S}_k^L}{\arg\max} \prod_{l=1}^{L} P\left(\mathbf{y}_l^k/\mathbf{x}_l^k\right) \times \prod_{l=1}^{L} P\left(\mathbf{x}_l^k\right),\end{aligned}$$

where the likelihood $P(\mathbf{y}_l^k/\mathbf{x}_l^k)$ is Gaussian, arising from the input-output wireless channel observation model in (1) while the prior probability distribution $P(\mathbf{x}_l^k)$ follows a Gibbs (Boltzmann) distribution and is given by the Gibbs measure [6]. This has been extensively studied in works such as [7], [8], where it has been demonstrated that the *a posteriori* probability maximization problem further simplifies to the TV regularized cost function optimization,

$$\hat{\mathcal{X}} = \underset{\mathcal{X} \in \mathbb{S}_k^L}{\arg\min} \sum_{l=1}^{L} \left(\|\mathbf{y}_l^k - \mathbf{H}_l^k \mathbf{x}_l^k\|_2^2 + \beta \|\mathbf{x}_l^k\|_{TV}\right). \tag{3}$$

The quantity β above represents the L_1 TV regularization weight factor, similar to [6], and it has been demonstrated in [4] that the TV norm is equivalent to the L_1 norm of the difference vector i.e. $\|\mathbf{x}_l^k\|_{TV} = \|\mathbf{D}\mathbf{x}_l^k\|_1$, where $\mathbf{D}$ is the finite difference operator along the directions of the connected causal neighbors and is defined as follows,

$$\mathbf{D}\mathbf{x}_l^k = \begin{bmatrix} \mathbf{w}\left(\mathbf{x}_l^k\right) - \mathbf{w}\left(\mathbf{x}_{l-n-1}^k\right) \\ \mathbf{w}\left(\mathbf{x}_l^k\right) - \mathbf{w}\left(\mathbf{x}_{l-n}^k\right) \\ \mathbf{w}\left(\mathbf{x}_l^k\right) - \mathbf{w}\left(\mathbf{x}_{l-n+1}^k\right) \\ \mathbf{w}\left(\mathbf{x}_l^k\right) - \mathbf{w}\left(\mathbf{x}_{l-1}^k\right) \end{bmatrix},$$

and see (4)–(5), shown at the bottom of the next page, where $\mathbf{w}: \mathbb{S}_b \rightarrow \mathbb{R}$ is the decoding function which computes the coefficient value for the corresponding modulated symbol vector. Hence, substituting the above TV regularization factor in the likelihood cost function in (3), the optimization problem for image decoding can be obtained as given in (4), where $\mathcal{U}(l)$ represents the set of causal neighbor blocks in the neighborhood of the lth block of the coded image. The above likelihood cost function can be minimized through a novel application of the Viterbi algorithm, to compute the optimal decoded sequence $\hat{\mathcal{X}}$ as follows. Let $\mathcal{U}_d(l) = \{j | 1 \leq (l-j) \leq L, j \in \{n-1, n, n+1\}\}$ denote the causal decoded neighbors of the previous row. Let the set of all valid symbol vectors be defined as $\mathbb{S} \triangleq \bigcup_{b \in \mathbb{B}} \mathbb{S}_b$ where $\mathbb{B}$ is the set of symbol vector lengths required to encode the quantized components. Consider now a trellis with $N_S = |\mathbb{S}|$ states where $|\mathbb{S}|$ is the cardinality of the set $\mathbb{S}$ and each state corresponds to $\mathbf{s}_i \in \mathbb{S}$, $1 \leq i \leq N_S$ as shown in Fig. 1. One can now define the state metric $\Psi_l(i)$ as given in (5) and the branch metric $\rho(i,j)$ between state i at stage l and state j at stage $l-1$ as $\rho(i,j) = \beta |\mathbf{w}(\mathbf{s}_i) - \mathbf{w}(\mathbf{s}_j)|$. At each transmitted symbol stage $l \geq 2$, the accumulated metric $\Phi_l(i)$ and the survivor node $\nu_l(i)$ for the surviving path terminating in the ith node are given as,

$$\Phi_l(i) = \Psi_l(i) + \min_{1 \leq j \leq N_S} \{\Phi_{l-1}(j) + \rho(i,j)\},$$
$$\nu_l(i) = \arg\min_{1 \leq j \leq N_S} \{\Phi_{l-1}(j) + \rho(i,j)\},$$

where $\Phi_l(i)$ is initialized as $\Phi_1(i) = \Psi_1(i)$ i.e. for $l = 1$ we assign the state metric value to the accumulated metric. The regularization weight factor β is determined by the minimum MSE criterion to minimize the decoding error. Subsequently, we find the minimum accumulated metric at the last symbol stage $l = n$ as $\hat{i}(n) = \arg\min_{1 \leq i \leq N_S} \Phi_n(i)$. The decoded symbol vector sequence $\hat{\mathbf{x}}_l^k$ is given as, $\hat{\mathbf{x}}_n^k = \mathbf{s}_{\hat{i}(n)}$ and $\hat{\mathbf{x}}_l^k = \mathbf{s}_{\hat{i}(l)}$ where $\hat{i}(l) = \nu_{l+1}(\hat{i}(l+1)), \forall l = (n-1), \cdots, 2, 1$. Therefore, similar to the conventional Viterbi algorithm, after obtaining the minimum accumulated metric state corresponding to the last symbol in the row, we trace back the minimum distance path through the survivor nodes, which corresponds to the least total variation regularized cost achieving decoded image stream. This procedure is repeated for all the m image rows. This scheme can be readily extended to video sequences and color images as follows. For optimal video decoding, one can consider the three dimensional spatio-temporal connected causal neighbors for TV regularization, similar to [4]. In the case of color images, the algorithm can be alternately applied to the intensity and chroma components of the coded image. Next we present simulation results to illustrate the performance of the proposed image reconstruction scheme with different image encoding schemes.

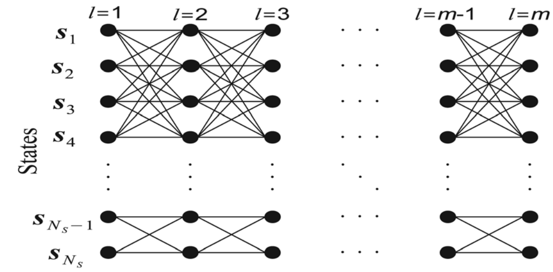

Fig. 1. Trellis structure for the proposed TVSD based image reconstruction.

IV. Simulation results

To simulate the performance of the robust total variation based image reconstruction scheme in a WSN, we consider Block Truncation Coding (BTC) and JPEG coded wireless image transmission for the wireless sensor network. The BTC is a simple yet effective image compression scheme [9], [10], which is well suited for WSN image transmission. We compute the mean (μ) and standard deviation (σ) of all the pixel elements belonging to every $b \times b$ image block where $b \geq 2$. The elements $B_{i,j}$, $1 \leq i,j \leq b$ of the bit plane $\mathbf{B}_p$ are given as $\mathbf{1}_{[\mu,\infty)}(p_{i,j})$, where $\mathbf{1}_{[\mu,\infty)}$ denotes the indicator function corresponding to the set $[\mu,\infty)$. Thus each block of the coded image comprises of $K_l = 3$ coded components which are μ, σ and $\mathbf{B_p}$ with $m = \frac{M}{b}$ and $n = \frac{N}{b}$. The mean μ and standard deviation σ are subsequently quantized and encoded using BPSK modulation as K dimensional symbol vectors, where the bit-plane component $\mathbf{B}_p$ is encoded as a b^2-length BPSK modulated symbol vector. These symbol vectors are subsequently transmitted through a wireless channel. At the receiver, the proposed scheme is now employed for decoding the received signal vectors corresponding to μ, σ to obtain their decoded values $\hat{\mu}$, $\hat{\sigma}$ and $\hat{\mathbf{B}}_p$ is recovered using the decoder given in (2). Finally, the reconstructed value $\hat{p}_{i,j}$ corresponding to pixel (i,j) is computed as,

$$\hat{p}_{i,j} = \hat{\mu} + \hat{\sigma}(-1)^{\left(1-\hat{B}_{i,j}\right)} \left(\frac{q}{b^2-q}\right)^{\frac{1}{2}\left(1-2\hat{B}_{i,j}\right)},$$

where q is the number of pixels such that $\mathbf{1}_{[\mu,\infty)}(\hat{B}_{i,j}) = 1$. The special case of $b = 1$ corresponds to uncoded transmission of the K dimensional BPSK encoded symbol vector corresponding to the pixel value at (i,j). To further validate the performance of the proposed scheme, we also consider the JPEG image encoding scheme [11], [12] which achieves a good compression

$$\hat{\mathcal{X}} = \arg\min_{\mathcal{X} \in \mathcal{S}_k^L} \sum_{l=1}^{L} \left(\|\mathbf{y}_l^k - \mathbf{H}_l^k \mathbf{x}_l^k\|_2^2 + \frac{\beta}{|\mathcal{U}(l)|} \sum_{j \in \mathcal{U}(l)} \left| \mathbf{w}\left(\mathbf{x}_l^k\right) - \mathbf{w}\left(\mathbf{x}_{l-j}^k\right) \right| \right), \mathcal{U}(l) = \{j | 1 \leq (l-j) \leq L, j \in \{1, n-1, n, n+1\}\}. \tag{4}$$

$$\Psi_l(i) = \begin{cases} \left\|\mathbf{y}_l^k - \mathbf{H}_l^k \mathbf{s}_i\right\|_2^2 + \frac{\beta}{|\mathcal{U}_d(l)|} \sum_{j \in \mathcal{U}_d(l)} \left| \mathbf{w}(\mathbf{s}_i) - \mathbf{w}\left(\hat{\mathbf{x}}_{l-j}^k\right) \right| & \text{if} \quad \mathbf{s}_i \in \mathbb{S}_{\mathrm{b}_l^k} \subseteq \mathbb{S}. \\ \infty, & \text{otherwise}. \end{cases} \tag{5}$$

Fig. 2. Test image set: *Lena*, *Cameraman*, *House*.

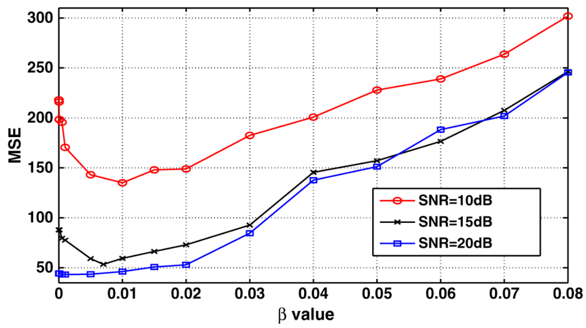

Fig. 3. Optimum β value based on MSE criterion for different SNR values.

efficiency along with an improved reconstruction quality and is thus well suited for WSN image transmission, as reported in [13]. The Huffman entropy coded quantized DC and AC components corresponding to each 8×8 block are modulated as BPSK symbol vectors followed by transmission over the wireless channel. At the receiver, the proposed scheme is applied for Viterbi based total variation decoding of the coded DC components, while the remaining coded AC symbol vectors are decoded employing the conventional decoder in (2). The reconstructed value $\hat{p}_l(i,j)$ corresponding to pixel (i,j) of the lth block is obtained by performing the 2-D IDCT, as given in (6), on the resulting lth block $\hat{P}_l(u,v)$ of the decoded and dequantized DC and AC components of the transmitted image followed by inverse level shifting. Both the above compression schemes are applied on the image set comprising of the standard *Lena*, *Cameraman*, *House* images of size 256×256 i.e. $M = N = 256$ and shown in Fig. 2. The wireless channel is Rayleigh fading with channel coefficient $h = \frac{1}{\sqrt{2}}(P + \jmath Q)$, where P, Q are generated as independent zero mean Gaussian random variables of variance unity. Therefore, the average gain of the fading wireless channel is given as $E\{|h|^2\} = 1$. We consider an SNR in the range of $10 - 20$ dB, with the symbol power normalized to unity. Therefore, the SNR is given as $\frac{1}{\sigma_\eta^2}$. For the simulation, we calculate the optimal value of the regularization parameter β using the minimum MSE criterion. The approximate bit rates for the JPEG encoded images are in the range of 0.5 to 0.8 bits/pixel. In Fig. 3 from the plot, we observe that the optimal β values corresponding to the lowest MSE are in the range $[0.005, 0.01]$. Fig. 4 shows the reconstructed images for the proposed TVSD and conventional ML decoding schemes. Table I shows the PSNR enhancement for the proposed total variation based reconstruction scheme in comparison to the conventional ML decoder for various SNR values; see (6), shown at the bottom of the page

Fig. 4. Test image *Lena* recovered at $\mathrm{SNR} = 10$ dB (ML), $\mathrm{SNR} = 10$ dB (TVSD), 15 dB (ML), 15 dB (TVSD) (left to right) for the encoding methods: BTC ($b = 1$), BTC ($b = 2$) and JPEG (top to bottom).

TABLE I
COMPARISON OF PSNR FOR ML AND TVSD SCHEMES APPLIED ON TEST IMAGES FOR BTC ($b = 1$), BTC ($b = 2$), BTC ($b = 4$) AND JPEG

SNR		10 dB		15 dB		20 dB	
Case	Image	ML	TVSD	ML	TVSD	ML	TVSD
BTC ($b = 1$)	*Lena*	21.59	39.87	26.62	44.53	31.23	49.74
	Cameraman	21.38	33.36	26.21	38.56	30.80	43.72
	House	21.35	33.40	26.21	38.82	30.97	44.37
BTC ($b = 2$)	*Lena*	14.29	15.30	15.01	15.36	15.26	15.37
	Cameraman	13.32	14.19	14.04	14.34	14.29	14.40
	House	12.75	13.38	13.22	13.43	13.37	13.42
BTC ($b = 4$)	*Lena*	12.40	12.82	12.78	12.88	12.89	12.92
	Cameraman	12.05	12.66	12.55	12.71	12.70	12.74
	House	10.49	10.57	10.62	10.66	10.68	10.70
JPEG	*Lena*	24.36	26.21	27.81	29.51	31.20	31.29
	Cameraman	22.43	24.29	24.65	27.06	28.17	28.52
	House	26.26	29.25	30.09	31.25	32.93	32.94

V. CONCLUSION

A total variation regularization based scheme has been presented for optimal image/video stream decoding in multimedia communication based wireless sensor networks. The proposed scheme employs a novel L_1 norm regularization factor to exploit the bounded variation property of the image for reconstruction. It has been demonstrated that the Viterbi algorithm can then be implemented to estimate the optimal transmit image stream based on appropriately defined total variation regularized state and branch metrics. Simulation results demonstrate a superior image reconstruction performance for the proposed TVSD scheme in comparison to the conventional ML scheme in terms of both decoded image quality and PSNR.

$$\hat{p}_l(i,j) = \sum_{u=0}^{7}\sum_{v=0}^{7} \alpha(u)\alpha(v)\hat{P}_l(u,v)\cos\left[\frac{\pi u\left(i+\frac{1}{2}\right)}{8}\right]\cos\left[\frac{\pi v\left(j+\frac{1}{2}\right)}{8}\right];\ 0 \le i,j \le 7,$$
$$\alpha(x) = \begin{cases} \sqrt{\frac{1}{8}}, & \text{if} \quad \mathrm{x} = 0. \\ \sqrt{\frac{2}{8}}, & \text{otherwise.} \end{cases} \tag{6}$$

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