# Multiple Description Coding using a New Bitplane-LVQ Scheme 

Infall Syafalni<br>School of Electrical and Electronics Engineering<br>Universiti Sains Malaysia<br>Pulau Pinang, Malaysia<br>is.lm09@student.usm.my

M. F. M. Salleh<br>School of Electrical and Electronics Engineering<br>Universiti Sains Malaysia<br>Pulau Pinang, Malaysia<br>fadzlisalleh@eng.usm.my


#### Abstract

In this paper, a novel Bitplane-LVQ technique to compress subbands bitplane coefficients is proposed for multiple description coding (MDC) system. The MDC system utilizes three descriptions with one central decoder and three side decoders. The significant bitplanes subband coefficients are encoded using lattice $D_{2}$ which the number of bitplanes ( $k$ ) ties with the amount of compression ratio. The residual bitplanes of the subband coefficients are compressed using Multistage $\mathbf{A}_{2}$ Lattice Vector Quantization ( $\mathbf{M A}_{2} L V Q$ ) technique. This paper also presents the design of two new different lattice labeling algorithms; one is for the significant subset bitplanes and the other for the residual bitplane. Experimental results show that the proposed MDC with Bitplane-LVQ scheme can reach very low encoding bit-rate with good performance in PSNR for central decoder.


Keywords-MDC;bitplane;LVQ;wavelet transform

## I. Introduction

In recent years, the demand for high performance and reliability data transmission over wireless network has increased. Multiple Description Coding (MDC) scheme is a potential technique that combat packet loss and improves communication. Nowadays, the development of MDC schemes has received considerable attention from many researchers [1].

Vector Quantization techniques are employed in many applications in multimedia communication [2]. There have been many research efforts done regarding Lattice Vector Quantization (LVQ) as presented in [3-4]. The main reason for the choice of this technique is due to its lower computational loads and design complexity.

The work of multiple description lattice vector quantization (MDLVQ) is first proposed by Servetto, Vaishampayan and Sloane in [5], where the lattice points are used to represent the descriptions. In [6], the authors explain the details on how the codebook is utilized in the MDC system.

Recent research activities in MDLVQ techniques are readily available in [7-8]. In [7], Ostergaard explains the used of three symmetric channels in MDLVQ. Hui Bai in [8] optimizes the MDLVQ scheme and applies the scheme for wavelet based image coding.

Wavelet based image coding scheme for single description system have been well explored by many researchers as presented in [9-11]. The latest technique in
this work is to employ the bit plane coding as presented in [9-11]. Shapiro's Embedded Zerotree Wavelet (EZW) in [9] reveals the first efficient bit plane compression scheme in wavelet-based image coding. In the later work by Said and Pearlman [10] on set partitioning in hierarchical trees (SPIHT) algorithm improves EZW algorithm and it is successfully applied to both lossy and lossless compression. The latest work is in JPEG2000 compression scheme [11] which is developed based on EZW algorithm. The scheme now is used as the latest international image compression standard.

In this paper, a novel Bitplane-LVQ scheme that consists of two coding techniques is proposed for multiple description coding (MDC) system. The first technique encodes the significant bitplanes subband coefficients using lattice $\mathrm{D}_{2}$ where the number of bitplanes $(k)$ indicates the amount of compression ratio. The second technique encodes the residual bitplanes using Multistage $\mathrm{A}_{2}$ Lattice Vector Quantization ( $\mathrm{MA}_{2} \mathrm{LVQ}$ ) technique.

The MDC system utilizes three descriptions with three side decoders and one central decoder. This paper also presents the design of two different lattice labeling algorithms for the significant subset planes and residual bitplanes respectively. Experimental results show that the proposed Bitplane-LVQ scheme and the new labeling algorithms can reach very low encoding bit rate with good PSNR performance for central decoder.

This paper is organized as follows. In Section II, an overview of $\mathrm{MA}_{2} \mathrm{LVQ}$ and bitplane coding is given. In Section III, the proposed scheme with encoding and decoding labeling algorithms is presented in details. The performance of proposed scheme is examined in Section IV and Section V concludes the paper.

## II. Preliminaries

## A. Lattice Vector Quantization

A lattice usually is defined as a point having $n$ dimension that maps an arbitrary vector $U \in R^{n}$ reproduction vectors $u_{0}, u_{1}, u_{2}, . . u_{n}$ in $R^{n}$ plane. Let say a lattice $\Lambda$ in $R^{n}$ plane consisting of all integral combinations of a set of linearly independent vectors.

$$
\begin{equation*}
\Lambda_{n}=\left\{Y \in R^{m} \mid Y=u_{1} a_{1}+\ldots+u_{n} a_{n}\right\} \tag{1}
\end{equation*}
$$

where $a_{1}, \ldots, a_{n}$ are linearly independent vectors in $m$ dimensional real Euclidean space $R^{m}$ with $m \geq n$, and $u_{1}, \ldots, u_{n}$ are in $Z$.

Let the codewords point, $c_{i}$ is a point in a lattice $\operatorname{coset} \Lambda$, the region of a lattice is given as;

$$
\begin{equation*}
\mathrm{V}\left(\Lambda, \mathrm{c}_{\mathrm{i}}\right)=\left\{\mathrm{u} \in \mathrm{R}^{\mathrm{n}} \mid\left\|\mathrm{u}-\mathrm{c}_{\mathrm{i}}\right\| \leq\left\|\mathrm{u}-\mathrm{c}_{\mathrm{j}}\right\|, \mathrm{c}_{\mathrm{i}} \in \Lambda, \forall \mathrm{c}_{\mathrm{j}} \in \Lambda\right\} \tag{2}
\end{equation*}
$$

Each input vector will be quantized by lattice $\Lambda$ having region $V$. And the zero-centered Voronoi region $V(\Lambda, 0)$ is defined as;

$$
V(\Lambda, 0)=V\left(\Lambda, c_{i}\right)-c_{i} \ldots(3)
$$

## B. Multistage $A_{2}$ Lattice Vector Quantization

Multistage Lattice Vector Quantization ( $\mathrm{MA}_{2} \mathrm{LVQ}$ ) refines a lattice vector into more details points. The sublattice is defined by $V_{n}$ where the size of sublattice is scaled by $1 / 2^{\mathrm{n}} V_{0}$. The zero centered Voronoi lattice regions are represented as;

$$
V_{0}\left(\Lambda_{0}, 0\right), V_{1}\left(\Lambda_{1}, 0\right), V_{2}\left(\Lambda_{2}, 0\right), \ldots, V_{n}\left(\Lambda_{n}, 0\right)
$$

Let say the region of lattice is depicted by $V . V_{l}$ is the sublattice with half scale of $V_{0}$. The input $u$ is a vector that is quantized by lattice. Figure 1 shows the example of proposed $\mathrm{MA}_{2} \mathrm{LVQ}$. The source $u$ is quantized to the nearest vector $c_{i}$. The distortion between source and nearest point in lattice is represented as $d_{i}$.

Let $\Lambda$ is an $A_{2}$ lattice. Given $V_{0}$ and $V_{1}$ are the main and sublattice forming one stage of $\mathrm{MA}_{2} \mathrm{LVQ}$. The source vector, $u$ is going to be quantized using $\mathrm{MA}_{2} \mathrm{LVQ}$. Hence, the distortion $d_{0}$ is given by $\left\|u-c_{0}\right\|^{2}$ and the distortion $d_{1}$ is given by $\left\|d_{0}-c_{1}\right\|^{2}$. To obtain $d_{1}$, firstly, the codeword of $u$ is calculated by equation (2) resulting $V_{0}\left(A_{0}, c_{0}\right)$. Then, the zero-centered $V_{1}\left(A_{1}, 0\right)$ is given by $V_{0}\left(A_{0}, c_{0}\right)-c_{0}$. So, the codeword of $d_{0}$ is $V_{1}\left(A_{1}, c_{1}\right)$ that represents the second stage value of quantization.


Figure 1. Multistage LVQ and the vector representation of quantization.

## C. Distortion of Multistage $A_{2}$ Lattice Vector Quantization

One of the parameter of a lattice can be seen by distortion performance. This parameter shows how good a lattice in quantization. The distortion of a lattice can be defined as [12];

$$
\begin{equation*}
D_{0}=\sum_{i=1}^{N} \int_{\Omega}\left\|u-c_{i}\right\|^{2} f_{u}(u) d u \tag{4}
\end{equation*}
$$

where $\Omega$ is the coverage area of the lattice, $u$ is the source vector, $c_{i}$ is the code vector and $f_{u}(u)$ is a probability density function of the source vector $u$. Therefore, the distortion can be found by subtraction each element of source from codewords.

$$
\begin{equation*}
D_{s}=\sum_{i=1}^{N} \int_{\Omega}\left\|D_{s-1}-r^{s} c_{i}\right\|^{2} f_{u}(u) d u \tag{5}
\end{equation*}
$$

The distortion of MLVQ that has $s$ stages is defined by equation (5) where $s=1,2,3, \ldots, m$. The ratio $r$ indicates the reduced scale of the sublattice. We use the reduced scale of $1 / 2$ for each stage $(r=1 / 2)$. The value of $f_{u}(u)$ is the same for every $s$, because the same lattice used to form sublattice. Finally, the distortion of $\mathrm{MA}_{2} \mathrm{LVQ}$ can be simplified as the following equation;

$$
\begin{equation*}
D_{s}=\sum_{i=1}^{N} \int_{\Omega}\left\|u-\lambda_{s}\right\|^{2} f_{u}(u) d u \tag{6}
\end{equation*}
$$

where $D_{s}$ shows the distortion in $s$ stages and $\lambda_{s}$ is a constant that approach the value of $u$ with the increasing of stage $s$.

## D. Subband Bitplane Coding

Discrete Wavelet Transform (DWT) has been adopted in several data compression schemes such as EZW [9], SPHIT [10], and JPEG2000 [11].


Figure 2. Three Level Discrete Wavelet Transform of Goldhill Image.
Figure 2 represents DWT with three levels of decompositions.


Figure 3. Multiple Description Coding with Three Channels Using BLVQ

In DWT, the energy resolution is decreasing from left top corner to the right bottom corner. This is why we can expect the detail coefficients to get smaller as we move from high (left top) to low level (right bottom).

Lets assumes that the original image is defined by a set of pixel values $p_{i, j}$, where $(i, j)$ is the pixel coordinate in an image. The transformation is depicted as;

$$
c=\Omega(p) \ldots(7)
$$

where $\Omega(\cdot)$ represents a DWT. The coefficient of this transformation is represented by $c$. Let $\hat{c}$ is the reconstructed coefficient value after decoding process. The reconstructed image is shown as;

$$
\hat{p}=\Omega^{-1}(\hat{c}) \ldots(8)
$$

and the distortion measure of the coding process is represented by the mean squared-error of shown in following equation;

$$
\begin{equation*}
D_{m s e}(p-\hat{p})=\frac{\|p-\hat{p}\|^{2}}{N}=\frac{1}{N} \sum_{i} \sum_{j}\left(p_{i, j}-\hat{p}_{i, j}\right)^{2} \ldots \tag{9}
\end{equation*}
$$

In this work, the bitplane coding is used to encode the wavelet coefficients. The significant coefficients are separated into several bitplanes by testing each coefficient in the subband with the maximum magnitude value found. Ones the tests for all the coefficients in the subband are done, that results as the first significant coefficient bitplane. The maximum number of bit can be represented as following equation;

$$
n=\left\lfloor\log _{2}\left(\max _{(i, j)}\left\{\left|c_{i, j}\right|\right\}\right)\right\rfloor \ldots(10)
$$

Then the comparator test value is reduced by $2^{n-1}$ in order to obtain the subsequent bitplanes. This technique is well defined in [11]. The test separates the coefficients into subsets $B$ bitplane that contains the most significant bits as described by following equation;

$$
S_{n}(B)=\left\{\begin{array}{l}
1, \text { if } 2^{n} \leq\left|c_{i, j}\right| \leq 2^{n+1}  \tag{11}\\
0, \text { else }
\end{array}\right.
$$

This process is done for several iterations (the maximum iteration is determined by $n$ ).

## III. Proposed Scheme

## A. Bitplane-LVQ Coding scheme

The Bitplane-LVQ (Bi-LVQ) coding scheme consists of two important LVQ techniques. First, the $\mathrm{D}_{2}$ LVQ technique is used to encode the significant subband coefficients. Second, the $\mathrm{MA}_{2} \mathrm{LVQ}$ technique is used to encode the residual subband coefficients.

Figure 3 shows the proposed the entire Bi-LVQ scheme for MDC system. First, an input image is decomposed by DWT. After that, two of the subbands are separated into several bitplanes. The number of bitplane $(k)$ indicates the amount of compression ratio to be achieved. The first few planes (or just one plane) are compressed using $\mathrm{D}_{2}$ LVQ technique which then followed by its labeling algorithm. The residual plane then is encoded using $\mathrm{MA}_{2} \mathrm{LVQ}$ technique prior the use of its labeling algorithm.

The labels are then separated into three balanced descriptions by mean of the description splitter process. Then they are losslessly compressed using the arithmetic coding before being transmitted over the wireless channels.

The reverse process happens in the decoding stage at the receiver. IF one of the descriptions is lost, the scheme resorts to the estimation decoder process in order to estimate the lost description and reconstruct the image. Otherwise, all of the descriptions are received and the scheme will use the central decoder to reconstruct the image.

There are two bitplane subsets in this system. First is significant bitplane subset that is obtained via $\mathrm{D}_{2}$ LVQ technique. The second bitplane subset is obtained by substracting the significant bitplane subband from the original subband, and then the residual data are quantized using $\mathrm{MA}_{2} \mathrm{LVQ}$. This technique of multistage LVQ uses the multistage order of two.

Lets the output of DWT as $[B]$ to be in a matrix form, and lets the matrix $[A]$ contains the bits obtained from the significant test Eq. (11). The coefficient of $[A]$ is denoted as;

$$
\begin{equation*}
a_{(i, j)}=S_{n}\left(b_{(i, j)}\right) \ldots \tag{12}
\end{equation*}
$$

Thus the matrix $[A]$ is denoted as;

$$
\begin{equation*}
[A]_{k}=S_{n-k}\left([B]_{k}\right) \ldots \tag{13}
\end{equation*}
$$

where $[A]$ and $[B]$ consist of the $a_{(i, j)}$ and $b_{(i, j)}$ coefficients.

$$
\begin{align*}
& {[B]=\left[\begin{array}{cc}
b_{(1,1)} & \cdots \\
\vdots & b_{(i, j)}
\end{array}\right] \ldots}  \tag{14}\\
& {[A]=\left[\begin{array}{cc}
a_{(1,1)} & \cdots \\
\vdots & a_{(i, j)}
\end{array}\right] \ldots} \tag{15}
\end{align*}
$$

The process of separating the significant bits from the subband is shown by following equations;

$$
\begin{gather*}
{[B]_{1}=[B]_{0}-[A]_{0} \times 2^{n} \ldots}  \tag{16}\\
{[B]_{2}=[B]_{1}-[A]_{1} \times 2^{n-1} \ldots} \tag{17}
\end{gather*}
$$

[ $A$ ] is the subset that contains the significant bits. The number of bitplane subsets to be encoded is defined as $k$. In Eq. (16) and Eq. (17), the values of $[B]_{1}$ represents the first residual subset. Thus, the next significant bitplane subset $\left([B]_{1},[B]_{2}, \ldots,[B]_{k}\right)$ is produced by same operation demonstrated by following equations;

$$
\begin{gather*}
{[B]_{k}=[B]_{k-1}-[A]_{k-1} \times 2^{n-k+1} . .}  \tag{18}\\
{[B]_{k}=[B]_{0}-\sum_{i=0}^{k}[A]_{i} \times 2^{n-i} \ldots} \tag{19}
\end{gather*}
$$

The distortion of the bitplane coding has been shown by Eq. (9) in section II. The distortion can also be expressed by following equation;

$$
\begin{equation*}
D_{m s e}(p-\hat{p})=D_{m s e}(c-\hat{c})=\frac{1}{N} \sum_{i} \sum_{j}\left(c_{i, j}-\hat{c}_{i, j}\right)^{2} \ldots \tag{20}
\end{equation*}
$$

From Eq. (15), the coefficient $\hat{c}_{i, j}$ is the key in determining the distortion. This means that the coefficients with larger magnitude should be transmitted first, because they have larger information content.

Now, let a DWT coefficient be denoted as $c$. The binary representation of this coefficient is given by $b_{1}, b_{2}, \ldots, b_{n+1}$ where $b_{1}$ is the most significant bit and $b_{n+1}$ is the less significant bit. Therefore, the decimal representation of the DWT coefficient is expressed as;

$$
\begin{gather*}
c=2^{n} b_{1}+2^{n-1} b_{2}+\cdots+2^{0} b_{n+1} \cdots \\
c=\sum_{i=0}^{n} 2^{n-i} b_{i+1} \cdots(22) \tag{22}
\end{gather*}
$$

The performance of this coding is indicated by the quality of the reconstructed image using mean square error (PSNR) for a given bit-rate (bpp) that shows the amount of compression.

Lets the bitplane decoding value is $\hat{c}_{k}$ which constructs the $k$-th most significant bitplane. The higher the $k$ value, the better the quality of the reconstructed image. However, this affects the bit rate.

$$
\begin{gather*}
\hat{c}_{k}=2^{n} b_{1}+2^{n-1} b_{2}+\cdots+2^{n-k+1} b_{k} \ldots \text { (23) } \\
\hat{c}_{k}=\sum_{i=0}^{k-1} 2^{n-i} b_{i+1} \ldots \text { (24) } \tag{24}
\end{gather*}
$$

The parameter $n$ represents the number of bit associated with the maximum coefficient value. Then, the coefficient distortion can be expressed as;

$$
\begin{equation*}
d_{c o f f}=c-\hat{c}_{k} \ldots \tag{25}
\end{equation*}
$$

and the decimal representation of the coefficient distortion from the remaining bits of that particular coefficient can be denoted as;

$$
\begin{gather*}
d_{c o f f}=2^{n-k} b_{k+1}+2^{n-k-1} b_{k+2}+\cdots+2^{0} b_{n+1} \cdots \text { (26) }  \tag{26}\\
d_{c o f f}=\sum_{i=k}^{n} 2^{n-i} b_{i+1} \cdots \text { (27) }
\end{gather*}
$$

In this equation, it is clear that the coefficient distortion can be reduced by increasing the number of transmitted significant bitplane subset.
The residual subset is quantized using hexagonal $\mathrm{MA}_{2} \mathrm{LVQ}$. At first, the residual values are normalized by $2^{n-k+1}$. Thus, the normalized input for $\mathrm{MA}_{2} \mathrm{LVQ}$ can be expressed as;

$$
\begin{equation*}
u_{q}=\frac{d_{\text {coff }}}{2^{n-k+1} \ldots} \tag{28}
\end{equation*}
$$

and according to Eq. (6), the normalized $\mathrm{MA}_{2} \mathrm{LVQ}$ distortion can be expressed as;

$$
\begin{equation*}
d_{n v q}=u_{q}-\lambda \ldots \tag{29}
\end{equation*}
$$

Then the total distortion of is expressed by;

$$
d_{t}=2^{n-k+1}\left(u_{q}-\lambda\right) \ldots \text { (30) }
$$

and the contribution of the hexagonal $\mathrm{MA}_{2} \mathrm{LVQ}$ in reducing the distortion can be seen in following equations;

$$
\begin{align*}
& d_{t}=d_{c o f f}-\hat{c}_{M A_{2} L V Q} \ldots  \tag{31}\\
& d_{t}=c-\hat{c}_{k}-\hat{c}_{M A_{2} L V Q} . \tag{32}
\end{align*}
$$

## B. Significant Coefficient Labeling

The quantized points after biplane coding are mapped to the labels by mean of labeling function. As mentioned, the bitplane data subsets consist of into two parts. First is significant bitplane subset which utililzes the significant bitplane labeling algorithm. Therefore, this subsection explains the method of labeling the significant bitplane.

The process of mapping or labeling the significant bitplane subset is shown in Figure 4. The significant bitplane subset is obtained using the significant tes process using Eq. (11). This is done by comparing each coefficient in the subband with the highest magnitude value. Thus, results the bitplane that consists of values of 0,1 or -1 .


Figure 4. Significant Subset Labeling Design using $\mathrm{D}_{2}$ with $\mathrm{N}=9$.
The labeling process uses only two coordinate values only which produces three labels as shown in Fig. 4. In this labeling design the D 2 lattice with 9 points (index $\mathrm{N}=9$ ) is chosen.

The labeling function of the significant subset is $\alpha$ that maps $\lambda \epsilon \Lambda$ into three labels $T_{1}, T_{2}$ and $T_{3}$.

$$
\alpha_{1}(\lambda)=T_{1}, \alpha_{2}(\lambda)=T_{2}, \alpha_{3}(\lambda)=T_{3} \ldots \text { (33) }
$$

## C. Insignificant Coefficient Labeling



Figure 5. Insignificant Subset Labeling Design using Multistage LVQ A ${ }_{2}$ with two stages $(\mathrm{N}=37)$.

The second labeling algorithm is designed for the residual subset bitplane. This subset bitplane are transmitted last over the network. In this labeling scheme, there are two important factors that affect the reconstruction of an image and the bit rate; i.e. the area of the hexagonal lattice and the choice of sublattice index.

The labeling function of the significant subset bitplane is $\beta$ that maps $\lambda \epsilon \Lambda$ into three labels $T_{1}, T_{2}, T_{3}$ as described below;

$$
\begin{equation*}
\beta_{1}(\lambda)=T_{1}, \beta_{2}(\lambda)=T_{2}, \beta_{3}(\lambda)=T_{3} \ldots \tag{34}
\end{equation*}
$$

Figure 5 illustrates portion of hexagonal lattice $\mathrm{A}_{2}$ with two stages of $\mathrm{MA}_{2} \mathrm{LVQ}$. The mapping $\beta$ is used to form the label $T_{1}, T_{2}$, and $T_{3}$ that will be transmitted over three channels. The core region of the lattice is labeled by label A. Then, the lattice structure spreads into six different directions as labeled by B, C, D, E, F and G.

Whenever a description is lost at the receiver the estimation algorithm is used to predict the missing label. On the contrary, if all of the channels are working fine, decoding process exhibit the maximum performance by the central decoder.

## D. Estimation Algorithm

In this subsection, the estimation algorithm is explained. There are three side decoders that receive different possible labels. When one of the descriptions is missing, this algorithm predicts and estimates the lost label. In this wor it is assumed that only one label is missing.


Figure 6. Three Possible Estimation Scheme, (a) when $\mathrm{T}_{1}$ is lost, (b) when $\mathrm{T}_{2}$ is lost, (c) when $\mathrm{T}_{3}$ is lost.

At the estimation decoder, the two received data are combined and used to predict the lost label. Figure 6 shows one of the possible conditions where the loss label happens
in side decoder. There are three possible combinations of side decoders i.e. $T_{2}, T_{3}$, when $T_{1}$ is lost (Fig. 6a), $T_{1}, T_{3}$, when $T_{2}$ is lost (Fig. 6b), and $T_{1}, T_{2}$, when $T_{3}$ is lost (Fig. $6 \mathrm{c})$. In order to reconstruct the image, the missing data must be estimated by predicting the third label.

In this works, there are two ways to fill the lost label. First is to use the non-optimized prediction technique i.e. by filling the lost label with the same label $A$ throughout. This is considered a good approximation since most of the VQ points consist of the label $A$. In this method, there is no need of any computation.

Secondly is to use the optimized prediction technique. This technique predicts the lost label by using the polarity of the existing labels. Lets $W$ be a quantity that quantify the polarity of the received labels given as the following;

$$
T_{1}+T_{2}=W \ldots(35)
$$

The polarity $W$ is used to determine the suitable missing label.

The estimation algorithm is described by Figure 7. If the neighboring polarity ( $W$ ) in the set is negative, then the lost label will be filled by a negative label. If the neighbor polarity $(W)$ in the set is positive, then the lost label will be filled by a positive label. Finally, if the neighboring polarity in the set is neither negative nor positive, the lost label will be filled by a zero-label.

```
Algorithm Optimized estimation(T
T
If W < 0
            T
Else if W > 0
    T
Else
    T
```

Figure 7. Estimation Algorithm to Opitimized Side Decoder.
For example, assuming that $T_{2}, T_{3}$, are received and $T_{1}$ is lost (Fig. 6a). Firstly, $\mathrm{T}_{1 \mathrm{a}}$ is determined by calculating the neighboring polarity ( $W$ ). This is done by summing the values of labels $\mathrm{T}_{3 \mathrm{~b}}$ and $\mathrm{T}_{2 \mathrm{~b}}$. Therefore, $\mathrm{T}_{1 \mathrm{a}}$ is determined according to the neighboring polarity ( $W$ ) quantity. Next, to get $\mathrm{T}_{1 \mathrm{~b}}$, there are two choices in determining the neighboring polarity $(W)$ i.e. $\mathrm{T}_{2 \mathrm{a}}+\mathrm{T}_{3 \mathrm{a}}$ and $\mathrm{T}_{2 \mathrm{c}}+\mathrm{T}_{3 \mathrm{c}}$. Any one combination of them can be used to determine $T_{1 b}$. Lastly $T_{1 c}$ is determined by summing the $\mathrm{T}_{3 \mathrm{~b}}$ and $\mathrm{T}_{2 \mathrm{~b}}$.

## IV. EXPERIMENTAL RESULTS

In this section, the performance results of Bi-LVQ coding scheme for MDC systems results are presented. The simulations are made using 512 by 512 gray Lena image.

First, we compare pure bitplane coding scheme with $\mathrm{Bi}-$ LVQ. Figure 8 represents the performance of pure bitplane and $\mathrm{Bi}-\mathrm{LVQ}$ within the increasing of plane.

From Figure 8, it can be seen that Bi-LVQ has better performance in PSNR with almost 10 dB better for various number of plane. This is due to the $\mathrm{MA}_{2} \mathrm{LVQ}$ technique
where the residual bitplane subsets are quantized using the hexagonal lattice. In this scheme, Bi-LVQ can reach 1 bpp compression at 9 bitplanes with 1 residual data transmittion.


Figure 8. Comparison Between Bitplane and Bi-LVQ.
Table I shows the performance of the central decoder. From that table, it can be seen that the performance of BiLVQ can perform well in very low bit rate.

TABLE I. Central Decoder Performance

| Bit Rate (bpp) | PSNR (dB) |
| :---: | :---: |
| 0.032 | 18.45 |
| 0.056 | 23.64 |
| 0.089 | 26.91 |
| 0.138 | 29.91 |
| 0.213 | 32.77 |
| 0.347 | 35.54 |



Figure 9. Lena Image with Non-Optimized Side Decoder, (a) Central Decoder (PSNR $=26.91 \mathrm{~dB})$, (b) Side Decoder $1($ PSNR $=12.57 \mathrm{~dB})$, (c) Side Decoder $2(\mathrm{PSNR}=12.66 \mathrm{~dB})$, (d) Side Decoder $3(\mathrm{PSNR}=12.70 \mathrm{~dB})$

Figure 9 shows the reconstructed images using the nonoptimized side decoder. It can be seen, the lost label forms a diagonal pattern in the reconstructed images. This is because of the diagonally scanned pattern of the input image, and some labels used after predictions are not correct.


Figure 10. Lena Image with Non-Optimized Side Decoder, (a) Central Decoder (PSNR = 26.91dB), (b) Side Decoder $1(\operatorname{PSNR}=16.53 \mathrm{~dB})$, (c) Side Decoder $2($ PSNR $=16.04 \mathrm{~dB})$, $(\mathrm{d})$ Side Decoder $3($ PSNR $=16.19 \mathrm{~dB})$

Figure 10 shows the reconstructed image using the optimized side decoder. It can be seen that the technique offers better performance than the non-optimized one. This technique uses an estimation algorithm to predict the lost label. However, some distortions on the reconstructed images cannot be fully recovered. This happens because some of the most significant coefficients (from the bitplane coding) are not predicted precisely at the side decoder.

TABLE II. COMPARISON BETwEEN Optimized Side DECODER AND Non-Optimized Side Decoder in PSNR

| Bit Rate <br> (bpp) | Optimized (dB) |  |  | Non-Optimized (dB) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Side 1 | Side 2 | Side 3 | Side 1 | Side 2 | Side 3 |
| 0.032 | 14.39 | 14.17 | 14.24 | 11.88 | 11.94 | 11.85 |
| 0.056 | 16.53 | 16.04 | 16.19 | 12.57 | 12.66 | 12.7 |
| 0.089 | 17.97 | 16.92 | 17.57 | 12.9 | 13 | 12.96 |
| 0.138 | 18.33 | 17.1 | 18.17 | 12.99 | 13.1 | 13 |
| 0.213 | 18.4 | 17.17 | 18.32 | 12.98 | 13.1 | 12.97 |
| 0.347 | 18.41 | 17.16 | 18.32 | 12.97 | 13.1 | 12.94 |

Table II shows the performance comparison of the side decoder estimation algorithm. The first three columns show the performance of the optimized side decoder algorithm that uses polarity to determine the lost label. The last three columns show the performance of the non-optimized decoder that uses label $A$ to fill the lost label. It can be seen that the optimized algorithm performance is $3-5 \mathrm{~dB}$ better than the non-optimized one.

From Table II, it can be seen that the performance of side decoder will reach saturation at certain bit rate. At bit rate $0.138 \mathrm{bpp}, 0.213 \mathrm{bpp}$, and 0.247 bpp , the PSNR of every side
decoder tends to be constant. This is because the missed prediction of the significant bits (bitplane subset data) of subband coefficients by the side decoder label estimator.

## V. CONCLUSION

In this paper, we proposed a novel Bi-LVQ scheme with MDC system for image coding. In additions, new labeling algorithms as well as new decoder estimation are designed. This proposed scheme separates the image into several planes. The first few planes consist of the significant bit and coded by the $\mathrm{D}_{2} \mathrm{LVQ}$. The residual data are encoded using $\mathrm{MA}_{2} \mathrm{LVQ}$. Every subset of significant bit is mapped to a lattice and separated into several descriptions and transmitted over three channels. The Bi-LVQ coding offers low bit rate compression with good quality decoding. The estimation algorithm is also used to optimize every side distortion.

## ACKNOWLEDGMENT

This work is funded in part by MOSTI Science Fund with Grant Number 6013353, and USM RU grant with Grant Number 814012 and USM Fellowship scheme.

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