## Doctor's Thesis

# Soft-Decision Decoding Algorithms for Binary Linear Block Codes 

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#### Abstract

This thesis consists of two parts. In the first part, effective solutions are presented for two basic problems related to the implementation of recursive maximum likelihood decoding (RMLD) of Reed-Muller codes. A $(64,40)$ subcode of the third order Reed-Muller code of length $64\left(\mathrm{RM}_{3,6}\right)$ is considered as an inner code in a concatenated coding system for NASA's high-speed satellite communications. In this system, because the error performance of the inner code is amplified by the outer code, a subcode with lower error probability is more desirable. Furthermore, the overall decoder for the $(64,40)$ subcode of $\mathrm{RM}_{3,6}$ code consists of 32 identical RMLD decoders and each such decoder processes a $(64,35)$ subcode or its coset parallel. The RMLD algorithm is computationally more efficient than the Viterbi decoding algorithm. However, the computational complexity of the RMLD algorithm depends on the sectionalization of a code trellis. In general, minimization of the computational complexity results in nonuniform sectionalization of a code trellis. From an implementation point of view, uniform sectionalization of a code trellis and regularity among the trellis sections are desirable.

First, we consider linear subcodes of $\mathrm{RM}_{r, m}$ whose bases are formed from the monomial basis of $\mathrm{RM}_{r, m}$ by deleting $\Delta K$ monomials of degree $r$ where $\Delta K<$ $\binom{m}{r}$. For such subcodes, a procedure for computing the number of minimum weight codewords is presented and we show how to delete $\Delta K$ monomials in order to obtain a subcode with the smallest number of codewords of the minimum


[^0]weight. For $\Delta K \leq 3$, a formula for the number of codewords of the minimum weight is presented. For $(64,40)$ subcodes, there are three equivalent classes. For each class, the number of minimum weight codewords, that of the second smallest weight codewords and simulation results on error probabilities of softdecision maximum likelihood decoding are presented.

Second, we consider how to choose the $(64,35)$ subcode of $\mathrm{RM}_{3,6}$ whose bases are formed from the monomial basis of $\mathrm{RM}_{3,6}$ by deleting seven monomials to minimize the total number of additions and comparisons in ACS(add-compareselect) procedure which roles a mainly part in RMLD.

In the second part, two new soft-decision iterative decoding algorithms are presented. Several iterative soft-decision decoding algorithms have been proposed to achieve a good error performance and a small computational complexity. In these decoding algorithms, an algebraic decoder with respect to chosen input words is iteratively used. Their performances are degraded mainly by the decoding failure of algebraic decoding and the duplication in generating candidate codewords.

We introduce "multiple GMD decoding" for binary linear block codes. In this decoding algorithm, GMD-like decoding is iterated around a few appropriately selected search centers. The original GMD decoding by Forney is a GMD-like decoding around the binary hard-decision sequence. Compared with the original GMD decoding, this decoding algorithm provides better error performance with increasing the number of iterations of erasure and error correction moderately. To reduce the number of iterations, we derive new sufficient conditions on the optimality of decoded codewords. For extended BCH codes, $\operatorname{EBCH}(64,24), \operatorname{EBCH}(128,85)$ and $\operatorname{EBCH}(128,99)$, simulation results show that the new approach provides better error performance than that of the original GMD decoding by adding two GMD-like decoding around two appropriately chosen centers to the original GMD decoding with relative small increment of iteration number.

Finally, we present a new method of choosing a sequence of search centers around which successive bounded distance- $t_{0} \triangleq\lfloor($ minimum distance -1$) / 2\rfloor$ decodings are carried out. To reduce the number of iterations of bounded distance decoding algorithm without any loss of error performance, we show new effective sufficient conditions on the optimality of decoded codewords as early termination
conditions.

## Keywords:

minimum weight codeword, Reed-Muller Code, extended BCH Codes, subcode, recursive maximum likelihood decoding, transitive invariant code, softdecision iterative decoding, multiple GMD decoding, early termination conditions

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## List of Publications

## Journal Papers

[1] T. Kasami, H. Tokushige, T. Fujiwara, H. Yamamoto and S. Lin, "A Recursive Maximum Likelihood Decoding Algorithm for Some Transitive Invariant Binary Codes," IEICE Trans. Fundamentals, vol. E81-A, no. 9, pp. 1916-1924, Sept. 1998.
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[1] H. Tokushige, T. Koumoto and T. Kasami, "An Improvement to GMD-like Decoding Algorithms," Proc. of 2000 IEEE International Symposium on Information Theory, Sorrento, Italy, pp. 396, Jun. 2000.
[2] H. Tokushige, Y. Tang, T. Koumoto and T. Kasami, "An Improvement to Chase-like Decoding Algorithm," Proc. of the International Symposium on Information Theory and Its Applications, Honolulu, USA, pp. 331-334, Nov. 2000.

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## Technical Report

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Related Codes," Technical Report of NAIST, no. NAIST-IS-97003, Jan. 1997.

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## Chapter 1

## Introduction

The notation $\mathrm{RM}_{r, m}$ denotes the Reed-Muller code (RM code) of length $2^{m}$ and degree $r$. A $(64,40)$ subcode of $\mathrm{RM}_{3,6}$ is considered as an inner code in a concatenated coding system for NASA's high-speed satellite communications [1, 3]. The inner code is decoded by a maximum likelihood decoder. Since the ReedSolomon $(255,223)$ code over $\operatorname{GF}\left(2^{8}\right)$ is used as the outer code, the number of information bits must be a multiple of 8 . This is the reason why a $(64,40)$ subcode of $\mathrm{RM}_{3,6}$ is used as the inner code. Therefore, the problem is how to choose such a subcode. In this system, because the error performance of the inner code is amplified by the outer code, a subcode with lower error probability is more desirable. The number of minimum weight codewords of the subcode is a reasonable design index.

A trellis-based recursive maximum likelihood decoding (RMLD) algorithm has been proposed [5]. This RMLD algorithm is more efficient than the conventional Viterbi decoding algorithm in both computational complexity for software implementation and hardware requirement for IC (integrated circuit) implementation. Furthermore, it allows parallel/pipeline processing to speed up the decoding process. The RMLD algorithm is devised based on a divide-and-conquer approach. A code trellis is first divided into appropriate sections. A metric table for each trellis section is formed and each table contains only the metrics of the distinct composite branches in the section and their labels. Metric tables for long trellis sections are formed recursively from tables for shorter trellis sections. At the end of the recursion process, there is only one table which contains only the most
likely codeword for a given received sequence and its corresponding metric. Computational complexity of this decoding algorithm depends on the sectionalization of a code trellis. Minimization of the computational complexity in general results in non-uniform sectionalization of a code trellis in which the trellis sections are not equal in length and do not have a regular structure. These facts cause implementation problems and require more circuits in IC implementation. Therefore, in some applications, it is desirable to trade-off computational complexity for simplicity and regularity in the trellis to reduce circuit requirements and gain decoding speed.

In chapter 2 , we consider how to evaluate the number of codewords of the minimum weight for linear subcodes of $\mathrm{RM}_{r, m}$ whose bases are formed from the monomial basis of $\mathrm{RM}_{r, m}$ by deleting $\Delta K$ monomials of degree $r$ where $\Delta K<$ $\binom{m}{r}$. For $\Delta K \leq 3$, a formula or an effective method which gives the number of codewords of the minimum weight is presented. We also show how to delete $\Delta K$ monomials in order to obtain the subcode with the smallest number of codewords of the minimum weight. For $(64,40)$ subcodes, there are three equivalent classes, each of which consists of all equivalent codes. For each class, the number of minimum weight codewords, the number of second smallest weight codewords and simulation results on error probabilities of soft-decision maximum likelihood decoding are shown. The class with the smallest number of minimum weight codewords provides the best error performance among three equivalent classes.

In chapter 3, we study the RMLD for a class of codes that are transitive invariant. This class of codes includes RM codes, extended and permuted primitive BCH codes (EBCH codes), and their subcodes. For this class of codes, the binary uniform sectionalization of a code trellis results in a simple regular structure among the sections so that the metric table construction procedure can be applied uniformly at each decoding recursion level. The metric tables at the same recursion level have the same size and structure. This simplifies the implementation of an RMLD algorithm. Furthermore, for transitive invariant codes, the binary uniform sectionalization of a code trellis results in almost the same computational complexity as an optimum sectionalization does. This provides an excellent trade-off between computational complexity and code trellis regularity for simple implementation.

The overall decoder for the $(64,40)$ subcode of $\mathrm{RM}_{3,6}$ code consists of 32 identical RMLD decoders based on binary sectionalization, each such decoder processes a $(64,35)$ subcode or its coset parallel. Then, the problem is how to choose a subcode to minimize the computational complexity. Because ACS(add-compareselect) procedure roles a main part in RMLD, the total number of additions and comparisons in ACS procedure is used as an evaluation index. We consider how to choose the $(64,35)$ subcode of $\mathrm{RM}_{3,6}$ whose bases are formed from the monomial basis of $\mathrm{RM}_{3,6}$ by deleting seven monomials to minimize the total number of additions and comparisons in ACS.

The iterative decoding algorithms, such as GMD and Chase II decoding algorithms, use an algebraic decoder iteratively with respect to successively chosen input words, called the search centers. Their performances are degraded by the decoding failure of algebraic decoding and the duplication in generating candidate codewords as simulation results show. By these facts, they do not achieve both a good error performance and a low computer complexity. We present new two iterative decoding algorithms and sufficient conditions on the optimality on the decoded codeword to avoid these drawbacks.

In chapter 4 , we present "multiple GMD decoding" [11, 13] for binary linear block codes. Some improved versions of GMD decoding have been proposed $[12,17,18]$ and performance analysis of GMD decoding has been presented [16]. Simulation results in [12] for several examples codes show that better error performance than for that of the improved version in [17] is provided by adding two bounded distance- $t_{0}(\triangleq\lfloor($ the minimum distance -1$) / 2\rfloor)$ decodings around two appropriately chosen centers to the original GMD decoding.

In this decoding algorithm, GMD-like decoding is iterated around a few appropriately selected search centers. The original GMD decoding by Forney [15] is a GMD-like decoding around the binary hard-decision sequence. For extended BCH codes, $\mathrm{EBCH}(64,24), \operatorname{EBCH}(128,85)$ and $\mathrm{EBCH}(128,99)$, compared with the original GMD decoding, this decoding algorithm provides better error performance by moderately increasing the number of iterations of erasure and error correction. To reduce the number of iterations, several sufficient conditions on the optimality of decoded codewords have been introduced [12, 20, $21,22]$. We derive new effective sufficient conditions and show the effectiveness
by simulation for $\operatorname{EBCH}(64,24), \operatorname{EBCH}(64,45), \operatorname{EBCH}(128,78), \operatorname{EBCH}(128,85)$ and $\operatorname{EBCH}(128,99)$.

In chapter 5, we present a new method of choosing the search centers of successive bounded distance- $t_{0}$ decodings for binary linear block codes. For BCH codes, $\mathrm{BCH}(63,30), \mathrm{BCH}(63,45)$ and $\mathrm{BCH}(127,92)$ codes, with the minimum distance, 13, 7 and 11, respectively, simulation results show the effectiveness of the choice of search centers. To reduce the number of iterations of bounded distance decoding algorithm without any loss of error performance, we derive new effective sufficient conditions on the optimality of decoded codewords as early termination conditions and show the effectiveness by simulation for $\mathrm{BCH}(63,30), \mathrm{BCH}(63,45), \mathrm{BCH}(127,85)$ and $\mathrm{BCH}(127,92)$.

## Chapter 2

## On the Number of Minimum Weight Codewords of Subcodes of Reed-Muller Codes

### 2.1 Definitions

We consider the number of minimum weight codewords in $\left(2^{m}, \sum_{i=0}^{r}\binom{m}{i}-\Delta K\right)$ linear subcodes of $\mathrm{RM}_{r, m}$ for $0<\Delta K<\binom{m}{r}$. The notation $N_{\min }(C)$ denotes the number of minimum weight codewords in a subcode $C$. Let $x_{1}, x_{2}, \ldots, x_{m}$ be $m$ variables. Let $P_{r, m}$ denote the set of binary polynomials with $m$ variables of degree $r$ or less and let $M_{r, m}$ denote the set of monomials in $P_{r, m}$. For a codeword of $\mathrm{RM}_{r, m}$, there is a unique polynomial in $P_{r, m}$ which represents the codeword [2, Ch.13, §3]. Hereafter, the polynomial is used in place of a codeword.

For $0<h \leq r$, define $J_{h} \triangleq\left\{\left\{j_{1}, j_{2}, \ldots, j_{h}\right\}: 1 \leq j_{1}<j_{2}<\cdots<j_{h} \leq m\right\}$, $J_{0} \triangleq\{\emptyset($ empty set $)\}$ and $J \triangleq \bigcup_{h=0}^{r} J_{h}$. For $\alpha_{1}$ and $\alpha_{2}$ in $J$, let $\alpha_{1} \cap \alpha_{2}$ denote the ordered set of those integers which are contained in both of $\alpha_{1}$ and $\alpha_{2}$. For $\alpha=\left\{j_{1}, j_{2}, \ldots, j_{h}\right\} \in J_{h}$ with $1 \leq h \leq r$, define $m_{\alpha}$ as the product of variables $x_{j_{1}}, x_{j_{2}}, \ldots, x_{j_{h}}$ and let $m_{\emptyset} \triangleq 1$. Polynomial $f \in P_{r, m}$ can be expressed uniquely as a linear sum of monomials in $M_{r, m}$, and for $\alpha \in J$, let $c_{\alpha}(f)$ denote the coefficient of $m_{\alpha}$ in the sum of $f$. For a set $X,|X|$ denotes the cardinality of $X$. For a binary $r \times n$ matrix $B$ and $\alpha=\left\{j_{1}, j_{2}, \ldots, j_{h}\right\} \in J_{h}$ with $j_{h} \leq n \leq m$, let $B_{\alpha}$ denote the submatrix of $B$ consisting of the $j_{1}$-th column, the $j_{2}$-th column, $\ldots$,
the $j_{h}$-th column of $B$.

### 2.2 Minimum Weight Codewords

Let $P_{r, m, \min }$ denote the set of those polynomials in $P_{r, m}$ which represent codewords of minimum weight $2^{m-r}$. Then, as shown in [2, Theorems 5, 7 and 8 in $\S 4$, Ch.13], $f \in P_{r, m, \min }$ if and only if $f$ is of the following form :

$$
f=\prod_{i=1}^{r}\left(a_{i}+\sum_{j=1}^{m} a_{i j} x_{j}\right)
$$

where

$$
\operatorname{rank}\left(\begin{array}{ccc}
a_{11} & \cdots & a_{1 m}  \tag{2.1}\\
\vdots & \ddots & \vdots \\
a_{r 1} & \cdots & a_{r m}
\end{array}\right)=r .
$$

Let $\Lambda_{r, m}$ denote the set of those $r \times(m+1)$ binary matrices whose submatrices consisting of the first $m$ columns have rank $r$. For $A \in \Lambda_{r, m}$, define

$$
\begin{equation*}
p(A) \triangleq \prod_{i=1}^{r}\left(a_{i m+1}+\sum_{j=1}^{m} a_{i j} x_{j}\right) \tag{2.2}
\end{equation*}
$$

where $a_{i j}$ denotes the $(i, j)$ element of $A$ for $1 \leq i \leq r$ and $1 \leq j \leq m+1$. For two polynomials $f$ and $g$ in $P_{r, m}$ and $0 \leq i<r$, we write $f \equiv g, \bmod P_{i, m}$ if and only if $f+g \in P_{i, m}$. Then, $p(A)$ is uniquely expanded as follows:

$$
\begin{align*}
p(A) & =\prod_{i=1}^{r}\left(a_{i m+1}+\sum_{j=1}^{m} a_{i j} x_{j}\right) \\
& \equiv \sum_{\alpha \in J_{r}} \operatorname{det}\left(A_{\alpha}\right) m_{\alpha}, \bmod P_{r-1, m} . \tag{2.3}
\end{align*}
$$

### 2.3 The Number of Minimum Weight Codewords of a Subcode Spanned by Monomials

For simplicity, we consider the case where the subcode $C$ of a RM code is spanned by monomials in $M_{r, m} \backslash \Delta M$ where $\Delta M \subseteq M_{r, m} \backslash M_{r-1, m}$ and $|\Delta M|=\Delta K$. Let
$\Delta J$ denote the subset of $J_{r}$ such that $\Delta M=\left\{m_{\alpha}: \alpha \in \Delta J\right\}$. The subcode $C$ is denoted also by $C(\Delta M)$ or $C(\Delta J)$. Then, $f=p(A)$ with $A \in \Lambda_{r, m}$ is a codeword in $C(\Delta J)$, if and only if

$$
\begin{equation*}
\operatorname{det}\left(A_{\alpha}\right)=0, \text { for } \alpha \in \Delta J . \tag{2.4}
\end{equation*}
$$

For different $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h} \in J$, define $F\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right) \triangleq\left\{f \in P_{r, m, \min }: c_{\alpha_{i}}(f)=\right.$ 1 for $1 \leq i \leq h\}$ and $\nu\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right) \triangleq\left|F\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right)\right|$. Then, for $\Delta J$ consisting of different $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}, N_{\min }(C(\Delta J))$ can be expressed by the principle of inclusion and exclusion as follows:

$$
\begin{align*}
N_{\min }(C(\Delta J))= & 2^{r} \prod_{i=0}^{m-r-1} \frac{2^{m-i}-1}{2^{m-r-i}-1}-\sum_{1 \leq i \leq h} \nu\left(\alpha_{i}\right)+\sum_{1 \leq i_{1}<i_{2} \leq h} \nu\left(\alpha_{i_{1}}, \alpha_{i_{2}}\right) \\
& \cdots+(-1)^{s} \sum_{1 \leq i_{1}<i_{2}<\cdots<i_{s} \leq h} \nu\left(\alpha_{i_{1}}, \alpha_{i_{2}}, \ldots, \alpha_{i_{s}}\right) \\
& \cdots+(-1)^{h} \nu\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right) \tag{2.5}
\end{align*}
$$

where the first term of the right-hand side is the number of minimum weight codewords of $\mathrm{RM}_{r, m}[2, \mathrm{Ch} .13, \S 5]$.

We consider how to evaluate $\nu\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right)$ for $1 \leq h \leq \Delta K$. The following lemma holds.

Lemma $1 \nu\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right)$ is equal to the number of $r \times(m+1)$ binary matrices $A$ 's such that
(1) $A_{\alpha_{1}}$ is the identity matrix,
and
(2) $\operatorname{det}\left(A_{\alpha_{i}}\right)=1$, for $2 \leq i \leq h$.
(Proof) (i) Let $A$ be a matrix satisfying the above conditions. Then, $p(A) \in$ $F\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right)$. Let $A$ and $A^{\prime}$ be two different matrices satisfying the above conditions. Let $a_{i, j}$ and $a_{i, j}^{\prime}$ denote the $(i, j)$ elements of $A$ and $A^{\prime}$, respectively. Without loss of generality, let $\alpha_{1}=\{1,2, \ldots, r\}$. If the $(m+1)$-th columns of $A$ and $A^{\prime}$ are different, then substitute 0 for variables $x_{j}$ for $r<j \leq m$ in $p(A)$ and $p\left(A^{\prime}\right)$. Then the resulting polynomials are different polynomials $\prod_{i=1}^{r}\left(x_{i}+a_{i m+1}\right)$ and $\prod_{i=1}^{r}\left(x_{i}+a_{i m+1}^{\prime}\right)$. If $A$ and $A^{\prime}$ have different $(i, j)$ elements, say $a_{i j}=1$ and
$a_{i j}^{\prime}=0$ where $1 \leq i \leq r$ and $r<j \leq m$, then substitute 0 for variables $x_{t}$ for $t \in\{i\} \cup\{r+1, r+2, \ldots, m\} \backslash\{j\}$. Then, the resulting polynomial of $p(A)$ contains monomials $x_{1} \ldots x_{i-1} x_{j} x_{i+1} \ldots x_{r}$ of degree $r$ and that of $p\left(A^{\prime}\right)$ contains no monomial of degree $r$. Hence, $p(A) \neq p\left(A^{\prime}\right)$.
(ii) Let $B$ be an $r \times(m+1)$ binary matrix such that $p(B) \in F\left(\alpha_{1}, \alpha_{2}, \ldots, \alpha_{h}\right)$. For $1 \leq i \leq r$, let the $i$-th row of $B$ be $\left(b_{i_{1}}, b_{i_{2}}, \ldots, b_{i_{m}}, b_{i_{m+1}}\right)$. For $1 \leq i<i^{\prime} \leq r$, let $B^{\prime}$ denote the matrix obtained from $B$ by replacing the $i^{\prime}$-th row of $B$ with $\left(b_{i_{1}^{\prime}}+b_{i_{1}}, b_{i_{2}^{\prime}}+b_{i_{2}}, \ldots, b_{i_{m}^{\prime}}+b_{i_{m}}, b_{i_{m+1}^{\prime}}^{\prime}+b_{i_{m+1}}+1\right)$. Then, $p\left(B^{\prime}\right)=p(B)$. By using this kind of row operation and permuting the rows, we can derive a matrix $A$ such that $p(B)=p(A)$ and $A$ meets the above conditions.

Renumbering the suffices of variables induces a permutation of the bit positions of codewords. Hence, an equivalent code is derived by the renumbering. Since equivalent codes have the same weight distribution, there is no loss of generality in assuming that $\alpha_{1}=\{1,2, \ldots, r\}$. Hereafter in this section, we assume this. For subsets $H_{1}$ and $H_{2}$ of $\{1,2, \ldots, m+1\}, A_{H_{1}, H_{2}}$ denotes the submatrix of $A$ consisting of $(i, j)$ elements of $A$ where $i \in H_{1}$ and $j \in H_{2}$. For $\alpha \in J$, define $\alpha^{0} \triangleq\{1,2, \ldots, m+1\} \backslash \alpha, \alpha^{1}=\alpha$ and $\alpha^{*} \triangleq\{1,2, \ldots, m+1\}$. For a sequence $\beta=b_{1} b_{2} \cdots b_{h}$ over $\{0,1, *\}$ with $1 \leq h \leq \Delta K$, define

$$
\begin{equation*}
n_{\beta} \triangleq \alpha_{1}^{b_{1}} \cap \alpha_{2}^{b_{2}} \cap \cdots \cap \alpha_{h}^{b_{h}} . \tag{2.6}
\end{equation*}
$$

(i) When $\Delta K=1$, from Lemma $1, \nu\left(\alpha_{1}\right)$ is given as follows:

$$
\begin{equation*}
\nu\left(\alpha_{1}\right)=2^{(m-r+1) r} \tag{2.7}
\end{equation*}
$$

From (2.5), we have that

$$
\begin{equation*}
N_{\min }(C)=2^{r} \prod_{i=0}^{m-r-1} \frac{2^{m-i}-1}{2^{m-r-i}-1}-2^{(m-r+1) r} . \tag{2.8}
\end{equation*}
$$

(ii) Consider the case of $\Delta K=2$ and $\Delta J=\left\{\alpha_{1}, \alpha_{2}\right\}$. Define $l \triangleq\left|\alpha_{1} \cap \alpha_{2}\right|$. By renumbering variables, we can assume that $\alpha_{1}=\{1,2, \ldots, r\}$ and $\alpha_{2}=$ $\{r+1-l, r+2-l, \ldots, 2 r-l\}$ where $0 \leq l<r$. Then, $\operatorname{det}\left(A_{\alpha_{2}}\right)=1$, if and only if the $(r-l) \times(r-l)$ submatrix $A_{n_{10}, n_{01}}$ is regular (refer to Fig. 2.1). The number of such regular submatrices is given by

$$
\prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right)
$$

There is no restriction of submatrix $A_{n_{11}, n_{01}}$. Then, the number of matrices $A$ such that $A_{\alpha_{1}}$ is the identity matrix and $\operatorname{det}\left(A_{\alpha_{2}}\right)=1$ is

$$
2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right)
$$

From Lemma 1,

$$
\begin{equation*}
\nu\left(\alpha_{1}, \alpha_{2}\right)=2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right) \tag{2.9}
\end{equation*}
$$

It follows from (2.5), (2.7) and (2.9) that

$$
\begin{align*}
N_{\min }(C)= & 2^{r} \prod_{i=0}^{m-r-1} \frac{2^{m-i}-1}{2^{m-r-i}-1}-\left\{\nu\left(\alpha_{1}\right)+\nu\left(\alpha_{2}\right)-\nu\left(\alpha_{1}, \alpha_{2}\right)\right\} \\
= & 2^{r} \prod_{i=0}^{m-r-1} \frac{2^{m-i}-1}{2^{m-r-i}-1}-2 \cdot 2^{(m-r+1) r} \\
& +2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right), \tag{2.10}
\end{align*}
$$

where $\Delta M=\left\{m_{\alpha_{1}}, m_{\alpha_{2}}\right\}$ and $l$ denotes the number of integers appearing in both of $\alpha_{1}$ and $\alpha_{2}$. The value of $N_{\min }(C)$ in (2.10) takes the minimum, if and only if $l=0$, that is, $\alpha_{1}$ and $\alpha_{2}$ are disjoint. This result is generalized in Theorem 1.
(iii) Consider the case of $\Delta K=3$ and $\Delta J=\left\{\alpha_{1}, \alpha_{2}, \alpha_{3}\right\}$. By renumbering of variables, there is no loss of generality in assuming that $\alpha_{1}=\{1,2, \ldots, r\}$ and the integers in nonempty sets $n_{100}, n_{101}, n_{110}$ and $n_{111}$ are arranged as shown in Fig 2.2, that is, for any $i_{1} \in n_{100}, i_{2} \in n_{101}, i_{3} \in n_{110}$ and $i_{4} \in n_{111}, 1 \leq i_{1}<$ $i_{2}<i_{3}<i_{4} \leq r$ (for an empty set, skip it). Then, since $A_{\alpha_{1}}\left(=A_{n_{1 * *}, n_{1 * *}}\right)$ is an identity matrix and therefore $A_{n_{10 *}, n_{11 *}}$ is a zero matrix and $A_{n_{11 *}, n_{11 *}}$ is an identity matrix, we have that $\operatorname{det}\left(A_{\alpha_{2}}\right)=1$, if and only if
(L1) submatrix $A_{n_{10 *}, n_{01 *}}$ is regular.
Note that $\left|n_{10 *}\right|=r-\left|n_{11 *}\right|=\left|n_{01 *}\right|$. Similarly, $\operatorname{det}\left(A_{\alpha_{3}}\right)=1$ if and only if
(L2) submatrix $A_{n_{1 * 0}, n_{0 * 1}}$ is regular.
Note that $\left|n_{1 * 0}\right|=r-\left|n_{1 * 1}\right|=\left|n_{0 * 1}\right|$ (refer to Fig. 2.2). From (L1) and (L2), we see that


Figure 2.1. The matrix $A$ by renumbering variables.
(L3) the columns of $A_{n_{10 *}, n_{011}}$ are linearly independent, and
(L4) the columns of $A_{n_{1 * 0}, n_{011}}$ are linearly independent.
The submatrix which consists of common rows and columns of $A_{n_{10 *}, n_{01 *}}$ and $A_{n_{1 * 0}, n_{0 * 1}}$ is $A_{n_{100}, n_{011}}$. Let $N_{23}$ denote the number of pairs of $A_{n_{10 *}, n_{011}}$ and $A_{n_{1 * 0}, n_{011}}$ satisfying (L3) and (L4). If one of $\left|n_{100}\right|,\left|n_{101}\right|,\left|n_{110}\right|$ and $\left|n_{011}\right|$ is zero, $N_{23}$ can be easily counted. For the case where they are all nonzeros, how to evaluate $N_{23}$ is shown in Appendix A.

Since the first to the $\left|n_{010}\right|$-th columns of $A_{n_{10 *}, n_{01 *}}$ are linearly independent of the $\left|n_{011}\right|$ rest linearly independent columns of $A_{n_{10 *}, n_{01 *}}$, the number of $A_{n_{10 *}, n_{010}}$ consisting of such columns is given by

$$
\begin{equation*}
\prod_{j=\left|n_{011}\right|}^{\left|n_{01 *}\right|-1}\left(2^{\left|n_{10 *}\right|}-2^{j}\right)=\prod_{j=\left|n_{011}\right|}^{\left|n_{10 *}\right|-1}\left(2^{\left|n_{10 *}\right|}-2^{j}\right) . \tag{2.11}
\end{equation*}
$$

Similarly, the number of $A_{n_{1 * 0}, n_{001}}$ is given by

$$
\begin{equation*}
\prod_{j=\left|n_{011}\right|}^{\left|n_{0 * 1}\right|-1}\left(2^{\left|n_{1 * 0}\right|}-2^{j}\right)=\prod_{j=\left|n_{011}\right|}^{\left|n_{1 * 0}\right|-1}\left(2^{\left|n_{1 * 0}\right|}-2^{j}\right) . \tag{2.12}
\end{equation*}
$$

The elements of the $(m+1)$-th column and submatrices $A_{n_{11 *}, n_{010}}, A_{n_{111}, n_{0 * 1}}$, $A_{n_{101}, n_{001}}$ and $A_{n_{1 * *}, n_{000}}$ are arbitrary. The total number of these elements is given by

$$
\begin{equation*}
2^{\left|n_{11} *\right| \cdot\left|n_{010}\right|+\left|n_{111}\right| \cdot\left|n_{0 * 1}\right|+\left|n_{101}\right| \cdot\left|n_{001}\right|} \times 2^{r\left(\left|n_{000}\right|+1\right)} . \tag{2.13}
\end{equation*}
$$

Then, it follows from the definition of $N_{23},(2.11),(2.12)$ and (2.13) that the number of matrices $A$ such that $A_{\alpha_{1}}$ is the identity matrix, $\operatorname{det}\left(A_{\alpha_{2}}\right)=1$ and $\operatorname{det}\left(A_{\alpha_{3}}\right)=1$ is

$$
\begin{align*}
N_{23} \times & \prod_{j=\left|n_{011}\right|}^{\left|n_{10}\right|-1}\left(2^{\left|n_{10 *}\right|}-2^{j}\right) \times \prod_{j=\left|n_{011}\right|}^{\left|n_{10 *}\right|-1}\left(2^{\left|n_{1 * 0}\right|}-2^{j}\right) \\
& \times 2^{\left|n_{11} *\right| \cdot\left|n_{010}\right|+\left|n_{111}\right| \cdot\left|n_{0 * 1}\right|+\left|+\left|n_{101}\right| \cdot\right| n_{001} \mid} \times 2^{r\left(\left|n_{000}\right|+1\right)}, \tag{2.14}
\end{align*}
$$

(refer to Fig. 2.2). From Lemma 1, $\nu\left(\alpha_{1}, \alpha_{2}, \alpha_{3}\right)$ is equal to the value of the formula (2.14).

For $\Delta K=4$, the evaluation of $\nu\left(\alpha_{1}, \alpha_{2}, \alpha_{3}, \alpha_{4}\right)$ where $\alpha_{1} \cap \alpha_{2} \cap \alpha_{3} \cap \alpha_{4} \neq \emptyset$ becomes more complicated. However, the method presented in Appendix A can be applied to more general cases.


Figure 2.2. The matrix $A$ by renumbering variables.

### 2.4 Subcodes with the Smallest Number of Minimum Weight Codewords

We consider how to delete $\Delta K$ monomials in order to obtain the subcode with the smallest number of minimum weight codewords. We first prove the following lemma.

Lemma 2 We assume that (a) there is an integer, say $m$, which is not contained in any $\alpha \in \Delta J$ and (b) there are two or more sets $\beta_{1}, \beta_{2}, \ldots, \beta_{p}$ in $\Delta J$ which have a common integer, say $m-1$, and no other sets in $\Delta J$ contain $m-1$. Let $\beta_{p}^{\prime} \in J_{r}$ denote the set obtained from $\beta_{p}$ by replacing $m-1$ with $m$ and $\Delta J^{\prime} \triangleq\left(\Delta J \backslash\left\{\beta_{p}\right\}\right) \cup\left\{\beta_{p}^{\prime}\right\}$. Then, we have the following inequality:

$$
\begin{equation*}
N_{\min }(C(\Delta J))>N_{\min }\left(C\left(\Delta J^{\prime}\right)\right) \tag{2.15}
\end{equation*}
$$

(Proof) For a subset $J^{\prime}$ of $J$, define $\Lambda\left(J^{\prime}\right) \triangleq\left\{A \in \Lambda_{r, m}: \operatorname{det}\left(A_{\alpha}\right)=0, \alpha \in J^{\prime}\right\}$. Then [2, Theorems 3 and 5, Appendix B],

$$
\begin{aligned}
N_{\min }\left(C\left(J^{\prime}\right)\right) & =\left|\left\{p(A): A \in \Lambda\left(J^{\prime}\right)\right\}\right| \\
& =\frac{\left|\Lambda\left(J^{\prime}\right)\right|}{\prod_{i=0}^{r-1}\left(2^{r}-2^{i}\right)} .
\end{aligned}
$$

Hence it is sufficient to show that

$$
\begin{equation*}
|\Lambda(\Delta J)|>\left|\Lambda\left(\Delta J^{\prime}\right)\right| \tag{2.16}
\end{equation*}
$$

For a binary $r \times(m+1)$ matrix $A$, let $A_{0}$ denote the $r \times(m-1)$ submatrix consisting of the first to the $(m-2)$-th columns and the $(m+1)$-th column of $A$. That is, $A_{0}=A_{\{1,2, \ldots, m+1\} \backslash\{m-1, m\}}$. For a binary $r \times(m-1)$ matrix $D$, define

$$
\begin{aligned}
\Lambda(\Delta J, D) & \triangleq\left\{A \in \Lambda(\Delta J): A_{0}=D\right\} \\
\Lambda\left(\Delta J^{\prime}, D\right) & \triangleq\left\{A^{\prime} \in \Lambda\left(\Delta J^{\prime}\right): A_{0}^{\prime}=D\right\}
\end{aligned}
$$

We will show that for any binary $r \times(m-1)$ matrix $D$,

$$
\begin{equation*}
|\Lambda(\Delta J, D)| \geq\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| \tag{2.17}
\end{equation*}
$$

and that there are binary $r \times(m-1)$ matrices $D$ 's such that

$$
\begin{equation*}
|\Lambda(\Delta J, D)|>\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| . \tag{2.18}
\end{equation*}
$$

Since $|\Lambda(\Delta J)|=\sum_{D}|\Lambda(\Delta J, D)|$ and $\left|\Lambda\left(\Delta J^{\prime}\right)\right|=\sum_{D}\left|\Lambda\left(\Delta J^{\prime}, D\right)\right|$, where $\sum_{D}$ denotes the sum over all binary $r \times(m-1)$ matrices, (2.17) and (2.18) imply (2.16) and therefore (2.15).

There are the following three cases of $D$ to be considered. Let $D_{o}$ denote the submatrix of $D$ consisting of the first $m-2$ columns of $D$.
(i) The rank of $D_{\beta_{p} \backslash\{m-1\}} \leq r-2$ : For any binary $r \times(m+1)$ matrix $A$ such that $A_{0}=D, \operatorname{det}\left(A_{\beta_{p}}\right)=\operatorname{det}\left(A_{\beta_{p}^{\prime}}\right)=0$. Hence, if $A^{\prime} \in \Lambda\left(\Delta J^{\prime}, D\right)$, then $A^{\prime} \in \Lambda(\Delta J, D)$. That is, (2.17) holds.
(ii) The rank of $D_{\beta_{p} \backslash\{m-1\}}=r-1$ :
(ii.1) First, we assume that the rank of $D_{o}$ is $r$. If there is a set $\alpha \in \Delta J \backslash$ $\left\{\beta_{1}, \beta_{2}, \ldots, \beta_{p}\right\}$ such that $\operatorname{det}\left(D_{\alpha}\right)=1$, then $\Lambda(\Delta J, D)=\Lambda\left(\Delta J^{\prime}, D\right)=\emptyset$. We consider the case where for any set $\alpha$ in $\Delta J \backslash\left\{\beta_{1}, \beta_{2}, \ldots, \beta_{p}\right\}, \operatorname{det}\left(D_{\alpha}\right)=0$. Then, for any binary $r \times(m+1)$ matrix $A\left(\right.$ or $\left.A^{\prime}\right)$ such that $A_{0}=D$ and $\operatorname{det}\left(A_{\beta_{i}}\right)=0$ with $1 \leq i \leq p\left(\right.$ or $A_{0}^{\prime}=D, \operatorname{det}\left(A_{\beta_{i}}^{\prime}\right)=0$ with $1 \leq i<p$ and $\left.\operatorname{det}\left(A_{\beta_{p}^{\prime}}^{\prime}\right)=0\right)$, $A \in \Lambda(\Delta J, D)\left(\right.$ or $\left.A^{\prime} \in \Lambda\left(\Delta J^{\prime}, D\right)\right)$.

Let $a_{i, j}$ denote the $(i, j)$ element of $A$ and $a_{i, j}^{\prime}$ denote the $(i, j)$ element of $A^{\prime}$. We will compare $|\Lambda(\Delta J, D)|$ with $\left|\Lambda\left(\Delta J^{\prime}, D\right)\right|$. We can expand $\operatorname{det}\left(A_{\beta_{i}}\right)$ on the ( $m-1$ )-th column of $A_{\beta_{i}}$ for $1 \leq i \leq p$ as follows:

$$
\begin{equation*}
\operatorname{det}\left(A_{\beta_{i}}\right)=\sum_{j=1}^{r} B_{i j} a_{j, m-1}=0, \text { for } 1 \leq i \leq p \tag{2.19}
\end{equation*}
$$

where $B_{i j}$ is a cofactor and is dependent on $D$ only. There is no restriction on $a_{1, m}, a_{2, m}, \ldots, a_{r, m}$. Let $\rho$ denote the rank of the coefficient matrix of (2.19) whose $(i, j)$ element is $B_{i j}$ for $1 \leq i \leq p$ and $1 \leq j \leq r$. Since $|\Lambda(\Delta J, D)|$ is the number of $a_{1, m-1}, a_{2, m-1}, \ldots, a_{r, m-1}, a_{1, m}, a_{2, m}, \ldots, a_{r, m}$ satisfying (2.19),

$$
\begin{equation*}
|\Lambda(\Delta J, D)|=2^{2 r-\rho} \tag{2.20}
\end{equation*}
$$

We can expand $\operatorname{det}\left(A_{\beta_{i}}^{\prime}\right)$ on the $(m-1)$-th column of $A_{\beta_{i}}^{\prime}$ for $1 \leq i<p$ and $\operatorname{det}\left(A_{\beta_{p}^{\prime}}^{\prime}\right)$ on the $m$-th column of $A_{\beta_{p}^{\prime}}^{\prime}$ as follows:

$$
\begin{align*}
\operatorname{det}\left(A_{\beta_{i}}^{\prime}\right) & =\sum_{j=1}^{r} B_{i j} a_{j, m-1}^{\prime}=0, \text { for } 1 \leq i<p,  \tag{2.21}\\
\operatorname{det}\left(A_{\beta_{p}^{\prime}}^{\prime}\right) & =\sum_{j=1}^{r} B_{p j} a_{j, m}^{\prime}=0 . \tag{2.22}
\end{align*}
$$

Let $\rho^{\prime}$ denote the rank of the coefficient matrix of $(2.21)$ whose $(i, j)$ elements is $B_{i j}$ for $1 \leq i<p$ and $1 \leq j \leq r$. Then,

$$
\begin{equation*}
\rho^{\prime}=\rho \text { or } \rho-1 \text {. } \tag{2.23}
\end{equation*}
$$

The number of $a_{1, m-1}^{\prime}, a_{2, m-1}^{\prime}, \ldots, a_{r, m-1}^{\prime}$ satisfying (2.21) is $2^{r-\rho^{\prime}}$. Since the rank of $A_{\beta_{p}^{\prime} \backslash\{m\}}^{\prime}\left(=D_{\beta_{p} \backslash\{m-1\}}\right)$ is $r-1$, one of $B_{p_{j}}$ with $1 \leq j \leq r$ is not zero. Hence, the number of $a_{1, m}^{\prime}, a_{2, m}^{\prime}, \ldots, a_{r, m}^{\prime}$ satisfying (2.22) is $2^{r-1}$. Consequently, we have that

$$
\begin{equation*}
\left|\Lambda\left(\Delta J^{\prime}, D\right)\right|=2^{2 r-\rho^{\prime}-1} \tag{2.24}
\end{equation*}
$$

From (2.20), (2.23) and (2.24), we see that

$$
\begin{equation*}
|\Lambda(\Delta J, D)| \geq\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| \tag{2.25}
\end{equation*}
$$

(ii.2) Next, we assume that the rank of $D_{o}$ is $r-1$. It is sufficient to consider the case that the first $r-1$ rows of $D_{o}$ are linearly independent and the last row of $D_{o}$ is a zero row. Since the rank of $D_{\beta_{p} \backslash\{m-1\}}$ is $r-1$, if $A \in \Lambda(\Delta J, D)$, then $a_{r, m-1}=0$ from $\operatorname{det}\left(A_{\beta_{p}}\right)=0$ and $a_{r, m}=1$ from $A \in \Lambda_{r, m}$. Conversely, if $a_{r, m-1}=0$ and $a_{r, m}=1$, then $\operatorname{det}\left(A_{\alpha}\right)=0$ for $\alpha \in \Delta J$ and $\operatorname{det}\left(A_{\beta_{p}^{\prime}}\right)=1$, that is, $A \in \Lambda(\Delta J, D)$. Hence, $|\Lambda(\Delta J, D)|=2^{2 r-2}$. Similarly, if $A^{\prime} \in \Lambda\left(\Delta J^{\prime}, D\right)$, then $a_{r, m}^{\prime}=0$ from $\operatorname{det}\left(A_{\beta_{p}^{\prime}}^{\prime}\right)=0$ and $a_{r, m-1}^{\prime}=1$ from $A^{\prime} \in \Lambda_{r, m}$. Hence, $\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| \leq 2^{2 r-2}$. Consequently

$$
\begin{equation*}
|\Lambda(\Delta J, D)| \geq\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| \tag{2.26}
\end{equation*}
$$

Note that if the rank of $D_{\beta_{p-1} \backslash\{m-1\}}$ is $r-1$, then $a_{r, m-1}^{\prime}=1$ implies $\operatorname{det}\left(A_{\beta_{p-1}}^{\prime}\right)=$ 1. That is, $\Lambda\left(\Delta J^{\prime}, D\right)$ is empty. Let $D$ be a binary $r \times(m-1)$ matrix as follows:
(a) the last row of $D$ is a zero row, (b) the rank of $D_{\beta_{p} \backslash\{m-1\}}$ is $r-1$ and (c) there is a one-to-one correspondence between the set of columns of $D_{\beta_{p} \backslash\{m-1\}}$ and that of $D_{\beta_{p-1} \backslash\{m-1\}}$ such that the corresponding columns are the same column vector. Then, the rank of $D_{\beta_{p-1} \backslash\{m-1\}}$ is $r-1$, and therefore,

$$
\begin{equation*}
|\Lambda(\Delta J, D)|>\left|\Lambda\left(\Delta J^{\prime}, D\right)\right| \tag{2.27}
\end{equation*}
$$

$$
\Delta \triangle
$$

Suppose that $r \Delta K \leq m$. From Lemma 2, we can remove the overlap among $\Delta J$ step by step to decrease the number of minimum weight codewords. Thus we have the following theorem.

Theorem 1 For $r \Delta K \leq m$, the value of $N_{\min }(C(\Delta J))$ takes the minimum, if and only if the sets in $\Delta J$ are mutually disjoint.

In case that $\Delta J$ consists of mutually disjoint sets, a formula for $N_{\min }(C(\Delta J))$ is readily derived from (2.5) and Lemma 1.
$\mathrm{RM}_{r, m}$ code is spanned by the set of codewords with the minimum weight [2, Ch.13, $\S 5]$. We can consider subcodes of RM codes which are spanned by a set of codewords with the minimum weight. The basis of this subcode is formed from that of a RM code by deleting $\Delta K$ codewords of the minimum weight which are linearly independent each other. Then, for $r \Delta K \leq m$, we can replace the $\Delta K$ codewords to $\Delta K$ monomials of degree $r$ by an affine transformation. Hence, this case is reduced to the case that we have considered in Sections 2.3 and 2.4.

Example 1 Consider the number of minimum weight codewords of $(64,40)$ subcodes of the $(64,42) \mathrm{RM}$ code, that is, $\mathrm{RM}_{3,6}$. Table 2.1 shows the number of minimum weight codewords of a subcode whose basis is formed from that of the $(64,42)$ RM code by deleting two monomials. By renumbering the suffices of variables, there are exactly three cases, that is, $\Delta M_{0}=\left\{x_{1} x_{2} x_{3}, x_{4} x_{5} x_{6}\right\}$, $\Delta M_{1}=\left\{x_{1} x_{2} x_{3}, x_{3} x_{4} x_{5}\right\}$ and $\Delta M_{2}=\left\{x_{1} x_{2} x_{3}, x_{2} x_{3} x_{4}\right\}$. The code $C\left(\Delta M_{0}\right)$ with the smallest number of minimum weight codewords has the smallest block error probabilities at $E_{b} / N_{0}=2.0,3.0,4.0$ and 5.0 dB as is shown in Table 2.1.

The result in Sections 2.3 and 2.4 can be generalized to the case where monomials of degree $r-1$ may be deleted, that is, $\Delta M \subseteq M_{r, m} \backslash M_{r-2, m}$, by using the following

Table 2.1. Minimum Weight Codewords of $(64,40)$ subcode of $\mathrm{RM}_{3,6}$.

| $\Delta M$ | The number of <br> minimum weight | The block error probabilities at $E_{b} / N_{0}$ for <br> soft-decision maximum likelihood decoding |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2.0 dB | 3.0 dB | 4.0 dB | 5.0 dB |
|  | 4312 | $8.54 \times 10^{-2}$ | $1.33 \times 10^{-2}$ | $9.68 \times 10^{-4}$ | $2.93 \times 10^{-5}$ |
| $\Delta M_{1}$ | 4504 | $8.67 \times 10^{-2}$ | $1.36 \times 10^{-2}$ | $9.97 \times 10^{-4}$ | $3.38 \times 10^{-5}$ |
| $\Delta M_{2}$ | 5016 | $8.99 \times 10^{-2}$ | $1.46 \times 10^{-2}$ | $1.09 \times 10^{-3}$ | $3.66 \times 10^{-5}$ |

fact: For $\alpha=\left(j_{1}, j_{2}, \ldots, j_{r-1}\right) \in J_{r-1}$, let $A_{\alpha}$ denote the $r \times r$ submatrix of $A$ consisting of the $j_{1}$-th, the $j_{2}$-th, $\ldots$, the $j_{r-1}$-th and the $(m+1)$-th columns of $A$. Then, we have that

$$
\begin{equation*}
p(A) \equiv \sum_{\alpha \in J_{r-1} \cup J_{r}} \operatorname{det}\left(A_{\alpha}\right) m_{\alpha}, \bmod P_{r-2, m} \tag{2.28}
\end{equation*}
$$

We consider the case where the subcode $C$ of a RM code is spanned by monomials in $M_{r, m} \backslash \Delta M$ where $\Delta M \subseteq M_{r-2, m},|\Delta M|=2$ and $\Delta M=\left\{\alpha_{1}, \alpha_{2}\right\}$ for $\alpha_{1} \in J_{r-1}$ and $\alpha_{2} \in J_{r}$.

Consider the case of $|\Delta M|=1$ and $\alpha_{1} \in J_{r-1}$. There is no loss of generality in assuming that $\alpha_{1}=(1,2, \ldots, r-1)$. The first to the $r-1$-th columns of $A$ are linearly independent and there exists unique $j$ satisfying the following conditions:
(1) $r \leq j \leq m$,
(2) the first to the $r-1$-th and the $i$-th columns of $A$ for $r \leq i<j$ are linearly depend,
and
(3) the first to the $r-1$-th and the $j$-th columns of $A$ are linearly independent.

For any $j$, we evaluate the number $N_{j}$ of matrices such that
(1') the submatrix consisting of the first to the $r-1$-th and the $j$-th columns of $A$ is the identity matrix, and
$\left(2^{\prime}\right)$ the first to the $r-1$-th and $m+1$-th columns of $A$ are linearly independent.

Then, the total sum of $N_{j}$ for $r \leq j \leq r$ is $\nu\left(\alpha_{1}\right)$, that is

$$
\begin{equation*}
\nu\left(\alpha_{1}\right)=\sum_{j=r}^{m} N_{j} . \tag{2.29}
\end{equation*}
$$

Consider the case of $|\Delta M|=2$. Let $l$ denotes the number of integer appearing in both of $\alpha_{1}$ and $\alpha_{2}$. By renumbering variables, we can assume that $\alpha_{1}=$ $(r+1-l, r+2-l, \ldots, 2 r-1-l)$ and $\alpha_{2}=(1,2, \ldots, r)$ where $0 \leq l<r$. Then, $\operatorname{det}\left(A_{\alpha_{1}}\right)=1$, if and only if the $(r-l) \times(r-l)$ submatrix consisting of the first $r-l$ rows and the $j_{1}$-th, the $j_{2}$-th, $\ldots$, the $j_{r-1}$-th and the $(m+1)$-th columns of $A$ is regular. There is no restriction of the submatrix consisting of columns of $A$, excluding the first $(2 r-1-l)$ columns an the $(m+1)$-th column. Then, the number of matrices $A$ such that $A_{\alpha_{2}}$ is the identity matrix and $\operatorname{det}\left(A_{\alpha_{1}}\right)=1$ is

$$
\begin{equation*}
2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right) \tag{2.30}
\end{equation*}
$$

From Lemma 1,

$$
\begin{equation*}
\nu\left(\alpha_{1}, \alpha_{2}\right)=2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right) . \tag{2.31}
\end{equation*}
$$

It follows from (2.5), (2.7), (2.29) and (2.31) that

$$
\begin{align*}
N_{\min }(C)= & 2^{r} \prod_{i=0}^{m-r-1} \frac{2^{m-i}-1}{2^{m-r-i}-1}-\sum_{j=r}^{m} N_{j}-2^{(m-r+1) r} \\
& +2^{r\{m+1-(2 r-l)\}} \cdot 2^{(r-l) l} \cdot \prod_{j=0}^{r-l-1}\left(2^{r-l}-2^{j}\right) \tag{2.32}
\end{align*}
$$

Example 2 Consider the number of minimum weight codewords of $(64,40)$ subcodes of the $(64,42) \mathrm{RM}$ code. Table 2.2 shows the number of minimum weight codewords of a subcode of a RM code is spanned by monomials in $M_{r, m} \backslash \Delta M$ where $\Delta M \subseteq M_{r-2, m},|\Delta M|=2$ and $\Delta M=\left\{\alpha_{1}, \alpha_{2}\right\}$ for $\alpha_{1} \in J_{r-1}$ and $\alpha_{2} \in J_{r}$. By renumbering the suffices of variables, there are exactly three cases, that is, $\Delta M=\left\{x_{1} x_{2} x_{3}, x_{4} x_{5}\right\},\left\{x_{1} x_{2} x_{3}, x_{3} x_{4}\right\}$ and $\left\{x_{1} x_{2} x_{3}, x_{2} x_{3}\right\}$.

Table 2.2. $N_{\min }(C(\Delta M))$ where $\Delta M \subseteq M_{r, m} \backslash M_{r-2, m},|\Delta M|=2$ and $\Delta M=$ $\left\{\alpha_{1}, \alpha_{2}\right\}$ for $\alpha_{1} \in J_{r-1}$ and $\alpha_{2} \in J_{r}$.

| $\Delta M$ | The number of <br> minimum weight codewords |
| :---: | :---: |
| $x_{1} x_{2} x_{3}, x_{4} x_{5}$ | 4568 |
| $x_{1} x_{2} x_{3}, x_{3} x_{4}$ | 4760 |
| $x_{1} x_{2} x_{3}, x_{2} x_{3}$ | 5272 |

### 2.5 Conclusion

We have presented a formula or an effective method which gives the number of minimum weight codewords in a $\left(2^{m}, \sum_{i=0}^{r}\binom{m}{i}-\Delta K\right)$ linear subcode $C$ of $\mathrm{RM}_{r, m}$ code which is spanned by monomials with $m$ variables of degree $r$ or less over $\mathrm{GF}(2)$ for $\Delta K \leq 3$. Next, it has been shown in Theorem 1 how to delete $\Delta K$ monomials in order to obtain the subcode with the smallest number of codewords of the minimum weight for $r \Delta K \leq m$. In Example 1, we have shown the numbers of minimum weight codewords of all such $(64,40)$ subcodes of $\mathrm{RM}_{3,6}$ and those error probabilities of soft-decision maximum likelihood decoding by simulation.

## Chapter 3

## A Recursive MLD Algorithm for Some Transitive Invariant Binary Block Codes

### 3.1 A Review of RMLD Algorithm

Consider a binary ( $n, k$ ) linear block code $C$ for error control over an AWGN channel using BPSK signaling.

For a positive integer $n$, let $V^{n}$ denote the vector space of all the $n$-tuples over $\operatorname{GF}(2)$. For an $n$-tuple $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{n}\right) \in V^{n}$, let $\mathrm{wt}(\boldsymbol{u})$ be the Hamming weight (or simply weight) of $\boldsymbol{u}$. Let $x$ and $y$ be two nonnegative integers such that $0 \leq x<y \leq n$. For an $n$-tuple $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{n}\right) \in V^{n}$, define $p_{x, y} \boldsymbol{u} \triangleq\left(u_{x+1}, u_{x+2}, \ldots, u_{y}\right)$, and $p_{x, y}(C) \triangleq\left\{p_{x, y} \boldsymbol{u}: \boldsymbol{u} \in C\right\}$. Then $p_{x, y}(C)$ is a linear code of length $y-x$. Let $C_{x, y}$ denote the subcode of $C$ which consists of those codewords whose components are all zero except for the $y-x$ components from the $(x+1)$-th bit position to the $y$-th bit position. For simplicity, we use the notation $C_{x, y}^{\mathrm{tr}}$, for the truncated code $p_{x, y}\left(C_{x, y}\right)$.

For a linear block code $A$ and its linear subcode $B, A / B$ denotes the set of cosets of $B$ in $A$, called partition of $A$ with respect to $B$. For two binary tuples $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{i}\right)$ and $\boldsymbol{v}=\left(v_{1}, v_{2}, \ldots, v_{j}\right)$, let $\boldsymbol{u} \circ \boldsymbol{v}$ denote the concatenation of $\boldsymbol{u}$ and $\boldsymbol{v},\left(u_{1}, u_{2}, \ldots, u_{i}, v_{1}, v_{2}, \ldots, v_{j}\right)$, and for block codes $A$ and $B, A \circ B$ denotes $\{\boldsymbol{u} \circ \boldsymbol{v}: \boldsymbol{u} \in A, \boldsymbol{v} \in B\}$. For a set $X,|X|$ denotes the cardinality of $X$.

For integers $x$ and $y$ such that $0 \leq x<y \leq n$, let $L_{x, y}$ denote the cosets of $C_{x, y}^{\mathrm{tr}}$ in the partition $p_{x, y}(C) / C_{x, y}^{\mathrm{tr}}$, i.e.,

$$
\begin{equation*}
L_{x, y} \triangleq p_{x, y}(C) / C_{x, y}^{\mathrm{tr}} \tag{3.1}
\end{equation*}
$$

$L_{x, y}$ plays a key role in RMLD algorithm.
Let $D$ be a coset in $L_{x, y}$. For a vector $\boldsymbol{u} \in D$, let $m(\boldsymbol{u})$ denote the correlation metric of $\boldsymbol{u}$ with the received sequence (from the $(x+1)$-th bit position to the $y$-th bit position). Define

$$
\begin{equation*}
m(D) \triangleq \max _{\boldsymbol{u} \in D} m(\boldsymbol{u}) \tag{3.2}
\end{equation*}
$$

which is called the metric of coset $D$. Let $l(D)$ denote the vector in $D$ that has the largest (correlation) metric in $D$. This $(y-x)$-tuple $l(D)$ is called the label of coset $D$.

Form a metric table for $L_{x, y}$ which consists of the pairs,

$$
(m(D), l(D))
$$

for all the cosets in $L_{x, y}$. This metric table is called $L_{x, y}$-table. Note that for $x=0$ and $y=n, L_{0, n}=\{C\}$. When $L_{0, n}$-table is constructed, it stores the most likely codeword and its correlation metric. The RMLD algorithm for decoding $C$ is simply a recursive procedure for constructing $L_{x, y^{-}}$-tables for long trellis sections from short trellis sections.

Assume that $y-x \geq 2$. Let $z$ be an integer such that $x<z<y$. For each $D \in L_{x, y}$, define $A_{z}(D) \triangleq\left\{D_{z} \in L_{x, z}: D_{z} \subseteq p_{x, z}(D)\right\}$. Since $D$ is in $p_{x, y}(C) / C_{x, y}^{\mathrm{tr}}$ and $D_{z}$ is in $p_{x, z}(C) / C_{x, z}^{\mathrm{tr}}, D_{z}$ is in $p_{x, z}\left(p_{x, y}(C) /\left(C_{x, z}^{\mathrm{tr}} \circ C_{z, y}^{\mathrm{tr}}\right)\right)$, that is, for each $D_{z}$, there is a binary $(y-x)$-tuple $\boldsymbol{u}$ such that $D_{z}=\left\{p_{x, z} \boldsymbol{u}+\boldsymbol{v}: \boldsymbol{v} \in C_{x, z}^{\mathrm{tr}}\right\}$ and there is exactly one coset in $L_{z, y},\left\{p_{z, y} \boldsymbol{u}+\boldsymbol{v}: \boldsymbol{v} \in C_{z, y}^{\mathrm{tr}}\right\}$, denoted $\operatorname{adj}\left(D_{z}, D\right)$, such that

$$
\begin{equation*}
D_{z} \circ \operatorname{adj}\left(D_{z}, D\right) \subseteq D \tag{3.3}
\end{equation*}
$$

Hence $\left|A_{z}(D)\right|$, denoted $A_{x, y ; z}$, is given by

$$
\begin{equation*}
A_{x, y ; z}=\left|C_{x, y}^{\mathrm{tr}}\right| /\left(\left|C_{x, z}^{\mathrm{tr}}\right| \cdot\left|C_{z, y}^{\mathrm{tr}}\right|\right) \tag{3.4}
\end{equation*}
$$

Then, it follows from (3.3) that

$$
\begin{equation*}
D=\bigcup_{D_{z} \in A_{z}(D)} D_{z} \circ \operatorname{adj}\left(D_{z}, D\right) \tag{3.5}
\end{equation*}
$$

and

$$
\begin{align*}
m(D) & =\max _{D_{z} \in A_{z}(D)}\left\{m\left(D_{z}\right)+m\left(\operatorname{adj}\left(D_{z}, D\right)\right)\right\}  \tag{3.6}\\
l(D) & =l\left(D_{z}^{\prime}\right) \circ l\left(\operatorname{adj}\left(D_{z}^{\prime}, D\right)\right) \tag{3.7}
\end{align*}
$$

where the maximum of the right-hand side of (3.6) is taken by $D_{z}^{\prime} \in A_{z}(D)$. Note that $m\left(D_{z}^{\prime}\right)$ and $l\left(D_{z}^{\prime}\right)$ are stored in the $L_{x, z}$ - table and $m\left(\operatorname{adj}\left(D_{z}^{\prime}, D\right)\right)$ and $l\left(\operatorname{adj}\left(D_{z}^{\prime}, D\right)\right)$ are stored in the $L_{z, y^{-}}$table. Therefore, from (3.6) and (3.7), $L_{x, y^{-}}$ table can be constructed from $L_{x, z^{-}}$and $L_{z, y}$-tables.

The $L_{0, n}$-table for $C$ (or decoding $C$ ) can be obtained by executing the following recursive procedure RMLD- $C(x, y)$ :
(1) Construct $L_{x, x+1^{-}}$table directly, or
(2) if $y-x \geq 2$, then choose an integer $z$ such that $x<z<y$. Execute RMLD$C(x, z)$ and RMLD- $C(z, y)$ to form $L_{x, z^{-}}$and $L_{z, y^{-}}$tables. Construct the $L_{x, y}$-table from $L_{x, z^{-}}$-table, $L_{z, y}$-table and $A_{z}(D)$ by using (3.6) and (3.7).

A straightforward method for solving (3.6) is add-compare-select(ACS) which is used in conventional Viterbi algorithm. Let $\gamma(x, y ; z)$ denote the number of additions and comparisons in ACS for solving (3.6). Then

$$
\begin{align*}
\gamma(x, y ; z) & =\sum_{D \in L_{x, y}}\left(2\left|A_{z}(D)\right|-1\right) \\
& =\left(2 A_{x, y ; z}-1\right)\left|L_{x, y}\right| \tag{3.8}
\end{align*}
$$

### 3.2 Transitive Invariant Block Codes

For a positive integer $m$, let $P_{m}$ denote the set of Boolean polynomials of $m$ variables, $x_{1}, x_{2}, \ldots, x_{m}$, which take values 0 or 1 . Consider a Boolean polynomial $f \triangleq f\left(x_{1}, x_{2}, \ldots, x_{m}\right)$ in $P_{m}$. For each combination of values of $x_{1}, x_{2}, \ldots, x_{m}$,
the polynomial $f$ takes a truth value either 0 or 1 . For the $2^{m}$ combinations of values of $x_{1}, x_{2}, \ldots, x_{m}$, the truth values of $f$ forms a $2^{m}$-tuple over $\operatorname{GF}(2)$.

For a nonnegative integer $l$ less than $2^{m}$, let $\left(b_{l_{1}}, b_{l_{2}}, \ldots, b_{l_{m}}\right)$ be the standard binary representation of $l$ such that

$$
\begin{equation*}
l=b_{l_{1}}+b_{l_{2}} 2+\cdots+b_{l_{m}} 2^{m-1} \tag{3.9}
\end{equation*}
$$

For a given Boolean polynomial $f \in P_{m}$, we form the following $2^{m}$-tuple:

$$
\begin{equation*}
\boldsymbol{v}=\left(v_{1}, v_{2}, \ldots, v_{2^{m}}\right) \tag{3.10}
\end{equation*}
$$

where

$$
\begin{equation*}
v_{l+1}=f\left(b_{l_{1}}, b_{l_{2}}, \ldots, b_{l_{m}}\right) \tag{3.11}
\end{equation*}
$$

with $0 \leq l<2^{m}$. We say that the Boolean polynomial $f$ represents the vector $\boldsymbol{v}$. We use the notation $\boldsymbol{v}_{m}(f)$ (or simply $\boldsymbol{v}(f)$ when there is no confusion) for the vector represented by $f$.

There are $2^{2^{m}}$ Boolean polynomials in $P_{m}$. It follows from (3.10) and (3.11) that these polynomials uniquely define all the $2^{m}$-tuples over $\mathrm{GF}(2)$. For a subset $X \subseteq P_{m}$, define

$$
\boldsymbol{v}_{m}(X) \triangleq\left\{\boldsymbol{v}_{m}(f): f \in X\right\}
$$

which is a subset of the vector space of all the $2^{m}$-tuples over GF(2). Therefore, for a binary block code $C$ of length $2^{m}$, there exists a subset $P_{C}$ of $P_{m}$ such that $C=\boldsymbol{v}_{m}\left(P_{C}\right)$. This Boolean polynomial representation of block codes of length $2^{m}$ is quite useful in analyzing their structural properties [2]. The most well known example is the Boolean polynomial representation of RM codes. For $0 \leq r \leq m$, let $P_{r, m}$ denote the set of polynomials of degree $r$ or less in $P_{m}$. Let $\mathrm{RM}_{r, m}$ denote the $r$-th order RM code of length $n \triangleq 2^{m}$. Then, the $\mathrm{RM}_{r, m}$ is given by $\boldsymbol{v}_{m}\left(P_{r, m}\right)$, i.e.,

$$
\begin{equation*}
\operatorname{RM}_{r, m}=\boldsymbol{v}_{m}\left(P_{r, m}\right)=\left\{\boldsymbol{v}_{m}(f): f \in P_{r, m}\right\} . \tag{3.12}
\end{equation*}
$$

Let $C$ be a binary block code of length $2^{m}$ which is specified by a subset $P_{C}$ of polynomials in $P_{m}$. We introduce the following definition:

Definition $1 C$ is said to be binary transitive invariant (or b-transitive invariant), if and only if for any $f\left(x_{1}, x_{2}, \ldots, x_{m}\right) \in P_{C}$ and $\left(a_{1}, a_{2}, \ldots, a_{m}\right) \in V_{m}$,

$$
\begin{equation*}
f\left(x_{1}+a_{1}, x_{2}+a_{2}, \ldots, x_{m}+a_{m}\right) \in P_{C} . \tag{3.13}
\end{equation*}
$$

That is, if $f \in P_{C}$ represents a vector $\boldsymbol{v}=\left(v_{1}, v_{2}, \ldots, v_{2^{m}}\right) \in \boldsymbol{v}_{m}\left(P_{C}\right)$, then for $\left(a_{1}, a_{2}, \ldots, a_{m}\right) \in V_{m}, f\left(x_{1}+a_{1}, x_{2}+a_{2}, \ldots, x_{m}+a_{m}\right)$ represents another vector $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{2^{m}}\right) \in \boldsymbol{v}_{m}\left(P_{C}\right)$.

This transitive operation simply permutes the components of $\boldsymbol{v}_{m}(f)$. For $0 \leq l<2^{m}$, the component $v_{l+1}$ of $\boldsymbol{v}_{m}(f)$ at the position $l+1=\sum_{i=1}^{m} b_{l_{i}} 2^{i-1}+1$ is permuted to the position

$$
l^{\prime}+1=\sum_{i=1}^{m}\left(b_{l_{i}}+a_{i}\right) 2^{i-1}+1 .
$$

RM codes [4] and extended and permuted binary primitive BCH codes [9] are b-transitive invariant. Let $C_{w}$ denote the set of codewords in $C$ with weight $w$, i.e.,

$$
C_{w} \triangleq\{\boldsymbol{u} \in C: \mathrm{wt}(\boldsymbol{u})=w\} .
$$

It is clear that, for a b-transitive invariant code $C$, the subcode $C_{w}$ is also btransitive invariant. For a polynomial $f\left(x_{1}, x_{2}, \ldots, x_{m}\right) \in P_{m}$, define $\partial f$ as follows:
$\partial f \triangleq\left\{f\left(x_{1}+a_{1}, x_{2}+a_{2}, \ldots, x_{m}+a_{m}\right)-f\left(x_{1}, x_{2}, \ldots, x_{m}\right):\left(a_{1}, a_{2}, \ldots, a_{m}\right) \in V_{m}\right\}$.

Then we have the following lemma:
Lemma 3 If $C$ is a binary linear code of length $2^{m}$, then there is a subset $Q_{C}$ of $P_{m}$ such that $C$ is spanned by $\boldsymbol{v}_{m}\left(Q_{C}\right) . C$ is b-transitive invariant if and only if for $f \in Q_{C}$, each polynomial in $\partial f$ can be expressed as a linear sum of polynomials in $Q_{C}$.

For two monomials $t_{1}=x_{i_{1}} x_{i_{2}} \cdots x_{i_{p}}$ and $t_{2}=x_{j_{1}} x_{j_{2}} \cdots x_{j_{q}}, t_{1}$ is said to be a subterm of $t_{2}$ or $t_{2}$ is said to be a superterm of $t_{1}$, if and only if $\left\{i_{1}, i_{2}, \ldots, i_{p}\right\} \subseteq$ $\left\{j_{1}, j_{2}, \ldots, j_{q}\right\}$. Then, for a monomial $t$ in $P_{m}$, each polynomial in $\partial t$ (defined by (3.14)) can be expressed as a linear sum of subterms of $t$ other than $t$ itself. Suppose that a linear code $C$ is spanned by $\boldsymbol{v}_{m}\left(M_{B}\right)$ (or simply $M_{B}$ ), where $M_{B}$ is a set of monomials in $P_{m}$. Then, it follows from Lemma 3 that $C$ is b-transitive invariant, if and only if the following closure condition (CS) on subterms holds: (CS) For $t \in M_{B}$, all subterms of $t$ are in $M_{B}$.

Let $f\left(x_{1}, x_{2}, \ldots, x_{m}\right)$ be a polynomial in $P_{m}$ and $\left\{b_{1}, b_{2}, \ldots, b_{h}\right\}$ be a set of binary constants (i.e. $b_{i}=0$ or 1 for $1 \leq i \leq h$ ). Let $f_{b_{1} b_{2} \cdots b_{h}}$ be the polynomial obtained from $f\left(x_{1}, x_{2}, \ldots, x_{m}\right)$ by setting $x_{m-h+1}=b_{1}, x_{m-h+2}=b_{2}, \ldots, x_{m}=$ $b_{h}$. Then $f_{b_{1} b_{2} \cdots b_{h}}$ is a Boolean polynomial of $m-h$ variables, $x_{1}, x_{2}, \ldots, x_{m-h}$ in $P_{m-h}$. Let $\beta$ represent the binary sequence $b_{1} b_{2} \cdots b_{h}$, i.e., $\beta \triangleq b_{1} b_{2} \cdots b_{h}$. For simplicity, we use the notation $f_{\beta}$ for $f_{b_{1} b_{2} \cdots b_{h}}$. Let $j$ be the integer defined by $\beta=b_{1} b_{2} \cdots b_{h}$ as follows:

$$
\begin{equation*}
j \triangleq \sum_{i=1}^{h} b_{i} 2^{i-1} \tag{3.15}
\end{equation*}
$$

Then we can readily see that

$$
\begin{equation*}
p_{j 2^{m-h},(j+1) 2^{m-h}}\left(\boldsymbol{v}_{m}(f)\right)=\boldsymbol{v}_{m-h}\left(f_{\beta}\right) . \tag{3.16}
\end{equation*}
$$

For $f\left(x_{1}, x_{2}, \ldots, x_{m}\right) \in P_{m}$, binary sequences $\beta=b_{1} b_{2} \cdots b_{h}$ and $\beta^{\prime}=b_{1}^{\prime} b_{2}^{\prime} \cdots b_{h}^{\prime}$ with $1 \leq h \leq m$, define

$$
\begin{align*}
& f^{\prime}\left(x_{1}, x_{2}, \ldots, x_{m}\right) \\
& \quad \triangleq f\left(x_{1}, x_{2}, \ldots, x_{m-h}, x_{m-h+1}+b_{1}+b_{1}^{\prime}, x_{m-h+2}+b_{2}+b_{2}^{\prime}, \ldots, x_{m}+b_{h}+b_{h}^{\prime}\right) \tag{3.17}
\end{align*}
$$

$j \triangleq \sum_{i=1}^{h} b_{i} 2^{i-1}$ and $j^{\prime} \triangleq \sum_{i=1}^{h} b_{i}^{\prime} 2^{i-1}$. From (3.16), we have

$$
\begin{align*}
p_{j 2^{m-h},(j+1) 2^{m-h}}\left(\boldsymbol{v}_{m}(f)\right) & =\boldsymbol{v}_{m-h}\left(f_{\beta}\right)=\boldsymbol{v}_{m-h}\left(f_{\beta^{\prime}}^{\prime}\right) \\
& =p_{j^{\prime} 2^{m-h},\left(j^{\prime}+1\right) 2^{m-h}}\left(\boldsymbol{v}_{m}\left(f^{\prime}\right)\right) . \tag{3.18}
\end{align*}
$$

If $C$ is b-transitive invariant, then $f^{\prime} \in P_{C}$ if and only if $f \in P_{C}$. Hence, from (3.18),

$$
\begin{equation*}
p_{j^{2 m-h},(j+1) 2^{m-h}}(C)=p_{j^{\prime} 2^{m-h},\left(j^{\prime}+1\right) 2^{m-h}}(C) \tag{3.19}
\end{equation*}
$$

Similarly, we have that

$$
\begin{equation*}
C_{j 2^{m-h},(j+1) 2^{m-h}}^{\mathrm{tr}}=C_{j^{\prime} 2^{m-h},\left(j^{\prime}+1\right) 2^{m-h}}^{\mathrm{tr}} . \tag{3.20}
\end{equation*}
$$

From (3.1), (3.19) and (3.20), we have the following theorem.
Theorem 2 Suppose a linear block code $C$ of length $2^{m}$ is b-transitive invariant. Then for $1 \leq h \leq m$ and $0 \leq j<2^{h}, L_{j 2^{m-h},(j+1) 2^{m-h}}$ for $C$ is the same for all $j$.

Theorem 2 says that for a b-transitive invariant code $C$ of length $2^{m}$, if we divide the code (or code trellis) into sections of length $2^{m-h}$, all the sections have the same structural properties with respect to the operations of the RMLD algorithm proposed in [5].

### 3.3 Decoding of Binary Transitive Invariant Codes with the RMLD Algorithm

Let $C$ be a binary linear block code of length $2^{m}$ which is b-transitive invariant. Suppose $C$ is decoded with the RMLD algorithm. From Theorem 2, we see that if we sectionalize the code uniformly at each recursion level, all the sections will have the same $L_{x, y}$. Consequently, the RMLD- $C(x, y)$ procedure is applied uniformly among all the sections to construct $L_{x, y}$-tables from tables at a lower level based on (3.6) and (3.7). This uniformity (or regularity) is very advantageous in implementation. In hardware implementation, this results in identical circuits for all the sections [1].

Based on Theorem 2, we propose the following binary (uniform) sectionalization. At each level, we always choose $x$ and $y$ such that $0 \leq x<y<2^{m}$, $y-x \geq 2, x+y$ even and $z=(x+y) / 2$. At the 0 -th level (or top level), we set
$x=0, y=2^{m}$ and $z=2^{m-1}$. At the first level, the code is partitioned into two sections with

$$
(x, y) \in\left\{\left(0,2^{m-1}\right),\left(2^{m-1}, 2^{m}\right)\right\} .
$$

Each section is of length $2^{m-1}$. At the second level, each section at the first level is partitioned into two equal sections, each section is of length $2^{m-2}$. This results in four sections with

$$
\begin{aligned}
(x, y) \in & \left\{\left(0,2^{m-2}\right),\left(2^{m-2}, 2^{m-1}\right)\right. \\
& \left.\left(2^{m-1}, 2^{m-2}+2^{m-1}\right),\left(2^{m-2}+2^{m-1}, 2^{m}\right)\right\}
\end{aligned}
$$

For $0 \leq h<m$, at the $h$-th level, the code is partitioned into $2^{h}$ sections with

$$
\begin{equation*}
(x, y) \in\left\{\left(j 2^{m-h},(j+1) 2^{m-h}\right): 0 \leq j<2^{h}\right\} . \tag{3.21}
\end{equation*}
$$

Each section is of length $2^{m-h}$. The above sectionalization process continues until $y-x=2$. At the bottom of the sectionalization, each section consists of two code bits. This results in a sectionalization tree shown in Figure 3.1.


Figure 3.1. Binary Sectionalization.
In decoding $C$ using the RMLD algorithm, all the $L_{x, y}$-tables at the bottom of the sectionalization tree are constructed directly using the methods proposed
in [5]. As the recursion moves up to higher levels of the tree, each $L_{x, y}$-table is constructed from two tables, $L_{x, z}$-table and $L_{z, y}$-table, with $z=(x+y) / 2$ at a lower level. Suppose the $h$-th level of recursion has been completed. We have all the $L_{x, y}$-tables for each $(x, y)$ in the boundary of (3.21). The decoder moves up to the $(h-1)$-th level. At this level, the $L_{x, y}$-table with $x=j 2^{m-h+1}$ and $y=$ $(j+1) 2^{m-h+1}$ is constructed from $L_{x, z}$-table and $L_{z, y}$-table with $z=(2 j+1) 2^{m-h}$. The recursion process continues until it reaches to the top of the tree. At this point, $L_{0, n}$-table is constructed, which contains only the most likely codeword and its metric. Decoding is then completed.

The above binary sectionalization is most suitable for parallel/pipeline processing, while the decoder is processing all the sections of a received word in parallel at one recursion level, it is also processing other received words at other recursion levels. This parallel/pipeline architecture is desired in high-speed data communication where a decoder must operate at a high speed.

For a transitive invariant linear block code of length $2^{m}$ using RMLD algorithm based on binary sectionalization, it follows from (3.8) and Theorem 2 that the total number of additions and comparison required to construct all the $L_{x, y}$-tables based on (3.6) using ACS procedure is given by

$$
\begin{equation*}
\gamma=\sum_{h=0}^{m-1}\left(2 A_{0,2^{m-h}: 2^{m-h-1}}-1\right)\left|L_{0,2^{m-h}}\right| \cdot 2^{h} \tag{3.22}
\end{equation*}
$$

For a given code $C$, the computational complexity can be evaluated once $A_{0,2^{m-h} ; 2^{m-h-1}}$ and $L_{0,2^{m-h}}$ for $0 \leq h<m-1$ are known. For a nonlinear subcode $C^{\prime}$ of a binary linear block code $C, L_{x, y}$ is defined as $\left\{D \cap p_{x, y}\left(C^{\prime}\right) \neq \emptyset: D \in p_{x, y}(C) / C_{x, y}^{\mathrm{tr}}\right\}$. Then RMLD can be generalized to decoding of $C^{\prime}$ [9]. If $C$ and $C^{\prime}$ are transitive invariant, then Theorem 2 can be extended to $C^{\prime}$. For example, Theorem 2 holds for $C_{w}$ with $0<w \leq 2^{m}$.

### 3.4 Structural and Computational Complexity Analysis

In the following, we first analyze the structure of

$$
L_{x, y}=p_{x, y}(C) / C_{x, y}^{\mathrm{tr}}
$$

and $A_{x, y ; z}$. Once their structures are known, the computational complexity of the RMLD algorithm can be evaluated. The analysis is based on Boolean polynomial representation of $C$.

Suppose that a binary transitive invariant linear code $C$ is spanned by $\boldsymbol{v}_{m}\left(M_{B}\right)$ where $M_{B}$ is a set of monomials in $P_{m}$. Using binary sectionalization, we set

$$
\left\{\begin{array}{l}
x \triangleq j 2^{m-h}  \tag{3.23}\\
y \triangleq(j+1) 2^{m-h}
\end{array}\right.
$$

for $0 \leq h<m$ and $0 \leq j<2^{h}$. Let $\mathbf{0}_{l}$ denote the all-zero $l$-tuple over GF(2). It is easy to see that
(1) $p_{x, y}(C)$ is spanned by

$$
\begin{equation*}
M_{B, \mathbf{0}_{h}} \triangleq\left\{x_{i_{1}} x_{i_{2}} \cdots x_{i_{p}} \in M_{B}: 1 \leq i_{1}<i_{2}<\cdots<i_{p} \leq m-h\right\} \tag{3.24}
\end{equation*}
$$

and
(2) $C_{x, y}^{\mathrm{tr}}$ is spanned by

$$
\begin{align*}
& M_{B} / x_{m-h+1} x_{m-h+2} \cdots x_{m} \triangleq\left\{x_{i_{1}} x_{i_{2}} \cdots x_{i_{p}}: 1 \leq i_{1}<i_{2}<\cdots<i_{p} \leq m-h\right. \\
&\text { and } \left.x_{i_{1}} x_{i_{2}} \cdots x_{i_{p}} x_{m-h+1} x_{m-h+2} \cdots x_{m} \in M_{B}\right\} . \tag{3.25}
\end{align*}
$$

Then, it follows from (3.1) and (3.4) that for code $C$,

$$
\begin{align*}
\log _{2}\left|L_{x, y}\right|= & \left|M_{B, \mathbf{o}_{h}}\right|-\left|M_{B} / x_{m-h+1} x_{m-h+2} \cdots x_{m}\right|,  \tag{3.26}\\
\log _{2} A_{x, y ; z}= & \left|M_{B} / x_{m-h+1} x_{m-h+2} \cdots x_{m}\right| \\
& -2\left|M_{B} / x_{m-h} x_{m-h+1} \cdots x_{m}\right| \tag{3.27}
\end{align*}
$$

Now we consider RM codes. Recall that the $\mathrm{RM}_{r, m}$ is specified by the Boolean polynomials in $P_{r, m}$. Let $M_{r, m}$ be the set of all monomials in $P_{r, m}$. Since $\mathrm{RM}_{r, m}$ is spanned by the vectors in $\boldsymbol{v}_{m}\left(M_{r, m}\right)$, we obtain

$$
\begin{align*}
M_{r, m, \mathbf{0}_{h}}= & M_{\min \{r, m-h\}, m-h}  \tag{3.28}\\
M_{r, m} / x_{m-h+1} x_{m-h+2} \cdots x_{m}= & M_{r-h, m-h} \\
& (\text { empty for } r<h) . \tag{3.29}
\end{align*}
$$

It follows from (3.24) to (3.29) that we have Theorem 3 which gives the structure of $L_{x, y}$.

Theorem 3 For integers $x$ and $y$ defined by (3.23),
(1)

$$
\begin{equation*}
p_{x, y}\left(\mathrm{RM}_{r, m}\right)=\mathrm{RM}_{\min \{r, m-h\}, m-h} \tag{3.30}
\end{equation*}
$$

(2)

$$
\left[\mathrm{RM}_{r, m}\right]_{x, y}^{\mathrm{tr}}= \begin{cases}\mathrm{RM}_{r-h, m-h}, & \text { if } r \geq h  \tag{3.31}\\ \left\{\mathbf{0}_{2^{m-h}}\right\}, & \text { otherwise }\end{cases}
$$

(3) $L_{x, y}$ for $\mathrm{RM}_{m, r}$ is the same for all $j$ such that $0 \leq j<2^{h}$, and

$$
L_{x, y}= \begin{cases}\mathrm{RM}_{\min \{r, m-h\}, m-h} / \mathrm{RM}_{r-h, m-h}, & \text { for } r \geq h,  \tag{3.32}\\ \mathrm{RM}_{\min \{r, m-h\}, m-h} /\left\{\mathbf{0}_{2^{m-h}}\right\}, & \text { otherwise }\end{cases}
$$

(4)

$$
\begin{equation*}
\log _{2} A_{x, y ; z}=\binom{m-h-1}{r-h} \tag{3.33}
\end{equation*}
$$

Based on (3.22), (3.32), and (3.33), we can evaluate exactly the computational complexity of the RMLD algorithm for a RM code with binary sectionalization.

Example 3 A $(64,40)$ subcode of $\mathrm{RM}_{3,6}$ is being considered as an inner code in a concatenated coding system for NASA's high-speed satellite communications [3]. The overall decoder for the RM subcode consists of 32 identical maximum likelihood decoding (MLD) decoders, each such decoder processes a $(64,35)$ subcode $C$ or its coset in parallel. In this example, we assume that an RMLD decoder based on binary sectionalization is used, and consider how to choose the $(64,35)$ subcode $C$ of $\mathrm{RM}_{3,6}$ to minimize the total number $\gamma$ of additions and comparisons in ACS. We assume that a subset $M$ of $M_{r, m}$ satisfies the closure condition (CS). Let $C(M)$ denote the subcode of $\mathrm{RM}_{r, m}$ spanned by $M$, and let $t$ be a monomial in $M$ whose superterms are not in $M$. For $0 \leq h<m$, it follows from (3.26) and (3.28) that the difference between the values of $\log _{2}\left|L_{0,2^{m-h}}\right|$ (or
$\left.\log _{2} A_{0,2^{m-h} ; 2^{m-h-1}}\right)$ for $C(M)$ and $C(M \backslash\{t\})$ is independent of $M$. Let $\triangle L^{(h)}(t)$ (or $\left.\triangle A^{(h)}(t)\right)$ denote the difference. Table 3.1 shows $\triangle L^{(h)}(t)$ with $1 \leq h \leq 5$ and $\triangle A^{(h)}(t)$ with $0 \leq h \leq 5$ for $t \in M_{3,6} \backslash M_{1,6}$. For a subset $\triangle M$ of $M$ consisting of different monomials $t_{1}, t_{2}, \ldots, t_{k}$ such that there is no superterm of $t_{i}$ in $M \backslash\left\{t_{1}, t_{2}, \ldots, t_{i-1}\right\}$, the difference between the values of $\log _{2}\left|L_{0,2^{m-h}}\right|$ (or $\left.\log _{2} A_{0,2^{m-h} ; 2^{m-h-1}}\right)$ for $C(M)$ and $C(M \backslash \triangle M)$ is given by $\sum_{i=1}^{k} \triangle L^{(h)}\left(t_{i}\right)$, denoted $\triangle L^{(h)}(\triangle M)$ (or $\sum_{i=1}^{k} \triangle A^{(h)}\left(t_{i}\right)$, denoted $\triangle A^{(h)}(\triangle M)$ ). The total number $\gamma$ for $C\left(M_{6,3} \backslash \triangle M\right)$ with $|\triangle M|=7$ is given by

$$
\begin{align*}
\gamma & =\left(2 \cdot 2^{10-\triangle A^{(0)}(\Delta M)}-1\right) \cdot 2^{0} \cdot 2^{0} \\
& +\left(2 \cdot 2^{6-\triangle A^{(1)}(\Delta M)}-1\right) \cdot 2^{10-\Delta L^{(1)}(\Delta M)} \cdot 2^{1} \\
& +\left(2 \cdot 2^{3-\triangle A^{(2)}(\triangle M)}-1\right) \cdot 2^{10-\Delta L^{(2)}(\Delta M)} \cdot 2^{2} \\
& +\left(2 \cdot 2^{1-\triangle A^{(3)}(\triangle M)}-1\right) \cdot 2^{7-\Delta L^{(3)}(\Delta M)} \cdot 2^{3} \\
& +\left(2 \cdot 2^{0-0}-1\right) \cdot 2^{4-\Delta L^{(4)}(\Delta M)} \cdot 2^{4} \\
& +\left(2 \cdot 2^{0-0}-1\right) \cdot 2^{2-0} \cdot 2^{5} . \tag{3.34}
\end{align*}
$$

There are two cases to be considered.
(i) From the closure condition (CS) and $|\triangle M|=7, \triangle M$ can contain at most one monomial in $M_{2,6}$. Consider the case where $\triangle M$ contains one monomial $t$ in $M_{2,6}$. By considering the effect to $\gamma$ by $t$ and its all superterms based on Table 3.1, we see that we should choose $x_{1} x_{2}, x_{1} x_{2} x_{i}$ with $3 \leq i \leq 6$, and then $x_{1} x_{3} x_{4}$ and $x_{2} x_{3} x_{4}$. This choice of $\triangle M$, denoted $\Delta M_{1}$, yields the smallest $\gamma=7039$. If we choose one monomial of form $x_{i_{1}} x_{i_{2}} x_{5}$ other than $x_{1} x_{2} x_{5}$ instead of one of $x_{1} x_{3} x_{4}$ and $x_{2} x_{3} x_{4}$, then we have $\gamma=8959$, which is the third smallest value of $\gamma$.
(ii) $\triangle M \subseteq M_{3,6} \backslash M_{2,6}$ : Since each monomial of degree 3 can be chosen independently without violating the closure condition (CS), from Table 3.1 and (3.34) we see that we should choose $x_{1} x_{2} x_{3}$ first, $\left\{x_{i_{1}} x_{i_{2}} x_{4}: 1 \leq i_{1}<\right.$ $\left.i_{2}<4\right\}$ next and any three monomials in $\left\{x_{i_{1}} x_{i_{2}} x_{5}: 1 \leq i_{1}<i_{2}<5\right\}$. For this choice of $\triangle M$, denoted $\Delta M_{2}, \gamma=7807$, which is the second smallest value of $\gamma$.

Table 3.2 summarizes these choices of $\triangle M$. An RMLD decoder for $C\left(M_{3,6} \backslash \triangle M_{2}\right)$ is designed with VLSI [1], and a decoder for $C\left(M_{3,6} \backslash \triangle M_{1}\right)$ is being designed.

### 3.5 Conclusion

We have studied a class of linear block codes which are transitive invariant. A condition for a code to be transitive invariant has been proved. We have shown that transitive invariant block codes have uniform structure. This structure is advantageous for implementation of the RMLD algorithm based on a binary uniform sectionalization.

It follows from Examples 1 and 3 that $C\left(M_{3,6} \backslash \Delta M_{2}^{\prime}\right)$ with the smallest value of $\gamma$ and $C\left(M_{3,6} \backslash \Delta M_{3}^{\prime}\right)$ with the second smallest value of $\gamma$ are subcodes of $C\left(M_{3,6} \backslash \Delta M_{1}\right)$ which has the second smallest number of minimum weight codewords and that $C\left(M_{3,6} \backslash \Delta M_{1}^{\prime}\right)$ with the third smallest value of $\gamma$ is a subcode of $C\left(M_{3,6} \backslash \Delta M_{0}\right)$ with the smallest number of minimum weight codewords.

Table 3.1. $\Delta L^{(h)}(t)$ and $\Delta A^{(h-1)}(t)$ with $1 \leq h \leq 5$ for $t \in M_{3,6} \backslash M_{1,6}$.

|  | $\Delta L^{(h)}(t)^{\dagger}$ |  |  |  | $\Delta A^{(h)}(t)^{\dagger}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $t \backslash h$ | 1 | 2 | 3 | 4 | 0 | 1 | 2 | 3 |
| $x_{4} x_{5} x_{6}$ | -1 | -1 | -1 | 0 | -1 | -1 | -1 | 1 |
| $\begin{aligned} & x_{i} x_{5} x_{6} \\ & (1 \leq i<4) \end{aligned}$ | -1 | -1 | 0 | 0 | -1 | -1 | 1 | 0 |
| $\begin{aligned} & x_{i_{1}} x_{i_{2}} x_{6} \\ & \left(1 \leq i_{1}<i_{2}<5\right) \\ & \hline \end{aligned}$ | -1 | 0 | 0 | 0 | -1 | 1 | 0 | 0 |
| $\begin{aligned} & x_{i_{1}} x_{i_{2}} x_{5} \\ & \left(1 \leq i_{1}<i_{2}<5\right) \\ & \hline \end{aligned}$ | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\begin{aligned} & x_{i_{1}} x_{i_{2}} x_{4} \\ & \left(1 \leq i_{1}<i_{2}<4\right) \\ & \hline \end{aligned}$ | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| $x_{1} x_{2} x_{3}$ | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| $x_{5} x_{6}$ | -1 | -1 | 0 | 0 | -1 | -1 | 1 | 0 |
| $\begin{aligned} & x_{i} x_{6} \\ & (1 \leq i<5) \\ & \hline \end{aligned}$ | -1 | 0 | 0 | 0 | -1 | 1 | 0 | 0 |
| $\begin{aligned} & x_{i} x_{5} \\ & (1 \leq i<5) \end{aligned}$ | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\begin{aligned} & x_{i} x_{4} \\ & (1 \leq i<4) \end{aligned}$ | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\begin{aligned} & x_{i} x_{3} \\ & (1 \leq i<3) \end{aligned}$ | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| $x_{1} x_{2}$ | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |

Table 3.2. $\Delta L^{(h)}\left(\Delta M^{\prime}\right)$ and $\Delta A^{(h-1)}\left(\Delta M^{\prime}\right)$ with $1 \leq h \leq 5$ and $\gamma$ for $C\left(M_{3,6} \backslash \Delta M^{\prime}\right)$.

|  | $\Delta L^{(h)}(t)^{\ddagger}$ |  |  |  | $\Delta A^{(h)}(t)^{\ddagger}$ |  |  | $\gamma$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :---: |
| $\Delta M^{\prime} \backslash$ | $h$ | 1 | 2 | 3 | 4 | 1 | 2 |  |
| $\Delta M_{1}^{\prime}$ | 5 | 4 | 2 | 1 | 5 | 1 | 8959 |  |
| $\Delta M_{2}^{\prime}$ | 5 | 5 | 2 | 1 | 5 | 1 | 7039 |  |
| $\Delta M_{3}^{\prime}$ | 7 | 4 | 1 | 0 | 7 | 0 | 7807 |  |
| $\Delta L^{(5)}(t)=\Delta A^{(3)}(t)=\Delta A^{(4)}(t)=\Delta A^{(5)}(t)=0$ for $C\left(M_{3,6} \backslash \Delta M^{\prime}\right)$. |  |  |  |  |  |  |  |  |

## Chapter 4

## An Improvement to GMD-like Decoding Algorithms

### 4.1 Definitions

Suppose a binary $(N, K)$ linear block code $C$ with minimum weight $d_{\text {min }}$ is used for error control over the AWGN channel using BPSK signaling. Each codeword is transmitted with the same probability. Let $\boldsymbol{r}=\left(r_{1}, r_{2}, \ldots, r_{N}\right)$ be a received sequence and let $\boldsymbol{z}=\left(z_{1}, z_{2}, \ldots, z_{N}\right)$ be the binary hard-decision sequence obtained from $\boldsymbol{r}$ using the hard-decision function: $z_{i}=1$ for $r_{i}>0$ and $z_{i}=0$ for $r_{i} \leq 0$.

For a positive integer $n$, let $V^{n}$ denote the vector space of all binary $n$-tuples. For $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{N}\right) \in V^{N}$, the correlation between $\boldsymbol{u}$ and the received sequence $\boldsymbol{r}$ is given by $M(\boldsymbol{u})=\sum_{i=1}^{N} r_{i}\left(2 u_{i}-1\right)$. Then $M(\boldsymbol{z})=\sum_{i=1}^{N}\left|r_{i}\right| \geq M(\boldsymbol{u})$ for any $\boldsymbol{u} \in V^{N}$. Define $D_{-1}(\boldsymbol{u}) \triangleq\left\{i: u_{i} \neq z_{i}\right.$, and $\left.1 \leq i \leq N\right\}$ and

$$
\begin{equation*}
L(\boldsymbol{u}) \triangleq \sum_{i \in D_{-1}(\boldsymbol{u})}\left|r_{i}\right|=(M(\boldsymbol{z})-M(\boldsymbol{u})) / 2 \tag{4.1}
\end{equation*}
$$

$L(\boldsymbol{u})$ is called the correlation discrepancy of $\boldsymbol{u}$ with respect to $\boldsymbol{z}$. For a subset $U$ of $V^{N}$, let $\underline{L}[U]$ be defined as

$$
\underline{L}[U] \triangleq \begin{cases}\min _{\boldsymbol{u} \in U} L(\boldsymbol{u}), & \text { for } U \neq \phi  \tag{4.2}\\ \infty, & \text { for } U=\phi\end{cases}
$$

If $U \neq \phi$, let $\boldsymbol{v}[U]$ denote an $N$-tuple in $U$ such that $L(\boldsymbol{v}[U])=\underline{L}[U]$.
The maximum likelihood decoder decodes the received sequence $\boldsymbol{r}$ into the optimal codeword $c_{\text {opt }}$ for which

$$
\begin{equation*}
L\left(\boldsymbol{c}_{\mathrm{opt}}\right)=\underline{L}[C] . \tag{4.3}
\end{equation*}
$$

If $\boldsymbol{z}$ is a codeword, then $\boldsymbol{z}$ is the optimal codeword. A candidate codeword $\boldsymbol{c}$ is said to be better (or more likely) than another candidate codeword $\boldsymbol{c}^{\prime}$ if $L(\boldsymbol{c}) \leq L\left(\boldsymbol{c}^{\prime}\right)$. A candidate codeword $\boldsymbol{c}$ is said to be the best if $L(\boldsymbol{c})$ is the minimum among a specified set of candidate codewords.

For integers $i$ and $i^{\prime}$ with $1 \leq i \leq i^{\prime} \leq N$, define $\left[i, i^{\prime}\right] \triangleq\left\{i, i+1, \ldots, i^{\prime}\right\}$, and for $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{N}\right) \in V^{N}$, define $p_{i, i^{\prime}}(\boldsymbol{u}) \triangleq\left(u_{i}, u_{i+1}, \ldots, u_{i^{\prime}}\right)$ and for $\boldsymbol{u}^{\prime} \in V^{N}$, let $d_{\mathrm{H}, i, i^{\prime}}\left(\boldsymbol{u}, \boldsymbol{u}^{\prime}\right)$ denote the Hamming distance between $p_{i, i^{\prime}}(\boldsymbol{u})$ and $p_{i, i^{\prime}}\left(\boldsymbol{u}^{\prime}\right)$. For simplicity, we assume that the bit positions $1,2, \ldots, N$ are ordered according to the reliability order given as follows:

$$
\begin{equation*}
\left|r_{i}\right| \leq\left|r_{j}\right|, \text { for } 1 \leq i<j \leq N . \tag{4.4}
\end{equation*}
$$

### 4.2 GMD-Like decoding

For nonnegative integers $s$ and $t$ such that $s+2 t<d_{\text {min }}$ and $\boldsymbol{v} \in V^{N}$, the decoding which corrects $s$ erasures in the first $s$ bit positions and $t$ or less errors in the remaining bit positions of input $\boldsymbol{v}$ is called $(s, t)$-decoding with respect to $\boldsymbol{v}$. Then, the ( $s, t$ )-decoding with respect to $\boldsymbol{v}$ outputs a unique codeword, if exists, in

$$
\begin{equation*}
R \triangleq\left\{\boldsymbol{x} \in V^{N}: d_{\mathrm{H}, s+1, N}(\boldsymbol{x}, \boldsymbol{v}) \leq t\right\} . \tag{4.5}
\end{equation*}
$$

$R$ is called the search region of $(s, t)$-decoding with respect to $\boldsymbol{v}$. Define

$$
\begin{equation*}
\rho \triangleq\left(d_{\min }+p\right) / 2 \tag{4.6}
\end{equation*}
$$

where

$$
p= \begin{cases}0, & \text { for even } d_{\min }  \tag{4.7}\\ 1, & \text { for odd } d_{\min }\end{cases}
$$

For $\boldsymbol{v} \in V^{N}$, a GMD-like decoding with search center $\boldsymbol{v}$, denoted $\operatorname{GMD}(\boldsymbol{v})$, is defined as the iterative decoding consisting of $\rho$ stages whose $j$-th stage is the $(2 j-p-1, \rho-j)$-decoding with respect to $\boldsymbol{v}$ for $1 \leq j \leq \rho$. The original GMD proposed by Forney [15] is $\operatorname{GMD}(\boldsymbol{z})$. From (4.5), the search region of the $j$-th stage, denoted $R(\boldsymbol{v}, j)$, is

$$
\begin{equation*}
R(\boldsymbol{v}, j)=\left\{\boldsymbol{x} \in V^{N}: d_{\mathrm{H}, 2 j-p, N}(\boldsymbol{x}, \boldsymbol{v}) \leq \rho-j\right\} . \tag{4.8}
\end{equation*}
$$

Since the union of search regions from the first stage to the $j$-th stage, denoted $R_{\mathrm{p}}(\boldsymbol{v}, j)$, is

$$
\begin{equation*}
R_{\mathrm{p}}(\boldsymbol{v}, j)=\bigcup_{j^{\prime}=1}^{j}\left\{\boldsymbol{x} \in V^{N}: d_{\mathrm{H}, 2 j^{\prime}-p, N}(\boldsymbol{x}, \boldsymbol{v}) \leq \rho-j^{\prime}\right\}, \tag{4.9}
\end{equation*}
$$

the region which has not been searched (for candidate codewords) yet up to the $j$-th stage of $\operatorname{GMD}(\boldsymbol{v})$, denoted $\bar{R}_{\mathrm{p}}(\boldsymbol{v}, j)$, is given by

$$
\begin{equation*}
\bar{R}_{\mathrm{p}}(\boldsymbol{v}, j)=\left\{\boldsymbol{x} \in V^{N}: d_{\mathrm{H}, 2 j^{\prime}-p, N}(\boldsymbol{x}, \boldsymbol{v})>\rho-j^{\prime} \text { for } 1 \leq j^{\prime} \leq j\right\} \tag{4.10}
\end{equation*}
$$

Define $\bar{R}_{\mathrm{GMD}(\boldsymbol{v})} \triangleq \bar{R}_{\mathrm{p}}(\boldsymbol{v}, \rho)$, which denotes the region which is not searched for candidate codewords by $\operatorname{GMD}(\boldsymbol{v})$.

For a positive integer $h, h$-GMD decoding is defined as an iterative decoding algorithm which consists of successive $\operatorname{GMD}\left(\boldsymbol{v}^{(1)}\right), \operatorname{GMD}\left(\boldsymbol{v}^{(2)}\right), \ldots, \operatorname{GMD}\left(\boldsymbol{v}^{(h)}\right)$. For $i \geq 1$, the $N$-tuple $\boldsymbol{v}^{(i)} \in V^{N}$ is called the $i$-th search center of the $h$-GMD decoding. The first search center $\boldsymbol{v}^{(1)}$ is chosen as the hard-decision sequence $\boldsymbol{z}$, i.e. $\boldsymbol{v}^{(1)} \triangleq \boldsymbol{z}$. For $i>1$, the $i$-th search center $\boldsymbol{v}^{(i)}$ is chosen as the best word in the region which has not been searched by $(i-1)$-GMD decoding, that is,

$$
\begin{align*}
\boldsymbol{v}^{(i)}= & \boldsymbol{v}\left[\bigcap_{i^{\prime}=1}^{i-1} \bar{R}_{\mathrm{GMD}\left(\boldsymbol{v}^{\left(i^{\prime}\right)}\right)}\right] \\
= & \boldsymbol{v}\left[\boldsymbol{x} \in V^{N}: d_{\mathrm{H}, 2 j^{\prime}-p, N}\left(\boldsymbol{x}, \boldsymbol{v}^{\left(i^{\prime}\right)}\right)>\rho-j^{\prime}\right. \\
& \left.\left.\quad \text { for } 1 \leq j^{\prime} \leq j \text { and } 1 \leq i^{\prime}<i\right\}\right] . \tag{4.11}
\end{align*}
$$

It is shown in [12] that $\boldsymbol{v}^{(2)}=\left(v_{1}^{(2)}, v_{2}^{(2)}, \ldots, v_{N}^{(2)}\right)$ is given by

$$
v_{l}^{(2)}= \begin{cases}z_{l}+1, & \text { if } l+p \text { is even and } 1 \leq(l+p) / 2 \leq \rho  \tag{4.12}\\ z_{l}, & \text { otherwise }\end{cases}
$$

A simple and efficient algorithm for finding $\boldsymbol{v}^{(3)}$ has been derived [23]. For $1 \leq i \leq$ $h$ and $1 \leq j \leq \rho$, the $j$-th stage of the $i$-th $\operatorname{GMD}\left(\boldsymbol{v}^{(i)}\right)$ of $h$-GMD decoding is also called the $(i, j)$-th stage. Let $C_{j}^{(i)}$ denote the set of candidate codewords obtained from the $(1,1)$-th stage to the $(i, j)$-th stage. If $C_{j}^{(i)} \neq \phi$, let $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ be the best candidate codeword in $C_{j}^{(i)}$. If $C_{j}^{(i)}=\phi$, for convenience, define $\boldsymbol{c}_{\text {best }}^{(i)}(j) \triangleq *$ and $L(*)=\infty$. Then

$$
\begin{equation*}
L\left(\boldsymbol{c}_{\text {best }}^{(i)}(j)\right)=\underline{L}\left[C_{j}^{(i)}\right] . \tag{4.13}
\end{equation*}
$$

After the $(h, \rho)$-th stage, $\boldsymbol{c}_{\text {best }}^{(h)}(\rho)$ is output as the decoded codeword. If $\boldsymbol{c}_{\text {best }}^{(h)}(\rho)=$ *, then the decoding fails.

### 4.3 Early Termination Conditions

To reduce the number of $(s, t)$-decodings without any loss of error performance, we introduce new effective sufficient conditions on the optimality of decoded codewords as early termination conditions. Just after the $(i, j)$-th stage, $\left(\bigcap_{i^{\prime}=1}^{i-1} \bar{R}_{\operatorname{GMD}\left(\boldsymbol{v}^{\left(i^{\prime}\right)}\right)}\right) \cap$ $\bar{R}_{\mathrm{p}}\left(\boldsymbol{v}^{(i)}, j\right)$, denoted $\bar{R}(i, j)$, is the region which has not yet been searched for candidate codewords. Suppose that $\boldsymbol{c}_{\text {best }}^{(i)}(j) \neq *$. If there is a better candidate than $\boldsymbol{c}_{\text {best }}^{(i)}(j)$, then it is in the following region:

$$
\begin{equation*}
\bar{R}(i, j) \cap \bigcap_{\boldsymbol{c} \in C_{j}^{(i)}} \bar{O}_{d_{\min }}(\boldsymbol{c}), \tag{4.14}
\end{equation*}
$$

where $\bar{O}_{d_{\text {min }}}(\boldsymbol{c}) \triangleq\left\{\boldsymbol{x} \in V^{N}: d_{H, 1, N}(\boldsymbol{x}, \boldsymbol{c}) \geq d_{\min }\right\}$. Hence, the following condition $\operatorname{Cond}_{\mathrm{S}}^{(i)}(j)$ is a sufficient condition on the optimality of $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ :

$$
\begin{equation*}
\operatorname{Cond}_{\mathrm{S}}^{(i)}(j): L\left(\boldsymbol{c}_{\text {best }}^{(i)}(j)\right) \leq \underline{L}\left[\bar{R}(i, j) \cap \bigcap_{\boldsymbol{c} \in C_{j}^{(i)}} \bar{O}_{d_{\text {min }}}(\boldsymbol{c})\right] . \tag{4.15}
\end{equation*}
$$

Since simulation results show that two or more candidate codewords are generated very rarely by GMD-like decoding, the following simpler condition has almost the same effectiveness:

$$
\begin{equation*}
\operatorname{Cond}_{\mathrm{S}, 1}^{(i)}(j): L\left(\boldsymbol{c}_{\text {best }}^{(i)}(j)\right) \leq \underline{L}\left[\bar{R}(i, j) \cap \bar{O}_{d_{\min }}\left(\boldsymbol{c}_{\text {best }}^{(i)}(j)\right)\right] . \tag{4.16}
\end{equation*}
$$

For $1 \leq l \leq 4$, the following sufficient condition $\operatorname{Cond}_{\mathrm{S}, l}$ on the optimality of decoded codewords which are independent of search regions have been derived $[14$, 21, 22].

$$
\begin{equation*}
\operatorname{Cond}_{\mathrm{S}, l}: L\left(\boldsymbol{c}_{\mathrm{best}}\right) \leq \underline{L}\left[\bigcap_{\boldsymbol{c} \in C_{l}} \bar{O}_{d_{\min }}(\boldsymbol{c})\right] \tag{4.17}
\end{equation*}
$$

where $C_{l}$ denotes the $\min \left\{l,\left|C_{j}^{(i)}\right|\right\}$ best codewords among the candidate codewords generated up to the current $(i, j)$-th stage and $\boldsymbol{c}_{\text {best }}$ denotes the best in $C_{l}$. Cond $_{\mathrm{S}, 1}$ is called Taipale-Pursley condition [14]. $\operatorname{Cond}_{\mathrm{S}, 1}^{(i)}(j)$ is stronger than $\operatorname{Cond}_{\mathrm{S}, 1}$, because $\bar{R}(i, j)$ is taken into account. As shown in Section 4.4, the condition $\operatorname{Cond}_{\mathrm{S}, 1}^{(1)}(j)$ is more effective than the condition Cond ${ }_{\mathrm{S}, 1}$.

For simplicity, the following sufficient conditions on the optimality of decoded codewords are used as early termination conditions at the $(i, j)$-th stage of 3-GMD decoding in the simulation reported in Section 4.4.
(i) $i=1$ :
$\operatorname{Cond}_{\mathrm{S}, 1}^{(1)}(j)$, and $\operatorname{Cond}_{\mathrm{S}, 2}$,
(ii) $i=2$ :
$\operatorname{Cond}_{\mathrm{S}, 0}^{(2)}: L\left(\boldsymbol{c}_{\text {best }}^{(2)}(j)\right) \geq \underline{L}[\bar{R}(2, j)]$, and $\operatorname{Cond}_{\mathrm{S}, 2}$,
(iii) $i=3$ :

Cond $_{\mathrm{S}, 2}$.
The above conditions will be called Cond ${ }_{\mathrm{S}, \mathrm{NEW}}$. Simulation results show that $\operatorname{Cond}_{\mathrm{S}, 1}^{(1)}(j)$ and $\operatorname{Cond} \mathrm{S}_{\mathrm{S}, 0}^{(2)}$ are more effective than $\operatorname{Cond}_{\mathrm{S}, 2}$.

### 4.4 Simulation Results of $h$-GMD decoding with

$$
2 \leq h \leq 3
$$

Figures 4.1 to 4.3 show simulation results of block error probabilities for $\operatorname{EBCH}(64,24)$, $\operatorname{EBCH}(128,85)$ and $\operatorname{EBCH}(128,99)$ with the minimum distance, 16,14 and 10, respectively. For comparison, the block error probabilities for bounded distance$t_{0}\left(\triangleq\left\lfloor\left(d_{\text {min }}-1\right) / 2\right\rfloor\right)$ decoding and Chase decoding algorithm II [19] are shown.

Tables 4.1 and 4.2 show the following statistics with respect to signal to noise ratios $2.0 E_{b} / N_{0}$ and $4.0 E_{b} / N_{0}$ in dB for $\operatorname{EBCH}(64,24)$, respectively. The number of trials is 50000 . In the first part, the number of trials in which $\boldsymbol{z} \in C$ is shown. The remaining parts concern those trials in which $\boldsymbol{z} \notin C$. The second part concerns bounded distance- $t_{0}$ decoding with input $\boldsymbol{z}$, and the numbers of decoding failures, correct decoding and incorrect decoding are shown, respectively. The third part shows the numbers of decoding failure, correct decoding and incorrect decoding, respectively, of 3-GMD decoding. The first subpart shows the occurrence number of the event that the first candidate codeword is generated at the $(i, j)$-th stage for $1 \leq j \leq d_{\min } / 2$ and $1 \leq i \leq 3$. The second to fourth subparts show the occurrence number of the event that the best candidate codeword (= the output of 3 -GMD decoding) is generated at the $(i, j)$-th stage and the numbers of $\boldsymbol{c}_{\text {best }}{ }^{(i)}(j)$ 's which satisfy sufficient conditions on the optimality of decoded codewords Cond $_{\mathrm{S}, 1}$ and Cond ${ }_{\mathrm{S}, \mathrm{NEW}}$, respectively. Cond $_{\mathrm{S}, 1}$ has effect only for early stages.

The number of iteration of $h$-GMD decoding is at most $h\left(d_{\min }+p\right) / 2$. This number of iteration can be reduced considerably by using Cond $_{\mathrm{S}, \mathrm{NEW}}$. Define the rate of reduction as the ratio of the number of iterations of $(s, t)$-decoding to $3 \rho$. Since sufficient conditions can be used only when at least one candidate codeword has been generated, rates $\mu_{\mathrm{TP}}$ and $\mu_{\text {NEW }}$ are the averages of reduction rates by using $\operatorname{Cond}_{\mathrm{S}, 1}$ and $\operatorname{Cond}_{\mathrm{S}, \mathrm{NEW}}$, respectively, as early termination conditions over all the trials where at least one candidate codeword is generated. Tables 4.3 lists $\mu_{\mathrm{TP}}$ and $\mu_{\mathrm{NEW}}$ in percentage for $\operatorname{EBCH}(64,24), \operatorname{EBCH}(64,45)$, $\operatorname{EBCH}(128,78), \operatorname{EBCH}(128,85)$ and $\operatorname{EBCH}(128,99)$ with respect to signal to noise ratios $2.0 E_{b} / N_{0}$ and $4.0 E_{b} / N_{0}$.

### 4.5 Conclusion

We have introduced "multiple GMD decoding" for binary linear block codes. For extended BCH codes, simulation results show that the new approach provides better error performance than that of the original GMD decoding by adding two GMD-like decoding around two appropriately chosen centers to the original GMD decoding with relative small increment of iteration number.


Figure 4.1. Block error probability of $\mathrm{EBCH}(64,24)$


Figure 4.2. Block error probability of $\operatorname{EBCH}(128,85)$


Figure 4.3. Block error probability of $\operatorname{EBCH}(128,99)$

Table 4.1. $\mathrm{EBCH}(64,24)$ at $E_{b} / N_{0}=2.0 \mathrm{~dB}$

| $z \in C$ |  |  |  |  |  | 4 |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| bounded distance- $\left\lfloor\left(d_{\text {min }}-1\right) / 2\right\rfloor$ decoding |  |  |  |  |  | decoding failure |  |  | 33610 |
|  |  |  |  |  |  | correct decoding |  |  | 16373 |
|  |  |  |  |  |  | incorrect decoding |  |  | 17 |
| 3-GMD decoding |  |  |  |  |  | decoding failure |  |  | 24104 |
|  |  |  |  |  |  | correct decoding |  |  | 25774 |
|  |  |  |  |  |  | incorrect decoding |  |  | 122 |
|  | $i \backslash j$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| the occurance of | 1 | 19698 | 1481 | 882 | 485 | 292 | 140 | 38 | 9 |
| the first candidate | 2 | 1167 | 189 | 85 | 61 | 44 | 21 | 8 | 2 |
| codeword | 3 | 939 | 138 | 82 | 57 | 34 | 29 | 10 | 1 |
| the occurance of | 1 | 19690 | 1482 | 882 | 486 | 292 | 141 | 38 | 9 |
| the best candidate | 2 | 1166 | 189 | 85 | 61 | 44 | 21 | 8 | 3 |
| codeword | 3 | 944 | 138 | 82 | 57 | 34 | 29 | 10 | 1 |
| the number of codewords $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ | 1 | 8800 | 135 | 57 | 22 | 7 | 2 | 0 | 0 |
| which satisfy Cond ${ }_{\mathrm{S}, 1}$ | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| the number of codewords $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ | 1 | 8800 | 361 | 253 | 231 | 267 | 302 | 269 | 162 |
| which satisfy Cond $_{\text {S,new }}$ | 2 | 47 | 9 | 3 | 2 | 0 | 0 | 1 | 1 |

Table 4.2. $\operatorname{EBCH}(64,24)$ at $E_{b} / N_{0}=4.0 \mathrm{~dB}$

| $z \in C$ |  |  |  |  |  | 192 |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| bounded distance- $\left\lfloor\left(d_{\text {min }}-1\right) / 2\right\rfloor$ decoding |  |  |  |  |  | decoding failure |  |  | 8704 |
|  |  |  |  |  |  | correct decoding |  |  | 41293 |
|  |  |  |  |  |  | incorrect decoding |  |  | 3 |
| 3-GMD decoding |  |  |  |  |  | decoding failure |  |  | 2780 |
|  |  |  |  |  |  | correct decoding |  |  | 47208 |
|  |  |  |  |  |  | incorrect decoding |  |  | 12 |
|  | $i \backslash j$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| the occurance of | 1 | 43599 | 1068 | 622 | 391 | 227 | 110 | 45 | 13 |
| the first candidate | 2 | 366 | 73 | 32 | 40 | 17 | 11 | 4 | 2 |
| codeword | 3 | 276 | 51 | 28 | 25 | 7 | 10 | 9 | 2 |
| the occurance of | 1 | 43595 | 1067 | 623 | 392 | 227 | 111 | 45 | 13 |
| the best candidate | 2 | 368 | 73 | 32 | 40 | 17 | 11 | 4 | 2 |
| codeword | 3 | 275 | 51 | 28 | 25 | 7 | 11 | 9 | 2 |
| the number of codewords $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ | 1 | 37162 | 318 | 123 | 35 | 13 | 1 | 0 | 0 |
| which satisfy Cond ${ }_{\text {S, }}$ | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| the number of codewords $\boldsymbol{c}_{\text {best }}^{(i)}(j)$ | 1 | 37162 | 653 | 400 | 342 | 389 | 426 | 314 | 186 |
| which satisfy Conds,new | 2 | 88 | 9 | 4 | 4 | 2 | 4 | 1 | 0 |

Table 4.3. The average number of iteration (\%) of 3-GMD

| Code | $E_{b} / N_{0}=2.0 \mathrm{~dB}$ |  | $E_{b} / N_{0}=4.0 \mathrm{~dB}$ |  |
| :--- | ---: | ---: | ---: | ---: |
|  | $\mu_{\text {TP }}$ | $\mu_{\text {NEW }}$ | $\mu_{\text {TP }}$ | $\mu_{\text {NEW }}$ |
| $\operatorname{EBCH}(64,24)$ | $66.7 \%$ | $61.6 \%$ | $23.6 \%$ | $19.8 \%$ |
| $\operatorname{EBCH}(64,45)$ | $65.0 \%$ | $59.1 \%$ | $17.8 \%$ | $15.0 \%$ |
| $\operatorname{EBCH}(128,78)$ | $78.8 \%$ | $73.2 \%$ | $21.6 \%$ | $18.6 \%$ |
| $\operatorname{EBCH}(128,85)$ | $78.4 \%$ | $74.3 \%$ | $21.1 \%$ | $18.1 \%$ |
| $\operatorname{EBCH}(128,99)$ | $82.2 \%$ | $78.3 \%$ | $24.8 \%$ | $20.9 \%$ |

## Chapter 5

## An Improvement to Chase-like Decoding Algorithm

### 5.1 Definitions

Suppose a binary linear ( $N, K, d_{\min }$ ) block code $C$ is used for error control over the AWGN channel using BPSK signaling. Each codeword is transmitted with the same probability. For a positive integer $n$, let $V^{n}$ denote the vector space of all binary $n$-tuples. Let $\boldsymbol{r}=\left(r_{1}, r_{2}, \ldots, r_{N}\right)$ be a received sequence and let $\boldsymbol{z}=\left(z_{1}, z_{2}, \ldots, z_{N}\right)$ be the hard-decision sequence from $\boldsymbol{r}$ by using hard-decision function, $z_{i}=1$ for $r_{i}>0, z_{i}=0$ for $r_{i} \leq 0$. For simplicity, we assume that the bit positions $1,2, \ldots, N$ are ordered according to the reliability order given as $\left|r_{i}\right| \leq\left|r_{j}\right|$, for $1 \leq i<j \leq N$. For $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{N}\right) \in V^{N}$, the correlation between $\boldsymbol{u}$ and the received sequence $\boldsymbol{r}$ is given by $M(\boldsymbol{u})=\sum_{i=1}^{N} r_{i}\left(2 u_{i}-1\right)$. Then, $M(\boldsymbol{z})=\sum_{i=1}^{N}\left|r_{i}\right| \geq M(\boldsymbol{u})$ for any $\boldsymbol{u} \in V^{N}$. For $\boldsymbol{u} \in V^{N}$, define $D_{-1}(\boldsymbol{u}) \triangleq\{i$ : $u_{i} \neq z_{i}$, and $\left.1 \leq i \leq N\right\}$ and

$$
L(\boldsymbol{u}) \triangleq \sum_{i \in D_{-1}(\boldsymbol{u})}\left|r_{i}\right|=(M(\boldsymbol{z})-M(\boldsymbol{u})) / 2 .
$$

$L(\boldsymbol{u})$ is called the correlation discrepancy of $\boldsymbol{u}$ with respect to $\boldsymbol{z}$. For $U \subseteq V^{N}$, let $\underline{L}[U]$ be defined as

$$
\underline{L}[U] \triangleq \begin{cases}\min _{\boldsymbol{u} \in U} L(\boldsymbol{u}), & \text { for } U \neq \emptyset \\ \infty, & \text { for } U=\emptyset\end{cases}
$$

The maximum likelihood decoder outputs the optimal codeword $\boldsymbol{c}_{\text {opt }}$ which

$$
L\left(\boldsymbol{c}_{\mathrm{opt}}\right)=\underline{L}[C]
$$

from the received sequence $\boldsymbol{r}$. A codeword $\boldsymbol{c}$ is said to be better than another codeword $\boldsymbol{c}^{\prime}$ if $L(\boldsymbol{c}) \leq L\left(\boldsymbol{c}^{\prime}\right)$. For a nonempty subset $U \subseteq V^{N}$, a codeword $\boldsymbol{c}$ is said to be the best in $U$ if $L(\boldsymbol{c})=\underline{L}[U]$. For $U \neq \phi$, let $\boldsymbol{v}[U]$ denote a binary $N$-tuple in $U$ such that $L(\boldsymbol{v}[U])=\underline{L}[U]$. For integers $i$ and $j$ such that $1 \leq i<j \leq N$, define $[i, j] \triangleq\{i, i+1, \ldots, j\}$. For $\boldsymbol{u}=\left(u_{1}, u_{2}, \ldots, u_{N}\right)$ and $\boldsymbol{v}=\left(v_{1}, v_{2}, \ldots, v_{N}\right) \in V^{N}$, define $d_{H,[i, j]}(\boldsymbol{u}, \boldsymbol{v}) \triangleq\left|\left\{k \in[i, j]: u_{k} \neq v_{k}\right\}\right|$ and for a nonnegative integer $t$, $O(\boldsymbol{v}, t) \triangleq\left\{\boldsymbol{u} \in V^{N}: d_{H,[1, N]}(\boldsymbol{u}, \boldsymbol{v}) \leq t\right\}$ and $\bar{O}(\boldsymbol{v}, t) \triangleq V^{N} \backslash O(\boldsymbol{v}, t)$.

For a nonnegative integer $l=\sum_{i=1}^{N} b_{i} 2^{i-1}$ with $b_{i} \in\{0,1\}$, define $b(l) \triangleq\left(b_{1}, b_{2}, \ldots, b_{N}\right)$. For $0 \leq l<2^{N}$, define $E_{l} \triangleq\{b(i): 0 \leq i<l\}$. For a positive integer $l$ less than $N-t_{0}+1$, a Chase-like decoding algorithm, denoted Chase( $l$ ), is defined as an iterative decoding algorithm which performs bounded distance- $t_{0}$ decoding around $\boldsymbol{z}+\boldsymbol{b}(i)$ for $0 \leq i<l$. The original Chase decoding algorithm II introduced by Chase [24] is Chase $\left(2^{\left\lfloor d_{\min } / 2\right\rfloor}\right)$.

### 5.2 Decoding algorithm

If $\boldsymbol{z} \in C$, then $L(\boldsymbol{z})=\underline{L}[C]$, that is, $\boldsymbol{z}$ is the optimal decoded codeword. Assume that $\boldsymbol{z} \notin C$.

For $\boldsymbol{v} \in V^{N}$, the bounded distance- $t_{0}$ decoding around the vector $\boldsymbol{v}$, denoted $\operatorname{BDD}(\boldsymbol{v})$, outputs a unique codeword in $O\left(\boldsymbol{v}, t_{0}\right)$, if it exists.

In this paper, we consider the following iterative decoding algorithm. For a positive integer $h$, a nonnegative integer $t$ and $\boldsymbol{v}^{(i)} \in V^{N}$ with $1 \leq i \leq h$, $(h, t)$-IBDD decoding is defined as an iterative decoding algorithm which consists of successive $\operatorname{BDD}\left(\boldsymbol{v}^{(1)}\right), \operatorname{BDD}\left(\boldsymbol{v}^{(2)}\right), \ldots, \operatorname{BDD}\left(\boldsymbol{v}^{(h)}\right)$, where $\boldsymbol{v}^{(i)}$ is called the $i$-th search center of the $(h, t)$-IBDD decoding. Define $R(i) \triangleq \cup_{1 \leq i^{\prime} \leq i} O\left(\boldsymbol{v}^{\left(i^{\prime}\right)}, t_{0}\right)$ as the region which has been searched up to the $i$-th stage of $(h, t)$-IBDD decoding and $\bar{R}(i) \triangleq V^{N} \backslash R(i)$.

We adopt the following choice of search centers, called Selection $(t)$. The first search center $\boldsymbol{v}^{(1)}$ is $\boldsymbol{z}$. For $i>1$, search center $\boldsymbol{v}^{(i)}$ is chosen as

$$
\boldsymbol{v}^{(i)}=v\left[\cap_{1 \leq i^{\prime} \leq i-1} \bar{O}\left(\boldsymbol{v}^{\left(i^{\prime}\right)}, t\right)\right] .
$$

If $t=t_{0}$, then $\boldsymbol{v}^{(i)}=v[\bar{R}(i-1)]$.
Let $C(i)$ denote the set of candidate codewords obtained from the first stage to the $i$-th stage. If $C(i) \neq \emptyset$, let $\boldsymbol{c}_{\text {best }}(i)$ be the best codeword in $C(i)$. If $C(i)=\emptyset$, define $\boldsymbol{c}_{\text {best }}(i) \triangleq *$ and $L(*)=\infty$. Then $L\left(\boldsymbol{c}_{\text {best }}(i)\right)=\underline{L}[C(i)]$. After the $h$-th stage, $\boldsymbol{c}_{\text {best }}(h)$ is output as the decoded codeword. If $\boldsymbol{c}_{\text {best }}(h)=*$, then the decoding fails.

### 5.3 Early termination conditions

To reduce the number of bounded distance- $t_{0}$ decodings in $(h, t)$-IBDD without any degradation of error performance, we present new effective sufficient conditions on the optimality of decoded codewords as early termination conditions. Suppose that $\boldsymbol{c}_{\text {best }}(i) \neq *$. If there is a better codeword than $\boldsymbol{c}_{\text {best }}(i)$, it is in the following region: $\bar{R}(i) \cap \bigcap_{\boldsymbol{c} \in C(i)} \bar{O}\left(\boldsymbol{c}, d_{\text {min }}-1\right)$. The following condition $\operatorname{Cond}_{S}(i)$ is a sufficient condition on the optimality of $\boldsymbol{c}_{\text {best }}(i)$,

$$
\operatorname{Cond}_{S}(i): L\left(\boldsymbol{c}_{\text {best }}(i)\right) \leq \underline{L}\left[\bar{R}(i) \cap \bigcap_{c \in C(i)} \bar{O}\left(\boldsymbol{c}, d_{\text {min }}-1\right)\right] .
$$

For $1 \leq l \leq 4$, the following sufficient condition $\operatorname{Cond}_{S, l}$ on the optimality of decoded codewords which are independent of search regions have been derived.

$$
\operatorname{Cond}_{S, l}: L\left(\boldsymbol{c}_{\text {best }}(i)\right) \leq \underline{L}\left[\cap_{\boldsymbol{c} \in C_{l}} \bar{O}\left(\boldsymbol{c}, d_{\text {min }}-1\right)\right],
$$

where $C_{l}$ denotes the $\min \{l,|C(i)|\}$ best codewords among the candidate codewords generated up to the current $i$-th stage. Cond $_{S, 1}$ is Taipale-Pursley condition [12], denoted $\operatorname{Cond}_{\text {TP }} . \operatorname{Cond}_{S}(i)$ is stronger than $\operatorname{Cond}_{S, 1}$, because $\bar{R}(i)$ is taken into account. Cond $_{S}(i)$ is denoted Cond ${ }_{\text {NEW }}$.

### 5.4 Simulation results

By simulation, we have evaluated the effectiveness of the choice of parameter $t$ in $\operatorname{Selection}(t)$ with $1 \leq t \leq t_{0}$ for several BCH codes [31]. For $t=t_{0}$, $\boldsymbol{v}^{(i)}$ is the best in the region which was not searched before the $i$-th stage of $\left(h, t_{0}\right)$-IBDD decoding. From this fact, $t_{0}$ was thought to be a reasonable choice.

The simulation results show, however, that it is better to choose $t$ somewhat smaller than $t_{0}$. Figures 5.1, 5.2 and 5.3 show simulation results of block error probabilities of $(h, t)$-IDD with properly chosen parameter $t$ for $\operatorname{BCH}(63,30,13)$ code, $\mathrm{BCH}(63,45,7)$ code and $\mathrm{BCH}(127,92,11)$, respectively. For comparison, the block error probabilities for bounded distance- $t_{0}$ decoding and Chase $(h)$ are shown.

The reduction rate of $(h, t)$-IBDD is defined as $1-(\nu / h)$, where $\nu$ is the number of iterations of bounded distance- $t_{0}$ decoding. Since sufficient conditions can be used only when at least one candidate codeword has been generated, rates $\mu_{\mathrm{TP}}$ and $\mu_{\text {NEW }}$ denote the averages of reduction rates by using Cond $\mathrm{TP}_{\mathrm{TP}}$ and Cond ${ }_{\text {NEW }}$, respectively, as early termination conditions over all the trials where at least one candidate codeword is generated. Figures 5.4, 5.5, 5.6 and 5.7 show simulation results of the average of reduction rates of $(32,4)$-IBDD decoding for $\mathrm{BCH}(63,30,13), \mathrm{BCH}(63,45,7), \mathrm{BCH}(127,85,13)$ and $\mathrm{BCH}(127,92,11)$. To compute search centers $\boldsymbol{v}^{(i)}$ and the right-hand side of $\operatorname{Cond}_{S}(i)$, an integer programming approach [18] is adopted and lp_solve 3.0 is tentatively used.


Figure 5.1. Block error probability for $\mathrm{BCH}(63,30,13)$


Figure 5.2. Block error probability for $\mathrm{BCH}(63,45,7)$


Figure 5.3. Block error probability for $\mathrm{BCH}(127,92,11)$


Figure 5.4. Reduction rate of (32,4)-IBDD decoding for $\mathrm{BCH}(63,30,13)$


Figure 5.5. Reduction rate of (32, 2)-IBDD decoding for $\mathrm{BCH}(63,45,7)$


Figure 5.6. Reduction rate of (32,4)-IBDD decoding for $\operatorname{BCH}(127,85,13)$


Figure 5.7. Reduction rate of (32, 2)-IBDD decoding for $\operatorname{BCH}(127,92,11)$

## Chapter 6

## Conclusion

In this thesis, first, we have presented a formula for an effective method which gives the number of minimum weight codewords in a $\left(2^{m}, \sum_{i=0}^{r}\binom{m}{i}-\Delta K\right)$ linear subcode $C$ of $\mathrm{RM}_{r, m}$ code which is spanned by monomials with $m$ variables of degree $r$ or less over GF (2) for $\Delta K \leq 3$. Next, we have shown in Theorem 1 how to delete $\Delta K$ monomials in order to obtain the subcode with the smallest number of codewords of the minimum weight for $r \Delta K \leq m$. In Example 1, we have shown the numbers of minimum weight codewords of all such $(64,40)$ subcodes of $\mathrm{RM}_{3,6}$ and those error probabilities of soft-decision maximum likelihood decoding by simulation.

Second, we have studied a class of linear block codes which are transitive invariant. A condition for a code to be transitive invariant has been proved. We have shown that transitive invariant block codes have a uniform structure. This structure is advantageous for implementation of the RMLD algorithm based on a binary uniform sectionalization. We have shown that the binary sectionalization results in almost the same computational complexity as an optimum sectionalization for many transitive invariant example codes.

Third, we have introduced "multiple GMD decoding" for binary linear block codes. For extended BCH codes, simulation results show that the new approach provides better error performance than that of the original GMD decoding by adding two GMD-like decodings around two appropriately chosen centers to the original GMD decoding with a relatively small increment of iteration number.

Finally, we have presented a new method of choosing a sequence of search
centers around which successive bounded distance- $t_{0}$ decodings are carried out. For BCH codes, simulation results show that the new approach provides better error performance than that of Chase-like decoding which consists of the same number of bounded distance- $t_{0}$ decodings. To reduce the number of iterations of bounded distance decoding algorithm without any loss of error performance, we show new effective sufficient conditions on the optimality of decoded codewords as early termination conditions.

## Appendix

## A Formula for Evaluation $N_{23}$

In this Appendix, we consider the evaluation of $N_{23}$ in a somewhat general framework. In the evaluation of $N_{23}$, the following $B_{1}, B_{2}, D_{0}, D_{1}$ and $D_{2}$ represent $A_{n_{10 *}, n_{011}} A_{n_{1 * 0}, n_{011}}, A_{n_{100}, n_{011}}, A_{n_{101}, n_{011}}$ and $A_{n_{110}, n_{011}}$, respectively. For $h \in$ $\{0,1,2\}$, let $D_{h}$ be a binary $w_{h} \times l$ matrix where $w_{h}>0$ and $l>0$, and for $i \in\{1,2\}$, let $B_{i}$ denote the binary $\left(w_{0}+w_{i}\right) \times l$ matrix whose submatrix consisting of the first $w_{0}$ rows is $D_{0}$ and whose submatrix consisting of the last $w_{i}$ rows is $D_{i}$, that is,

$$
B_{i} \triangleq\left[\begin{array}{c}
D_{0} \\
D_{i}
\end{array}\right], \text { for } i \in\{1,2\}
$$

We consider the following condition:

$$
\operatorname{rank}\left(B_{i}\right)=l, \text { for } i \in\{1,2\}
$$

that is, the $l$ columns of $B_{i}$ are linearly independent.
The following conditions is necessary for the condition (A•2). Hereafter, we assume it.

$$
w_{0}+\min \left\{w_{1}, w_{2}\right\} \geq l
$$

For the evaluation of $N_{23}, w_{0}, w_{1}, w_{2}$ and $l$ represent $\left|n_{100}\right|,\left|n_{101}\right|,\left|n_{110}\right|$ and $\left|n_{011}\right|$, respectively, and since $\left|n_{100}\right|+\left|n_{101}\right|=\left|n_{10 *}\right|=\left|n_{01 *}\right|$ and $\left|n_{100}\right|+\left|n_{110}\right|=\left|n_{1 * 0}\right|=$ $\left|n_{0 * 1}\right|$ as shown in Section 2.3, $\left|n_{100}\right|+\min \left\{\left|n_{101}\right|,\left|n_{110}\right|\right\} \geq\left|n_{011}\right|$, that is (A•3) holds.

For $1 \leq j \leq l$, let $\varphi_{D_{0}}(j)$ denote the number of linearly independent columns in the first $j$ columns of $D_{0}$. Define $\Delta \varphi_{D_{0}}(j) \triangleq \varphi_{D_{0}}(j)-\varphi_{D_{0}}(j-1)$ for $1 \leq j \leq l$,
and $\varphi_{D_{0}}(0) \triangleq 0$. Since $0 \leq \Delta \varphi_{D_{0}}(j) \leq 1$ for $1 \leq j \leq l$ and $\varphi_{D_{0}}(l) \leq \min \left\{w_{0}, l\right\}$, $\Delta \varphi_{D_{0}} \triangleq\left(\Delta \varphi_{D_{0}}(1), \Delta \varphi_{D_{0}}(2), \ldots, \Delta \varphi_{D_{0}}(l)\right)$ is a binary $l$-tuple of weight min $\left\{w_{0}, l\right\}$ or less.

Conversely, for a binary $l$-tuple $\boldsymbol{v}=\left(v_{1}, v_{2}, \ldots, v_{l}\right)$ of weight $\min \left\{w_{0}, l\right\}$ or less, define $\phi_{\boldsymbol{v}}(j)$ for $0 \leq j \leq l$ recursively as follows:

$$
\begin{align*}
\phi_{\boldsymbol{v}}(0) & =0, \\
\phi_{\boldsymbol{v}}(j) & =\phi_{\boldsymbol{v}}(j-1)+v_{j} .
\end{align*}
$$

Let $V_{w_{0}}^{l}$ denote $\left\{\boldsymbol{v} \in V^{l}\right.$ : the weight of $\left.\boldsymbol{v} \leq w_{0}\right\}$ where $V^{l}$ denotes the set of binary $l$-tuples. Then, the following lemma is a direct consequence of the definition of $\varphi_{D_{0}}$.

Lemma 4 For $\boldsymbol{v} \in V_{w_{0}}^{l}$, the number of binary $w_{0} \times l$ matrices $D_{0}$ 's such that $\varphi_{D_{0}}=\phi_{\boldsymbol{v}}$ is given by

$$
\prod_{j=1}^{l} N_{\phi_{v}}(j)
$$

where

$$
N_{\phi}(j) \triangleq \begin{cases}2^{w_{0}}-2^{\phi_{\boldsymbol{v}}(j-1)}, & \text { if } \phi_{\boldsymbol{v}}(j)>\phi_{\boldsymbol{v}}(j-1) \\ 2^{\phi_{\boldsymbol{v}}(j-1)}, & \text { if } \phi_{\boldsymbol{v}}(j)=\phi_{\boldsymbol{v}}(j-1)\end{cases}
$$

Next, we consider the condition on $D_{i}$ with $i \in\{1,2\}$ that $\operatorname{rank}\left(B_{i}\right)=l$ for a given $D_{0}$. For $1 \leq j \leq l$ and $h \in\{0,1,2\}$, let $\boldsymbol{d}_{h, j}$ denote the $j$-th column of $D_{h}$, and for $i \in\{1,2\}$, let $\boldsymbol{b}_{i, j}$ denote the $j$-th column of $B_{i}$. For $1 \leq j \leq l$, there are two cases:

1. $\varphi_{D_{0}}(j)>\varphi_{D_{0}}(j-1)$ : Then, $\boldsymbol{d}_{0, j}$ is linearly independent of $\boldsymbol{d}_{0,1}, \ldots, \boldsymbol{d}_{0, j-1}$, and therefore, for any $\boldsymbol{d}_{i, j}, \boldsymbol{b}_{i, j}$ is linearly independent of $\boldsymbol{b}_{i, 1}, \ldots, \boldsymbol{b}_{i, j-1}$.
2. $\varphi_{D_{0}}(j)=\varphi_{D_{0}}(j-1)$ : Then, there is a binary $(j-1)$-tuple $\left(c_{1}, c_{2}, \ldots, c_{j-1}\right)$ such that

$$
\boldsymbol{d}_{0, j}=\sum_{s=1}^{j-1} c_{s} \boldsymbol{d}_{0, s}
$$

Let $\Gamma_{j}$ denote the set of all binary $(j-1)$-tuples $\left(c_{1}, c_{2}, \ldots, c_{j-1}\right)$ 's for which (A•9) holds. Then,

$$
\left|\Gamma_{j}\right|=2^{j-1-\varphi_{D_{0}}(j-1)} .
$$

For $B_{i}$ to satisfy (A•2), the following inequality must hold for any $j$ such that $\varphi_{D_{0}}(j)=\varphi_{D_{0}}(j-1):$

$$
\boldsymbol{d}_{i, j} \neq \sum_{s=1}^{j-1} c_{\boldsymbol{s}} \boldsymbol{d}_{i, s}, \text { for }\left(c_{1}, c_{2}, \ldots, c_{j-1}\right) \in \Gamma_{j} .
$$

Conversely suppose that for any $j^{\prime}$ such that $1 \leq j^{\prime}<j$ and $\varphi_{D_{0}}\left(j^{\prime}\right)=\varphi_{D_{0}}\left(j^{\prime}-1\right)$,

$$
\boldsymbol{d}_{i, j^{\prime}} \neq \sum_{s=1}^{j^{\prime}-1} c_{s} \boldsymbol{d}_{i, s}, \text { for }\left(c_{1}, c_{2}, \ldots, c_{j^{\prime}-1}\right) \in \Gamma_{j^{\prime}}
$$

Then, $\boldsymbol{b}_{i, 1}, \boldsymbol{b}_{i, 2}, \ldots, \boldsymbol{b}_{i, j-1}$ are linearly independent. Since (A•9) holds for any $\left(c_{1}, c_{2}, \ldots, c_{j-1}\right) \in \Gamma_{j}$, we see that for different $\left(c_{1}, c_{2}, \ldots, c_{j-1}\right)$ and $\left(c_{1}^{\prime}, c_{2}^{\prime}, \ldots, c_{j-1}^{\prime}\right)$ in $\Gamma_{j}$,

$$
\sum_{s=1}^{j-1} c_{s} \boldsymbol{d}_{i, s} \neq \sum_{s=1}^{j-1} c_{s}^{\prime} \boldsymbol{d}_{i, s}
$$

that is,

$$
\left|\left\{\sum_{s=1}^{j-1} c_{s} \boldsymbol{d}_{i, s}:\left(c_{1}, c_{2}, \ldots, c_{j-1}\right) \in \Gamma_{j}\right\}\right|=\left|\Gamma_{j}\right|=2^{j-1-\varphi_{D_{0}}(j-1)}
$$

In order that (A•11) holds, the following inequality must hold from (A•10):

$$
w_{i}>j-1-\varphi_{D_{0}}(j-1) .
$$

Suppose that (A•15) holds for any $j$ such that $1 \leq j \leq l$ and $\varphi_{D_{0}}(j)=\varphi_{D_{0}}(j-1)$. Then, for such $j, \boldsymbol{d}_{i, j}$ satisfying (A•11) can be chosen. Summarizing the above argument, we have the following lemma:

Lemma 5 For a given $D_{0}$, there are binary $w_{1} \times l$ matrix $D_{1}$ and $w_{1} \times l$ matrix $D_{2}$ for which (A-2) holds, if and only if for any $j$ such that $1 \leq j \leq l$ and
$\varphi_{D_{0}}(j)=\varphi_{D_{0}}(j-1),(\mathrm{A} \cdot 15)$ holds for $i \in\{0,1\}$. If this condition holds, then the number of pairs of matrices $D_{1}$ and $D_{2}$ satisfying (A•2) is given as follows:

$$
\prod_{j=1}^{l} N_{1}^{\prime}(j) N_{2}^{\prime}(j)
$$

where for $i \in\{0,1\}$,

$$
N_{i}^{\prime}(j) \triangleq \begin{cases}2^{w_{i}}, & \text { if } \varphi_{D_{0}}(j)>\varphi_{D_{0}}(j-1) \\ 2^{w_{i}}-2^{j-1-\varphi_{D_{0}}(j-1)}, & \text { if } \varphi_{D_{0}}(j)=\varphi_{D_{0}}(j-1)\end{cases}
$$

Since $\varphi_{D_{0}}(j)-\varphi_{D_{0}}(j-1)$ is 0 or 1 for $1 \leq j \leq l, j-1-\varphi_{D_{0}}(j-1)$ is monotonously nondecreasing as $j$ increases. If $\varphi_{D_{0}}(j)>\varphi_{D_{0}}(j-1)$ for all $j$ less than $l$, then $\varphi_{D_{0}}(l-1)=l-1$. Hence, $(\mathrm{A} \cdot 15)$ can be replaced by

$$
\varphi_{D_{0}}(l-1)>l-1-\min \left\{w_{1}, w_{2}\right\} .
$$

Define

$$
\begin{align*}
V_{w_{0}, w_{1}, w_{2}}^{l} \triangleq & \left\{\boldsymbol{v} \in V^{l} ; \text { the weight of } \boldsymbol{v} \leq w_{0}\right. \\
& \text { the weight of the first to the }(l-1) \text {-th component } \\
& \left.\geq l-\min \left\{w_{1}, w_{2}\right\}\right\} .
\end{align*}
$$

From (A•3), $V_{w_{0}, w_{1}, w_{2}}^{l}$ is not empty. Then, for a given $D_{0}$, there are $D_{1}$ and $D_{2}$ satisfying (A•2), if and only if

$$
\varphi_{D_{0}} \in V_{w_{0}, w_{1}, w_{2}}^{l}
$$

From the definition (A•20), we have that

$$
\left|V_{w_{0}, w_{1}, w_{2}}^{l}\right|=2 \sum_{i=l-\min \left\{w_{1}, w_{2}\right\}}^{w_{0}-1}\binom{l-1}{i}+\varepsilon\binom{l-1}{w_{0}}
$$

where if $w_{0}+\min \left\{w_{1}, w_{2}\right\}=l, \varepsilon=1$ and otherwise, $\varepsilon=0$.
The number of matrices $D_{0}, D_{1}$ and $D_{2}$ satisfying (A•2) is obtained by multiplying (A•6), (A•16) and (A•22). By substituting $\left|n_{100}\right|,\left|n_{101}\right|,\left|n_{110}\right|$ and $\left|n_{011}\right|$ for $w_{0}, w_{1}, w_{2}$ and $l$, respectively, $N_{23}$ is derived.

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