Robustly-optimal rate one-half binary convolutional codes

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TABLE II

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This theorem establishes a reduced exhaustive search method for a MAXPOL of any given degree. One searches all $k$, the $m_i$, and the $m_j$ such that $e \geq 0$, $r = k + 2(\sum m_i + \sum m_j)$, $m_i > 1$, $m_j \geq 3$, and $m_i \neq m_j$. Compute the exponent by

$$e = \left\lceil \log_2 k \right\rceil \left[ \text{int}\left( \left( \frac{2^{m_i} + 1}{2^{m_i} - 1} \right) \right) \right],$$

and keep the combination that yields the maximum $e$. ($\text{int}(x)$ denotes the upper integer part of $x$.) This search was programmed in a simple APL routine that produced the list in Table II of one MAXPOL per given degree. We observe that the MAXPOL exponents are very near to $2^{r+3}/2$ for which we have no explanation at this time.

REFERENCES


Robustly Optimal Rate One-Half Binary Convolutional Codes

ROLF JOHANNESSON

Abstract—Three optimality criteria for convolutional codes are considered in this correspondence: namely, free distance, minimum distance, and distance profile. Here we report the results of computer searches for rate one-half binary convolutional codes that are "robustly optimal" in the sense of being optimal for one criterion and optimal or near-optimal for the other two criteria. Comparisons with previously known codes are made. The results of a computer simulation are reported to show the importance of the distance profile to computational performance with sequential decoding.

Several distance measures have been proposed for convolutional codes, each of which is important for particular applications. In this correspondence we report the results of the search for "robustly optimal" convolutional codes, i.e., codes that are optimal for one distance measure and are also optimal or near-optimal for the other two distance measures. We have limited the search to binary codes of rate $R = 1/2$ as the case of greatest practical interest.

In a rate $R = 1/2$ binary convolutional code, the information sequence $i_0,i_1,i_2,\ldots$ is encoded as the sequence

$$t_0^{(1)}, t_1^{(1)}, t_2^{(1)}, t_3^{(1)}, \ldots$$

where

$$t_u^{(k)} = \sum_{j=0}^{lM} i_{u-j} g_j^{(k)}.$$

The parameter $M$ is the code memory and

$$G^{(k)} = [g_0^{(k)}, g_1^{(k)}, \ldots, g_{lM}^{(k)}]$$

for $k = 1,2$, are the code generators. The code is systematic when $G^{(1)} = [1,0,\ldots,0]$. The code is a quick-look-in (QLI) code [1] when

$$g_j^{(1)} = \begin{cases} g_j^{(1)}, & j \neq 1 \\ 1 + g_1^{(1)}, & j = 1. \end{cases}$$

QLI codes have some advantages in recovering the information sequence from the encoded sequence compared to general nonsystematic codes.

We shall find it convenient to write

$$t_{i_0,i_j} = (t_0^{(1)}, t_1^{(2)}, t_2^{(1)}, t_3^{(1)}, \ldots, t_{i_0,i_j}^{(1)}, t_{i_0,i_j}^{(2)}),$$

for the encoded path containing the first $n + 1 \sim branches" of the encoded sequence. The encoded path $t_{i_0,i_j}$ is called the first constraint length of the code. The jth order column distance [2] $d_j$ is the minimum Hamming distance between some $t_{i_0,i_j}$ resulting from an information sequence with $i_0 = 1$ and some $t_{i_0,i_j}$ with $i_0 = 0$. By linearity, $d_j$ is also the minimum of the Hamming weights of the paths $t_{i_0,i_j}$ resulting from information sequences with $i_0 = 1$.

The quantity $d_M$ is called the minimum distance of the convolutional code and determines the guaranteed error-correcting capability when the code is decoded by a "feedback decoder" [3]. The quantity $d_0$ is called the free distance of the code and has been found to be the principal determinant of decoding error probability when maximum-likelihood (or nearly so) decoding is used, i.e., for Viterbi decoding or sequential decoding [1, 4].

It has also been observed [1] that for good computational performance with sequential decoding, the column distances should "grow as rapidly as possible." We are led then to define the distance profile of the code as the $(M + 1)$-tuple

$$d = [d_0,d_1,\ldots,d_M]$$

and to say that a distance profile $d$ is superior to a distance profile $d'$ when there is some $n$ such that

$$d_j > d'_{j}, \quad j = 0, 1, \ldots, n = 1.$$

Thus $d > d'$ implies that the "early growth" of $d_j$ with $j$ is greater than that of $d'_j$ with $j$. (It could, of course, happen that for sufficiently large $j$, $d_j < d'_j$.)

We notice that only in the range $0 \leq j \leq M$ is each branch on a path $t_{i_0,i_j}$ affected by a new portion of the generator as one penetrates into the tree. The great dependence of the branches thereafter is due to the semi-infinite choice $d_w = \ldots
We shall say that a code is an optimal minimum distance (OMD) code (or an optimum free distance (ODF) code) or an optimum distance profile (ODP) code) when its minimum distance (or free distance or distance profile) is equal to or superior to that of any code with the same memory.

In Tables I–V we report the results of computer searches for binary convolutional codes that are robustly-optimal, i.e., optimal for one of the preceding distance measures and optimal or near-optimal for the other two. In cases where the optimum code is not unique, we have chosen a code with the fewest number of low-weight paths for the distance measure in question, e.g.,

\[d_1, d_2, \ldots, d_n,\] as does the fact that \(d_\infty\) is probably a description of the remainder of the column distances, which is quite adequate for all practical purposes.

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Fig. 1. Minimum distance $d_M$ and free distance $d_a$ for some rate $\frac{1}{2}$ convolutional codes.

Fig. 2. Minimum distance $d_M$ and free distance $d_a$ for some rate $\frac{1}{2}$ convolutional codes.
the fewest number of paths $t_{0,M}$ with Hamming weight $d_M$ resulting from information sequences with $i_0 = 1$ when $d_M$ is the distance measure in question.

In Table I we list ODP systematic codes for the range $1 \leq M < 14$. In all the tables we write the generators in the octal form where the first octal digit denotes $[g_0(g_1(g_2(g_3 g_4 g_5 g_6 g_7))); g_8(g_9); g_{10} g_{11}]$, the second denotes $[g_1(g_2(g_3 g_4 g_5 g_6 g_7); g_8(g_9); g_{10} g_{11} g_{12}]$, etc. (It should be noted that the “customary” octal notation for generators [5] uses $[g_0 g_1 g_2 g_3 g_4 g_5 g_6 g_7] g_8 g_9 g_{10}$ for the last octal digit, etc., so that the generators [1111] and [111101] become 17 and 75, respectively. In the notation here these would be 74 and 75, which we think better shows the fact that the former is a truncation of the latter.) In case of ties not resolved by the number of weight $d_M$ paths, we have chosen for Table I a code with the greatest $d_M$. The codes in Table I are all OMD codes as well as ODP codes. Since the “truncation” to smaller memory of an ODP code must give an ODP code for the reduced memory, the $M = 14$ code in Table I can be used to obtain an ODP code for all $M \leq 14$ but not necessarily one with the least number of low-weight paths.

For $M = 15$, we have found that an ODP code has $d_{15} = 8$ whereas an OMD code has $d_{15} = 5$ so there is no code that is both ODP and OMD for $M = 15$. We know of no other $M$ in the range $15 \leq M \leq 35$ with this property. In Table II we list the systematic ODP codes that we have found for $15 \leq M \leq 35$. For $M \geq 16$, the value of $d_M$ for OMD codes is unknown, but the codes in Table II have $d_M$ as large as any previously known codes. In fact, for $M = 30$ and $M = 34$, the codes in Table II have larger $d_M$ than any codes previously known. Moreover, the $M = 35$ code in Table II has $d_{35}$ superior to the best previously known systematic code, viz., the joint [6] code of Forney’s extension [7] of one of Bussgang’s optimal codes [6].

The excellence as regards $d_M$ of the systematic ODP codes in Tables I and II can be seen from Fig. 1 in which we have plotted $d_M$ for these codes and for the best of the codes found previously by Bussgang [6], Lin–Lyne [8], and Forney [7]. For comparison, we have also plotted the Gilbert lower bound [3] on $d_M$. To show the excellence of their $d_M$, we have also plotted $d_R$ for the ODP systematic codes and for the systematic codes found by Costello [2].

It should be mentioned that, in Table II (as well as later in Table III), a notation of $L$ indicates that $d_L$, which is a lower bound on $d_M$, is actually given rather than $d_M$, which is unknown. It is likely, however, that $d_M$ is in most, if not all, of these cases.

In Table III, we list the ODP QLI codes we have found for $1 \leq M \leq 23$. These codes, except when $M = 1$, are nonsystematic. QLI codes can generally achieve a greater $d_M$ for a given $M$ than is possible with systematic codes.

The excellence of the ODP QLI codes of Table III as regards $d_M$ and $d_R$ for these codes and $d_R$ for the QLI codes of Massey–Costello [1]. The ODP QLI codes of Table III appear very attractive for use with sequential decoding since 1) their QLI structure guarantees easy recovery of the information sequence from the encoded sequence with small “error amplification” [1]; 2) their ODP property ensures good computational performance; and 3) their large $d_M$ ensures a small decoding error probability.

In Table IV, we list the QLI codes that we have found to have the greatest $d_M$ for any QLI codes for $1 \leq M \leq 13$. For $M \leq 5$ these codes are also OFD, but for $M > 6$ larger $d_M$ is possible only with more general nonsystematic codes. Ties were resolved using first $d_R$ and then $d_M$ as further optimality criteria. The codes of Table IV appear attractive for use with Viterbi decoders for $1 \leq M \leq 5$.

In Table V, we list ODP general nonsystematic convolutional codes with ties resolved first according to $d_M$ and then according to $d_R$. The codes for $M \leq 10$ and $M = 13$ are all OFD codes [5], and it is surprising that the ODP property can be obtained over such a wide range at no sacrifice in free distance.

The excellence as regards $d_M$ of the codes in Table V can be seen from Fig. 2 where we have plotted their $d_M$ as well as that of the “complementary codes” found earlier by Bahl–Jelinek [9]. The codes of Table V are attractive candidates for use with Viterbi decoding when the QLI feature is of no interest. The $M = 5$ code in Table V is quite remarkable being simultaneously optimal for all three distance measures and also being QLI.

To illustrate the importance of the ODP property for sequential decoding computation, we have simulated the performance of a stack sequential decoder [10] on a binary symmetric channel (BSC) for 1) the ODP QLI code with $M = 23$, $d_M \geq d_1 = 19$, and $d_M = 11$ of Table III; 2) the $M = 23$ Massey–Costello QLI code [1] with $d_M \geq d_1 = 17$ and $d_M = 9$, which is currently being used by NASA in several deep-space programs; and 3) the $M = 23$ Bahl–Jelinek complementary code [9] with $d_M = 24$ and $d_M = 10$. The results of decoding 1000 frames of 256 information bits in length for each of these codes are given in Tables VI and VII for BSC’s with crossover probability $p$ of 0.045 and 0.057, respectively. No decoding errors were made in any case. It can be seen from Tables VI and VII that the computational performance of the ODP QLI code is far superior to the Massey–Costello QLI code and slightly better than the Bahl–Jelinek code that (while having larger $d_M$) lacks the desirable QLI property.
ACKNOWLEDGMENT

I would like to acknowledge gratefully the assistance and encouragement of Prof. James L. Massey, who also suggested the names "distance profile" and "robustly optimal." Finally, I am indebted to the American-Scandinavian Foundation and the Swedish Telephone Company, L. M. Ericsson for their support.

REFERENCES


A Class of Binoid Single-Error-Correcting Codes

VASILE V. MASGRAS

Abstract—A new class of group binoid single-error-correcting codes is given. The codes are nonbinary group codes over the additive group of integers modulo q.

I. NOTATION AND DEFINITIONS

Let n and q (n > q) be two positive integers. We denote by \( (n)_q \) the radix-q representation of n. Suppose that this representation has s digits. Let \( I_k^q \) be the following set:

\[
I_k^q = \{ i \mid 1 \leq i \leq n, (i)_q = i_1 \cdots i_k-1 i_{k+1} \cdots i_s \},
\]

\[ 1 \leq j \leq q - 1, \quad 1 \leq k \leq s. \]

We denote by \( Z_q \) the additive group of integers (mod q).

Definition 1: The set \( C \subset Z_q^n \) is the nonbinary group code [3], such that

\[ c = (c_1, \cdots, c_n) \in C \]

if and only if

\[ \sum_{i \in I_k^q} c_i = 0 \pmod{q}, \quad 1 \leq j \leq q - 1, \quad 1 \leq k \leq s. \] (1)

If we let \( r = \#(I_k^q) \setminus \phi, 1 \leq i \leq q - 1, 1 \leq k \leq s \), then the group code has \( r \) check symbols and \( m = n - r \) information symbols.

For \( q = 2 \) and \( n = 2^s - 1 \), C is a binary Hamming code [1], [2]. For \( q > 2 \), C represents another nonbinary generalization of the Hamming code [3].

Definition 2: A pair of sets \((A, M)\) is a binoid [4], if the following two conditions are satisfied:

i) there are two operations \( \oplus : A \times A \to A \) and \( \otimes : A \times M \to A \);

ii) the set \( A \) is a group with respect to the \( \oplus \) operation.

A binoid \((A, M)\) is called distributive if the \( \otimes \) operation is distributive with respect to the \( \oplus \) operation, and it will be termed commutative if \( A \) is a commutative group. The set \( A^* = \{ a \mid a \in A, a \otimes m \neq a \otimes m' \forall m, m' \in M, m \neq m' \} \) is called the univalence domain. If, in addition, we have \( A^* = A \setminus \{0\}, (A, M) \) is termed a completely univalent binoid.

Definition 3: A set \( C \subset A^n \) is a binoid code [4], if there is a set \( M \) such that following conditions are satisfied:

i) \((A, M)\) is a binoid;

ii) \( C \) is a nonbinary group code (of length \( n \));

iii) the parity check matrix of \( C \) has its components from \( M \).

II. LINK THEOREM

Taking into account Definitions 1 and 3, we may formulate the following theorem.

Theorem 1: The nonbinary group code \( C \) of Definition 1 is always a binoid code for \( M = \{0,1\} \), where \( \otimes \) is modulo \( q \) addition and \( \oplus \) is ordinary multiplication.

Proof: This is obvious if we note that the code \( C \) is the null space of the matrix \( H = [\delta_{j,k}] \), where \( \delta_{j,k} \in M = \{0,1\} \) are defined in the following way:

\[ \delta_{j,k} = \begin{cases} 1, & \text{if } i \in I_k^j \\ 0, & \text{if } i \notin I_k^j \end{cases} \] Q.E.D.

Any group code \( C \) may be regarded as a binoid code. The binoid \((A, M)\) is completely univalent.

III. DETECTION AND CORRECTION OF SINGLE ERROR

Theorem 2: The nonbinary group code \( C \subset Z_q^n \) of Definition 1 is a single-error-correcting code.

Proof: Let \( c = (c_1, \cdots, c_n) \) be a codeword and \( b = (b_1, \cdots, b_n) \) be the received vector. We define

\[ d_k^j = \sum_{i \in I_k^j} b_i \pmod{q}. \] (2)

If we assume that no more than a single error occurred, then we suppose

\[ b_i = \begin{cases} c_i + p \pmod{q}, & \text{for } i \neq h \\ c_i + h \pmod{q}, & \text{for } i = h \end{cases} \]

where \( p \) and \( h \) are the value and position of the error. We have

\[ b_i = c_i \oplus \delta_{i,h} p, \]

where \( \delta_{i,h} \) is the Kronecker symbol.

From the (2) congruences we have

\[
d_k^j = \sum_{i \in I_k^j} b_i - \sum_{i \in I_k^j} \delta_{j,k}^i \oplus b_i = \sum_{i=1}^n \delta_{j,k} i \oplus c_i \oplus \sum_{i=1}^n \delta_{j,k}^i \otimes \delta_{i,h} p = 0 \quad \text{or} \quad \delta_{i,h}^p h = \begin{cases} p, & \text{if } h \in I_k^j \\ 0, & \text{if } h \notin I_k^j \end{cases}.\]

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