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Asymptotic comparison of ML and MAP detectors for multidimensional constellations
IEEE Transactions on Information Theory, 64(2): 1231-1240
http://dx.doi.org/10.1109/TIT.2017.2727521

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Asymptotic Comparison of ML and MAP Detectors for Multidimensional Constellations

Alex Alvarado, Erik Agrell, and Fredrik Brännström

Abstract—A classical problem in digital communications is to evaluate the symbol error probability (SEP) and bit error probability (BEP) of a multidimensional constellation over an additive white Gaussian noise channel. In this paper, we revisit this problem for nonequally likely symbols and study the behavior of the optimal maximum a posteriori (MAP) detector at asymptotically high signal-to-noise ratios. Exact closed-form asymptotic expressions for SEP and BEP for arbitrary constellations and input distributions are presented. The well-known union bound expressions for SEP and BEP for arbitrary constellations and a priori probabilities are essentially ignored. For ML detection, therefore favor the (suboptimal) ML approach where the a priori probabilities are ignored. For ML detection, the decision regions are the so-called V oronoi regions, which correspond to the codebook size and codeword length, respectively. For ML detection, the decision regions are the so-called Voronoi regions, which do not depend on the SNR, and thus, are simpler to implement. Error probability analysis of constellations for the AWGN channel has been extensively investigated in the literature, see e.g., [2]–[7]. In fact, this a problem treated in many—if not all—digital communication textbooks. To the best of our knowledge, and to our surprise, the general problem of error probability analysis for multidimensional constellations with arbitrary input distributions and MAP detection has not been investigated in such a general setup.

As the SNR increases, the MAP decision regions tend towards the ML regions. Intuitively, one would then expect that both detectors are asymptotically equivalent, which would justify the use of ML detection. In this paper, we show that this is not the case. MAP and ML detection give different SEPs and BEPs asymptotically, where the difference lies in the factors before the dominant Q-function expression. More precisely, the ratio between the SEPs with MAP and ML detection approaches a constant, and the ratio between their BEPs approaches another constant. These constants are analytically calculated for arbitrary constellations, labelings, and input distributions. To the best of our knowledge, this has never been previously reported in the literature. Numerical results support our analytical results and clearly show the asymptotic suboptimality of ML detection.

All the results in this paper are presented in the context of detection of constellations with arbitrary number of dimensions. These multidimensional constellations, however, can be interpreted as finite-length codewords from a code, where the cardinality of the constellation and its dimensionality correspond to the codebook size and codeword length, respectively. In this context, the results of this paper can be used to study the performance of the MAP and ML sequence decoders at asymptotically high SNRs.

This paper is organized as follows. In Section II, the model is introduced and in Section III, the error probability bounds are presented. The main results of this paper are given in Section IV. Conclusions are drawn in Section V. All proofs are deferred to Appendices.

II. PRELIMINARIES

A. System Model

The system model under consideration is shown in Fig. 1. We consider the discrete-time, real-valued, N-dimensional, AWGN channel

\[ Y = X + Z, \]

where the transmitted symbol \( X \) belongs to a discrete constellation \( \mathcal{X} = \{ x_1, x_2, \ldots, x_M \} \) and \( Z \) is an \( N \)-dimensional
vector, independent of \( X \), whose components are independent and identically distributed Gaussian random variables with zero mean and variance \( \sigma^2 \) per dimension. The conditional channel transition probability is

\[
f(y|x) = \frac{1}{(2\pi\sigma^2)^{N/2}} \exp\left(-\frac{\|y-x\|^2}{2\sigma^2}\right).
\]  

We assume that the symbols are distinct and that each of them is transmitted with probability \( p_i = \Pr\{X = x_i\}, 0 < p_i < 1 \). Neither the constellation points nor their probabilities depend on \( \sigma \). We use the set \( \mathcal{I} = \{1, \ldots, M\} \) to enumerate the constellation points. The average symbol energy is \( E_s = \sum_{i \in \mathcal{I}} p_i \|x_i\|^2 < \infty \). The Euclidean distance between \( x_i \) and \( x_j \) is defined as \( \delta_{ij} = \|x_i - x_j\| \) and the minimum Euclidean distance (MED) of the constellation as \( d = \min_{i,j \in \mathcal{I} : i \neq j} \delta_{ij} \).

For the BEP analysis, assuming that \( M \) is a power of two, we consider a binary source that produces length-\( m \) binary labels. These labels are mapped to symbols in \( \mathcal{X} \) using a binary labeling, which is a one-to-one mapping between the \( M = 2^m \) different length-\( m \) binary labels and the constellation points. The length-\( m \) binary labels have an arbitrary input distribution, and thus, the same distribution is induced on the constellation points. The binary label of \( x_i \) is denoted by \( c_i \), where \( i \in \mathcal{I} \). The Hamming distance between \( c_i \) and \( c_j \) is denoted by \( \gamma_{ij} \).

At the receiver, we assume that (hard-decision) symbol-wise decisions are made. The estimated symbol is then mapped to a binary label to obtain an estimate on the transmitted bits. \(^1\)

For any received symbol \( y \), the MAP decision rule is\(^2\)

\[
\hat{X}^{\text{map}}(y) = \arg\max_{j \in \mathcal{I}} \{p_j f(y|x_j)\}.
\]  

This decision rule generates MAP decision regions defined as

\[
\mathcal{R}_j^{\text{map}}(\sigma) = \{y \in \mathbb{R}^N : p_j f(y|x_j) \geq p_i f(y|x_i), \forall i \in \mathcal{I}\} \quad (4)
\]

for all \( j \in \mathcal{I} \). Similarly, the ML detection rule is

\[
\hat{X}^{\text{ml}}(y) = \arg\max_{j \in \mathcal{I}} \{f(y|x_j)\},
\]

which results in the decision regions

\[
\mathcal{R}_j^{\text{ml}}(\sigma) = \{y \in \mathbb{R}^N : f(y|x_j) \geq f(y|x_i), \forall i \in \mathcal{I}\} \quad (6)
\]

**Example 1:** Consider the 32-ary constellation with the nonuniform input distribution in [9, Fig. 2, Table I]\(^3\). The constellation is shown in Fig. 2, where the area of the constellation points is proportional to the corresponding probabilities. In Fig. 2, the MAP and ML decision regions in (4) and (6) are shown for three values of the noise variance. These results show how the MAP regions converge to the ML regions as the noise variance decreases. \(\triangle\)

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig2.png}
\caption{ML (dashed blue) and MAP (solid red) decision regions for the constellation in Example 1 and three values of the noise variance. The area of the constellation points is proportional to their probabilities. As the noise variance decreases, the MAP regions converge to the ML regions.}
\end{figure}

**B. Error Probability**

Throughout this paper, the SEP and BEP are denoted by \( P_e(\sigma) \) and \( P_b(\sigma) \), respectively. Furthermore, we are interested in the error probability (SEP and BEP) of both the MAP and

---

\(^1\)This detector based on symbols has been shown in [8] to be suboptimal in terms of BEP; however, differences are expected only at high BEP values.

\(^2\)Throughout the paper, the superscripts “map” and “ml” denote quantities associated with MAP and ML detection, respectively.

\(^3\)Using three shaping bits, which results in radii 1, 2.53, 4.30.
TABLE I
VALUES OF $\hat{X}$ AND $h_{ij}$ THAT USED IN (7)–(9) GIVE SEP AND BEP
EXPRESSIONS FOR BOTH THE MAP AND ML DETECTORS. THE LAST COLUMN SHOWS THE VALUES OF $w_{ij}$ FOR THE ASYMPTOTIC EXPRESSIONS IN SECTION IV.

<table>
<thead>
<tr>
<th>$P(\sigma)$</th>
<th>$\hat{X}$</th>
<th>$h_{ij}$</th>
<th>$w_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_s^{\text{map}}(\sigma)$</td>
<td>$\hat{X}_{\text{map}}$</td>
<td>1</td>
<td>$\sqrt{p_j/p_i}$</td>
</tr>
<tr>
<td>$P_s^{\text{ml}}(\sigma)$</td>
<td>$\hat{X}_{\text{ml}}$</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$P_b^{\text{map}}(\sigma)$</td>
<td>$\hat{X}_{\text{map}}$</td>
<td>$\gamma_{ij}$</td>
<td>$\sqrt{p_j/p_i}$</td>
</tr>
<tr>
<td>$P_b^{\text{ml}}(\sigma)$</td>
<td>$\hat{X}_{\text{ml}}$</td>
<td>$\gamma_{ij}$</td>
<td>1</td>
</tr>
</tbody>
</table>

ML detectors. To study these four error probabilities, we define the generic error probability function

$$P(\sigma) = \sum_{i \in I} p_i \sum_{j \in I, j \neq i} h_{ij} T_{ij}(\sigma), \quad (7)$$

where the transition probability $T_{ij}(\sigma)$ is given by

$$T_{ij}(\sigma) = \Pr\{ \hat{X}(Y) = x_j | X = x_i \} \quad (8)$$

$$= \Pr\{ Y \in R_{ij}(\sigma) | X = x_i \} \quad (9)$$

The expressions (7)–(9) represent both the MAP and ML detectors, as well as both the SEP and BEP, as explained in the following.

The error probability with MAP detection is obtaining by using $R_{ij}(\sigma) = R_{ij}^{\text{map}}(\sigma)$ in (9), where $R_{ij}^{\text{map}}(\sigma)$ is given by (4). Similarly, the use of $R_{ij}(\sigma) = R_{ij}^{\text{ml}}(\sigma)$ in (9), where $R_{ij}^{\text{ml}}(\sigma)$ is given by (6), leads to the error probability with ML detection.

To study the SEP, $h_{ij}$ in (7) should be set to one, which gives the well-known expression

$$P_s(\sigma) = \sum_{i \in I} p_i \sum_{j \in I, j \neq i} T_{ij}(\sigma). \quad (10)$$

Similarly, the BEP expression [10, Eq. (1)], [11, Eq. (1)]

$$P_b(\sigma) = \sum_{i \in I} p_i \sum_{j \in I, j \neq i} \frac{\gamma_{ij}}{m} T_{ij}(\sigma) \quad (11)$$

is obtained by using $h_{ij} = \gamma_{ij}/m$ in (7). The four cases discussed above are summarized in the first three columns of Table I.

## III. ERROR PROBABILITY BOUNDS

Error probability calculations for arbitrary multidimensional constellations and finite SNR are difficult because the decision regions defining the transition probabilities $T_{ij}(\sigma)$ in (9) are in general irregular. Therefore, to analytically study the error probability, bounding techniques are usually the preferred alternative. In this section, we present two lemmas that give upper and lower bounds on the transition probability $T_{ij}(\sigma)$. These bounds are expressed in terms of the Gaussian Q-function $Q(x) = (1/\sqrt{2\pi}) \int_x^\infty \exp(-\xi^2/2) \, d\xi$ and will then be used to upper- and lower-bound the SEP and BEP in Section IV.

**Lemma 1:** For any $i, j \in I, j \neq i$,

$$T_{ij}(\sigma) \leq Q\left(\frac{\Delta_{ij}(\sigma)}{\sigma}\right), \quad (12)$$

where

$$\Delta_{ij}(\sigma) = \begin{cases} \frac{\delta_{ij}}{\sigma} \left(1 + \frac{\sigma^2}{\delta_{ij}} \log \frac{p_j}{p_i}\right), & \text{for MAP,} \\ \frac{\delta_{ij}}{\sigma}, & \text{for ML.} \end{cases} \quad (13)$$

**Proof:** See Appendix A.

**Lemma 2:** For any $i, j \in I, j \neq i$ and any $\sigma < \tau_{ij}$,

$$T_{ij}(\sigma) \geq \begin{cases} \frac{1}{2} \left( Q\left(\frac{\Delta_{ij}(\sigma)}{\sigma}\right) - Q\left(\frac{d}{2\sigma} + \frac{r(\sigma)}{\sqrt{N\sigma}}\right) \right), & \text{if } \delta_{ij} > d, \\ \left(1 - 2Q\left(\frac{r(\sigma)}{\sqrt{N\sigma}}\right)\right)^{N-1}, & \text{if } \delta_{ij} = d, \end{cases} \quad (14)$$

where $\Delta_{ij}(\sigma)$ is given by (13),

$$r(\sigma) = \frac{d^2 - 4\sigma^2 \log \max_{a,b \in I} \left\{ \frac{p_a}{p_b} \right\}}{2(1 + \sqrt{3})d} \quad (15)$$

and

$$\tau_{ij} = d \left(2(1 + \sqrt{3})\sqrt{N} \log \left| \frac{p_i}{p_j} \right| + 4 \log \max_{a,b \in I} \left\{ \frac{p_a}{p_b} \right\} \right)^{-\frac{1}{2}}. \quad (16)$$

**Proof:** See Appendix B.

The results in Lemmas 1 and 2 can be combined with (7) to obtain upper and lower bounds on the error probability:

$$P(\sigma) \leq \sum_{i \in I} p_i \sum_{j \in I, j \neq i} h_{ij} Q\left(\frac{\Delta_{ij}(\sigma)}{\sigma}\right) \quad (17)$$

and

$$P(\sigma) \geq \sum_{i \in I} p_i \sum_{j \in I, \delta_{ij} = d} h_{ij} \left( Q\left(\frac{\Delta_{ij}(\sigma)}{\sigma}\right) - Q\left(\frac{d}{2\sigma} + \frac{r(\sigma)}{\sqrt{N\sigma}}\right) \right) \cdot \left(1 - 2Q\left(\frac{r(\sigma)}{\sqrt{N\sigma}}\right)\right)^{N-1}, \quad \sigma < \min_{i,j \in I} \tau_{ij}, \quad (18)$$

where $\Delta_{ij}(\sigma)$, $r(\sigma)$, and $\tau_{ij}$ are given by (13), (15), and (16), respectively. In the next section, it will be proved that both these bounds are tight for asymptotically high SNR.

## IV. HIGH-SNR ASYMPTOTICS OF THE SEP AND BEP

### A. Main Results

The following theorem gives an asymptotic expression for the error probability in (7), i.e., it describes the asymptotic behavior of the MAP and ML detectors, for both SEP and BEP. The results are given in terms of the input probabilities $p_i$, the Euclidean distances between constellation points $\delta_{ij}$, the MED of the constellation $d$, and the Hamming distances between the binary labels of the constellation points $\gamma_{ij}$. The results in this section will be discussed later in Section IV-B. Numerical results will be presented in Section IV-C.
where
\[ B = \sum_{i \in I} \sum_{j \in I} h_{ij} w_{ij} \] (20)
and where \( h_{ij} \) and \( w_{ij} \) are constants given in Table I and \( Q(\cdot) \) is the Gaussian Q-function.

Proof: See Appendix C. □

The following corollary shows that, at high SNR, the ratio between the error probability with MAP and ML detection approaches a constant \( R \leq 1 \). This constant shows the asymptotic suboptimality of ML detection: when \( R < 1 \) an asymptotic penalty is expected, but when \( R = 1 \) both detectors are asymptotically equivalent.

Corollary 4: For any input distribution and for either SEP or BEP,
\[ \lim_{\sigma \to 0} \frac{P_{\text{map}}(\sigma)}{P_{\text{ml}}(\sigma)} = R, \] (21)
where
\[ R = \frac{B_{\text{map}}}{B_{\text{ml}}} = \frac{1}{\sum_{i \in I} \sum_{j \in I} h_{ij} \sqrt{\frac{p_j}{p_i}}}, \] (22)
where \( h_{ij} \) is a constant given in Table I. Furthermore, \( R \leq 1 \) with equality if and only if \( p_i = p_j, \forall i, j : \delta_{ij} = d \).

Proof: See Appendix D. □

B. Discussion

Theorem 3 generalizes [12, Ths. 3 and 7] to arbitrary multidimensional constellations. Somewhat surprisingly, Theorem 3 in fact shows that [12, Ths. 3 and 7] apply verbatim to multidimensional constellations. The result in Theorem 3 for the particular case of SEP with ML detection also coincides with the approximation presented in [7, Eqs. (1)–(2)].

Theorem 3 can therefore be seen as a formal proof of the asymptotic approximation in [7, Eqs. (1)–(2)] as well as its generalization to MAP detection for SEP and to both MAP and ML detection for BEP.

Recognizing \( BQ(d/(2\sigma)) \) as the dominant term in the union bound, Theorem 3 in fact proves that the union bound is tight for both SEP and BEP with arbitrary multidimensional constellations, arbitrary labelings and input distributions, and both MAP and ML detection, which, to the best of our knowledge, has not been previously reported in the literature. The special case of SEP with uniform input distribution and ML detection was elegantly proved in [13, Eqs. (7.10)–(7.15)] using an asymptotically tight lower bound.  

Note that the lower bound in (18) is identical for MAP and ML detection when \( R = 1 \), since \( \Delta_{ij}(\sigma) = d/2 \) in both cases. The upper bound in (17), however, is always different for MAP and ML detection as long as the symbols are not equally likely, even when \( R = 1 \).

C. Examples

Example 2: Consider again the constellation in Example 1 (see Fig. 2) with the labeling specified in [9, Fig. 2]. Fig. 4 (a) shows the simulated BEPs (red markers) together with the upper bounds in (17) (green), the lower bounds in (18) (cyan), and the asymptotic approximations \( P_b(\sigma) \approx BQ(d/(2\sigma)) \) from (19) (blue). The solid and dotted curves represent MAP and ML detection, respectively. The lower bounds are only defined when \( E_b/\sigma^2 > 20.78 \text{ dB} \), due to the restrictions on \( \sigma \) in (18). These results show very small differences between the
MAP and ML detectors. To see the asymptotic behavior more clearly, Fig. 4 (b) shows the ratio between the eight curves in Fig. 4 (a) and $Q(d/(2\sigma))$. It is clear that the simulated BEPs closely follow the upper bounds at these SNR values. These results also show that both the upper and lower bounds converge to $B_b^{\text{map}} = 0.1450$ and $B_b^{\text{ml}} = 0.1495$ for MAP and ML detection, respectively, as predicted by Theorem 3. Unlike Fig. 4 (a), Fig. 4 (b) clearly shows the asymptotic difference between the MAP and ML detectors, since $R_b = 0.97$.

The gap between $P_b^{\text{map}}$ and $P_b^{\text{ml}}$ depends on the bit labeling, but not as strongly as on the probability distribution. It can be shown that for the probabilities in this example, $0.956 < R_b < 0.989$ for any labeling. On the other hand, for this labeling, $R_b$ can be made equal to any value in the interval $[0, 1]$ by changing the probabilities.

Corollary 4 gives necessary and sufficient conditions for the asymptotic optimality of ML detection for both SEP and BEP. A nonuniform distribution will in general give $R < 1$, although there are exceptions. Consider for example a constellation that can be divided into clusters, where all pairs of constellation points in different clusters are at distances larger than the MED. Then ML detection is asymptotically optimal (i.e., $R = 1$) if the probabilities of all constellations points within a cluster are equal, even if the clusters have different probabilities. In this special case, (20) for SEP yields $B_s^{\text{map}} = B_s^{\text{ml}} = \sum_{i \in I} p_i G_i$, where $G_i$ is the number of neighbors at MED from point $i$. We illustrate this concept with the following example.

**Example 4:** Fig. 5 (a) illustrates the two-dimensional constellation in [15, Fig. 3 (d)]. We let the symbols in the inner ring be used with probability $p_1$ each and the symbols in the outer ring with probability $p_2 = (1 - 4p_1)/12$. The radii of the two rings are $r_1 = 0.71d$ and $r_2 = 1.93d$, and the average symbol energy is $E_s = 4p_1 r_1^2 + 12p_2 r_2^2$. Fig. 5 (b) shows the simulated ratio $P_s(\sigma)/Q(d/(2\sigma))$ when $p_1 = 0.22$ and $p_2 = 0.01$ for ML (red circles) and MAP (red crosses) detection. The upper bounds in (17), the lower bounds in (18), and the asymptotic expression, all divided by $Q(d/(2\sigma))$, are included as green, cyan, and blue curves, respectively. In this case, the lower bounds for ML and MAP detection are
identical, as are the asymptotes. For this specific constellation, $G_i = 2$ for all $i \in \mathcal{I}$, and hence, $B_{\text{map}} = B_{\text{ml}} = 2$, independently of $p_1$ and $p_2$, which implies $R_b = 1$. In terms of BEP, $P_{b,\text{map}} = P_{b,\text{ml}}$, hence $R_b = 1$, regardless of both the labeling and $p_1$ and $p_2$. This shows that for this particular nonuniform constellation, both ML and MAP detectors are asymptotically equivalent for SEP and BEP for all labelings.

V. CONCLUSIONS

In this paper, an analytical characterization of the asymptotic behavior of the MAP and ML detectors in terms of SEP and BEP for arbitrary multidimensional constellations over the AWGN channel was presented. The four obtained results from Theorem 3 and Table I can be summarized as

$$P_{b,\text{map}}(\sigma) \approx Q\left(\frac{d}{2\sigma}\right) \sum_{i,j \in \mathcal{I}, \delta_{ij} = d} \frac{\gamma_{ij}}{m} \sqrt{p_i p_j},$$

$$P_{b,\text{ml}}(\sigma) \approx Q\left(\frac{d}{2\sigma}\right) \sum_{i,j \in \mathcal{I}, \delta_{ij} = d} \frac{\gamma_{ij}}{m} p_i,$$

$$P_{s,\text{map}}(\sigma) \approx Q\left(\frac{d}{2\sigma}\right) \sum_{i,j \in \mathcal{I}, \delta_{ij} = d} \sqrt{p_i p_j},$$

$$P_{s,\text{ml}}(\sigma) \approx Q\left(\frac{d}{2\sigma}\right) \sum_{i \in \mathcal{I}} p_i,$$

where the relative error in all approximations approaches zero as $\sigma \to 0$. The expressions for MAP and ML are equal if and only if $p_i = p_j, \forall i, j : \delta_{ij} = d$.

Somewhat surprisingly, the results in this paper are the first ones that address the problem in such a general setup. The theoretical analysis shows that for nonuniform input distributions, ML detection is in general asymptotically suboptimal. In most practically relevant cases, however, MAP and ML detection give very similar asymptotic results. The results in this paper are first-order only. An asymptotic analysis considering higher order terms is left for further investigation.

Most modern transceivers based on high-order modulation formats use a receiver that operates at a bit level (i.e., a bitwise receiver). Because of this, the binary labeling of the constellation plays a fundamental role in the system design. Furthermore, the use of nonequally likely symbols (probabilistic shaping) has recently received renewed attention in the literature. In this context, the asymptotic BER expressions

![Figure 4](image-url)

Fig. 4. Results obtained for the constellation in Example 3: (a) BEP with MAP and ML detection, and (b) ratio between BEPs in (a) and $Q(d/(2\sigma))$.

![Figure 5](image-url)

Fig. 5. Results obtained for the constellation in Example 4: (a) Constellation where the pairs of symbols at MED are marked with solid lines and the symbol probabilities are indicated by the point areas, and (b) asymptotic performance shown as the ratio between SEPs and $Q(d/(2\sigma))$. 


presented in this paper can be used to optimize both the constellations and the binary labeling. This is also left for further investigation.

ACKNOWLEDGMENT

We would like to thank Prof. F. R. Kschischang for insightful comments on our poster “Asymptotic Error Probability Expressions for the MAP Detector and Multidimensional Constellations,” presented at the Recent Results Poster Session of ISIT 2016, Barcelona.

APPENDIX A

PROOF OF LEMMA 1

For MAP detection, we have from (9) and (4) that

\[ T_{ij}^{\text{map}}(\sigma) \leq \Pr\{Y \in \mathcal{H}_{ij}^{\text{map}}(\sigma) | X = x_i\}, \]  
(27)

where \( \mathcal{H}_{ij}^{\text{map}}(\sigma) \) is the half-space determined by a pairwise MAP decision (see (3)–(4)), i.e.,

\[ \mathcal{H}_{ij}^{\text{map}}(\sigma) = \{ y \in \mathbb{R}^N : p_i f(y|x_i) \leq p_j f(y|x_j) \}. \]  
(28)

Using (2), (28) can be expressed as

\[ \mathcal{H}_{ij}^{\text{map}}(\sigma) = \left\{ y \in \mathbb{R}^N : \left\langle y - x_i, \frac{d_{ij}}{\delta_{ij}} \right\rangle \geq \Delta_{ij}(\sigma) \right\}, \]  
(29)

where \( \Delta_{ij}(\sigma) \) is given by (13) and \( d_{ij} = x_j - x_i \). The value of \( |\Delta_{ij}(\sigma)| \) is the shortest Euclidean distance between \( x_i \) and the hyperplane defining the half-space \( \mathcal{H}_{ij}^{\text{map}}(\sigma) \). For a geometric interpretation, see \( \mathcal{H}_{ij}^{\text{map}}(\sigma) \) in Fig. 6.

Using (29), (27) can be calculated as

\[ T_{ij}^{\text{map}}(\sigma) \leq \Pr\left\{ \left\langle Y - X, \frac{d_{ij}}{\delta_{ij}} \right\rangle \geq \Delta_{ij}(\sigma) \mid X = x_i \right\} \]  
(30)

\[ = Q\left( \frac{\Delta_{ij}(\sigma)}{\sigma} \right), \]  
(31)

where (31) follows from (1)–(2) by recognizing \( \langle Y - X, d_{ij}/\delta_{ij} \rangle \) as a zero-mean Gaussian random variable with variance \( \sigma^2 \).

The proof for the ML case is analogous but starts from (6) instead of (4). If follows straightforwardly that \( \mathcal{H}_{ij}^{\text{ml}}(\sigma) \) is also given by (29), where now \( \Delta_{ij}(\sigma) = \delta_{ij}/2 \) defines a hyperplane half-way between \( x_i \) and \( x_j \).

APPENDIX B

PROOF OF LEMMA 2

To lower-bound (9) for MAP detection, we first ignore all the contributions of constellation points not at MED, i.e., we use \( \Pr\{Y \in \mathcal{R}_{ij}^{\text{map}}(\sigma) \mid X = x_i\} \geq 0 \), for all \( j \) such that \( \delta_{ij} > d \). This gives the first case in (14).

The case of \( \delta_{ij} = d \) is addressed by first defining an \( N \)-dimensional hypersphere centered at the mid-point \( \bar{x}_{ij} = \frac{1}{2}(x_i + x_j) \) and of radius \( r(\sigma) \) defined in (15). Second, we inscribe an \( N \)-dimensional hypercube with half-side \( r(\sigma)/\sqrt{N} \) inside this hypersphere. And third, we rotate this hypercube so that one of its sides is perpendicular to \( d_{ij} \). We denote this hypercube by \( \mathcal{C}_{ij}(\sigma) \). For a geometric interpretation when \( N = 2 \), see Fig. 6.

To lower-bound (9), we integrate \( f(y|x) \) in (2) over the intersection of the MAP region \( \mathcal{R}_{ij}^{\text{map}}(\sigma) \) and the hypercube \( \mathcal{C}_{ij}(\sigma) \), i.e.,

\[ T_{ij}^{\text{map}}(\sigma) = \int_{\mathcal{R}_{ij}^{\text{map}}(\sigma) \cap \mathcal{C}_{ij}(\sigma)} f(y|x_i) \, dy \]  
(32)

\[ \geq \int_{\mathcal{R}_{ij}^{\text{map}}(\sigma) \cap \mathcal{C}_{ij}(\sigma)} f(y|x_i) \, dy. \]  
(33)

We will prove that for sufficiently low values of \( \sigma \), the integration region in (33) is an orthotope (hyperrectangle), as illustrated for \( x_i \) and \( x_j \) in Fig. 6. This will be done in three steps. We will show first that the hypercube \( \mathcal{C}_{ij}(\sigma) \) is nonempty, second that it does not intersect any region \( \mathcal{R}_k^{\text{map}}(\sigma) \) for \( k \notin \{i, j\} \), and third that \( \mathcal{C}_{ij}(\sigma) \) intersects both \( \mathcal{R}_k^{\text{map}}(\sigma) \) and \( \mathcal{R}_j^{\text{map}}(\sigma) \). Together these three facts imply that \( \mathcal{R}_i^{\text{map}}(\sigma) \cap \mathcal{C}_{ij}(\sigma) \) is an orthotope, whose dimensions are then determined, which allows the integral in (33) to be calculated exactly.

For the first step, combining (15) and (16) and rearranging terms yields for any \( i, j \in \mathcal{I} \) with \( j \neq i \)

\[ \frac{d^2}{\sigma^2} - \frac{d^2}{\tau_{ij}^2} = 2(1 + \sqrt{3}) \left( \frac{dr(\sigma)}{\sigma^2} - \sqrt{N} \log \left| \frac{p_i}{p_j} \right| \right). \]  
(34)

If \( \sigma < \tau_{ij} \), then (34) implies

\[ \frac{r(\sigma)}{\sqrt{N}} > \frac{\sigma^2}{d} \left| \log \frac{p_i}{p_j} \right|. \]  
(35)
This inequality, to which we will return later, shows that $r(\sigma) > 0$ and hence that $C_{ij}(\sigma)$ is not empty.

For the second step, we consider any $i, j, k \in I$ such that $\delta_{ij} = d$ and $k \notin \{i, j\}$. We have

\[
d^2 \leq \min_{\ell \in \{i, j\}} \|x_k - x_{\ell}\|^2
\]

\[
= \min_{\ell \in \{i, j\}} \|x_k - x_{\ell} - (x_{\ell} - x_{ij})\|^2
\]

\[
= \|x_k - x_{ij}\|^2 - 2 \max_{\ell \in \{i, j\}} \langle x_k - x_{ij}, x_{\ell} - x_{ij} \rangle + \frac{d^2}{4}
\]

\[
\leq \|x_k - x_{ij}\|^2 + \frac{d^2}{4},
\]

where (38) follows because $\|x_i - x_{ij}\|^2 = \|x_j - x_{ij}\|^2 = d^2/4$ and (39) because $x_i - x_{ij} = -(x_j - x_{ij})$ in the second term of (38). Hence, $\|x_k - x_{ij}\| \geq d\sqrt{3}/2$. Consider now any point $y \in C(\sigma)$. By the triangle inequality, $\|y - x_k\| \geq \|x_k - x_{ij}\| - \|y - x_{ij}\| \geq d\sqrt{3}/2 - r(\sigma)$ and $\|y - x_{ij}\| \leq \|x_i - x_{ij}\| + \|y - x_{ij}\| \leq d/2 + r(\sigma)$, which are then combined into

\[
\|y - x_k\|^2 - \|y - x_{ij}\|^2 \geq \left(\frac{d\sqrt{3}}{2} - r(\sigma)\right)^2 - \left(\frac{d}{2} + r(\sigma)\right)^2
\]

\[
= \frac{d^2}{2} - \left(1 + \sqrt{3}\right) dr(\sigma)
\]

\[
= 2\sigma^2 \log \max_{a,b \in I} \left\{ \frac{p_a}{p_b} \right\}
\]

\[
\geq 2\sigma^2 \log \frac{p_k}{p_i},
\]

where (42) follows from (15). Rearranging terms,

\[
p_k \exp\left(\frac{\|y - x_k\|^2}{2\sigma^2}\right) \leq p_i \exp\left(-\frac{\|y - x_{ij}\|^2}{2\sigma^2}\right),
\]

which via (2) and (4) implies $y \notin \mathcal{R}^\text{map}_{k}(\sigma)$. Hence, $C_{ij}(\sigma) \cap \mathcal{R}^\text{map}_{k}(\sigma) = \emptyset$ and (33) can be written as

\[
T_{ij}(\sigma) \geq \int_{\mathcal{H}_{ij}(\sigma) \cap C_{ij}(\sigma)} f(y|x_i) dy.
\]

For the third step, we return to (35), which holds for any pair $i, j \in I$ with $j \neq i$. In the special case when $\delta_{ij} = d$, (35) and (13) yield

\[
\frac{d}{2} - \frac{r(\sigma)}{\sqrt{N}} < \Delta_{ij}(\sigma) < \frac{d}{2} + \frac{r(\sigma)}{\sqrt{N}}.
\]

Since $\Delta_{ij}(\sigma)$ gives the distance between $x_i$ and $\mathcal{R}^\text{map}_{k}(\sigma)$, and $d/2 \pm r(\sigma)/\sqrt{N}$ gives the distance between $x_i$ and two opposite facets of the hypercube $C_{ij}(\sigma)$, (46) implies that $\mathcal{H}_{ij}(\sigma) \cap C_{ij}(\sigma)$ is a (nonempty) orthotope with thickness $d/2 + r(\sigma)/\sqrt{N} - \Delta_{ij}(\sigma)$. Carrying out the integration in (45) over this orthotope gives the second case of (14), which completes the proof of Lemma 2 for MAP detection.

The proof for ML detection is obtained similarly. The hypercube $C_{ij}(\sigma)$ is defined in the same way as before, and the analysis is identical up to (42). Equation (43) is replaced by $\|y - x_k\|^2 - \|y - x_{ij}\|^2 \geq 0$, which via (2) and (6) implies $y \notin \mathcal{R}_{k}^\text{ml}(\sigma)$. Hence, (45) is still valid and so is (46), except that $\Delta_{ij}(\sigma)$ in (46) is now equal to $d/2$ in accordance with (13). The thickness of $\mathcal{H}_{ij}(\sigma) \cap C_{ij}(\sigma)$ is thus $r(\sigma)/\sqrt{N}$, which proves (14) for ML detection.

APPENDIX C

PROOF OF THEOREM 3

To prove Theorem 3, we first use (7) to obtain

\[
\lim_{\sigma \to 0} \frac{T_{ij}(\sigma)}{Q(d/2\sigma)} = \sum_{i \in I} \lim_{\sigma \to 0} h_{ij} \frac{T_{ij}(\sigma)}{Q(d/2\sigma)}.
\]

As will become apparent later, the limit on the right hand side of (47) exists and, hence, so does the limit on the left hand side. To calculate the limit in the right hand side of (47), we will sandwich it using Lemmas 1 and 2.

For MAP detection, we first study the asymptotic behavior of the upper bound in Lemma 1

\[
\lim_{\sigma \to 0} \frac{T_{ij}^\text{map}(\sigma)}{Q(d/2\sigma)}
\]

\[
\leq \lim_{\sigma \to 0} \frac{Q(\Delta_{ij}(\sigma)/\sigma)}{Q(d/2\sigma)}
\]

\[
= \lim_{\sigma \to 0} \frac{Q(\Delta_{ij}(\sigma)/\sigma)}{Q(d/2\sigma)}
\]

\[
\leq \lim_{\sigma \to 0} \frac{\delta_{ij}}{2\sigma^2} \log \left(\frac{p_j}{p_i}\right)
\]

\[
= \lim_{\sigma \to 0} \frac{\delta_{ij}}{2\sigma^2} \log \left(\frac{p_j}{p_i}\right)
\]

\[
\leq 0, \quad \text{if } \delta_{ij} > d,
\]

\[
\leq \frac{\delta_{ij}}{2\sigma^2} \log \left(\frac{p_j}{p_i}\right), \quad \text{if } \delta_{ij} = d,
\]

where (50) follows from l’Hôpital’s rule [16, Sec. 11.2].

Next, we study the asymptotic behavior of the lower bound in Lemma 2 for $\delta_{ij} = d$ (the lower bound (14) is zero for $\delta_{ij} > d$). Assuming that all the limits exist, we obtain

\[
\lim_{\sigma \to 0} \frac{T_{ij}^\text{map}(\sigma)}{Q(d/2\sigma)}
\]

\[
\geq \lim_{\sigma \to 0} \frac{Q(\Delta_{ij}(\sigma)/\sigma)}{Q(d/2\sigma)}
\]

\[
= \left[ \lim_{\sigma \to 0} \frac{Q(\Delta_{ij}(\sigma)/\sigma)}{Q(d/2\sigma)} - \lim_{\sigma \to 0} \frac{Q(\Delta_{ij}(\sigma)/\sigma)}{Q(d/2\sigma)} \right]
\]

\[
\left(1 - 2Q\left(\frac{r(\sigma)}{\sqrt{N}}\right)^N\right).
\]
The first limit in (54) is the same as in (48)–(52). The second limit is zero and the last limit is one because by (15), \( \lim_{\sigma \to 0} r(\sigma) = d/(2(1 + \sqrt{3})) \). Hence, all limits exist and asymptotically, both lower and upper bounds converge to (52).

Using this in (47) gives

\[
\lim_{\sigma \to 0} \frac{P(\sigma)}{Q \left( \frac{d}{\sigma^2} \right)} = \sum_{i \in I} p_i \sum_{j \in I, \delta_{ij} = d} h_{ij} \sqrt{p_j} \frac{p_j}{p_i},
\]

which completes the proof for ML detection.

The proof for ML detection follows similar steps. Substituting \( \Delta_{ij}(\sigma) = \delta_{ij}/2 \) from (13) into (48) yields

\[
\lim_{\sigma \to 0} T_{ij}^{\text{ml}}(\sigma) = \lim_{\sigma \to 0} \frac{Q \left( \frac{\delta_{ij}}{\sigma} \right)}{Q \left( \frac{d}{\sigma^2} \right)}
\]

where

\[
\begin{cases} 
0, & \text{if } \delta_{ij} > d, \\ 
1, & \text{if } \delta_{ij} = d.
\end{cases}
\]

The asymptotic expression for the lower bound in (54) holds unchanged in the ML case too. In this case, the first limit is given by (57), the second is zero, and the third is one. This combined with (47) completes the proof for ML detection.

**APPENDIX D**

**PROOF OF COROLLARY 4**

Equations (21)–(22) follow immediately from (19)–(20). To prove \( R \leq 1 \), we need to prove

\[
\sum_{i,j \in I, \delta_{ij} = d} h_{ij} p_i - \sum_{i,j \in I, \delta_{ij} = d} h_{ij} \sqrt{p_j} p_i \geq 0.
\]

Using \( h_{ij} = h_{ji} \) and \( \delta_{ij} = \delta_{ji} \), we obtain

\[
\sum_{i,j \in I, \delta_{ij} = d} h_{ij} (p_i - \sqrt{p_j} p_i) = \frac{1}{2} \sum_{i \in I, \delta_{ij} = d} h_{ij} (p_i - \sqrt{p_j} p_i) + \frac{1}{2} \sum_{j \in I, \delta_{ij} = d} h_{ji} (p_j - \sqrt{p_i} p_j)
\]

\[
= \frac{1}{2} \sum_{i \in I, \delta_{ij} = d} h_{ij} (p_i + p_j - 2\sqrt{p_j} p_i)
\]

\[
= \frac{1}{2} \sum_{i \in I, \delta_{ij} = d} h_{ij} \left( \sqrt{p_i} - \sqrt{p_j} \right)^2 
\]

\[
\geq 0,
\]

which holds with equality if and only if \( p_i = p_j, \forall i,j : \delta_{ij} = d \).

**REFERENCES**


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