Handover Detection based on Dimension estimation

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***Abstract*—In this paper, we aim to derive closed-form expressions for the False Alarm probabilities associated with a given threshold for the Dimension Estimation Detector (DED) using the Akaike Information Criterion (AIC) and the Minimum Description Length (MDL) criterion. Particularly, we will formulate the DED algorithm as a binary hypothesis test utilizing AIC and MDL curves. According to the suggested statistical test, we'll quantify the probability of False Alarms in the DED algorithm at a set threshold. The validation of this new method is based on Numerical Applications simulated on Matlab.**

5G Networks, Handovers, Dimension Estimation, Performance Estimation, Probability of Detection.

I. Introduction

In recent decades, there has been a surging demand for Mobile Cellular Communications Systems [1], driven by users' desires for increasingly flexible, wireless, compact, and convenient devices. Consequently, this demand has led to the necessity for extensive network densification.

In this paper, our idea is to operate a new Handover Detection based on Dimension Estimation [2]. The study outlined in reference [3] recommends employing model selection tools such as the AIC and the MDL criterion to determine the characteristics of the sensed band. The mentioned tools served as detection rules for the Dimension Estimation Detector (DED) [4] [5].

Recent works [6] [7] have suggested the utilization of AIC as a promising technique in the context of Handover Detection.

It has been demonstrated in [5], that based on the number of independent eigenvectors derived from a given covariance matrix of the observed signal, conclusions can be drawn regarding the nature of this signal.

In this paper, we adopt the same framework to detect the presence of handovers. We explore the AIC criterion for sensing handover presence, focusing on analyzing the number of significant eigenvalues determined by the value minimizing the AIC criterion. Specifically, we will demonstrate that the number of significant eigenvalues is directly linked to the presence or absence of handovers. Simulations illustrate that the proposed technique enables blind handover detection in both time and frequency domains.

The rest of the paper is organized as follows. We start by providing the Formulation of the Problem in section II. A presentation of Dimension Estimation Detection in section III. The Probability of False Alarm is described in section IV. In section V, the numerical applications are provided for comparing our models. Our paper ends with a conclusion.

II. Problem Formulation

In this section, we delineate the channel model that will be consistently employed throughout the paper and formulate the problem.

The transmitted signal undergoes convolution with a multipath channel, to which Gaussian noise is subsequently added. The resulting received signal, represented by $q * 1$ complex vector x, can be expressed as,

$$x = As + n \tag{1}$$

where A is a $q * p$ complex matrix whose columns are determined by the anonymous parameters related to each signal. s is a $p * 1$ complex vector and n is a complex, stationary, and Gaussian noise with zero mean and covariance matrix $E(nn^H) = \sigma_n^2 I_n$. In this paper, we aim to ascertain the value of q based on N observations of x.

Since the noise is zero-mean and independent of the signals, the covariance matrix of $x(t)$ is defined as follows:

$$R = \Psi + \sigma^2 I \tag{2}$$

where

$$\Psi = ASA^H \tag{3}$$

with S denoting the covariance matrix of the signals, i.e., $S = E\{ss^H\}$, and σ^2 denotes an unidentified scalar. Furthermore, if q uncorrelated signals are present, the $p - q$ smallest eigenvalues of R are equal to the noise power σ_n^2.

Let us consider the following family of covariance matrix,

$$R^{(k)} = \Psi^{(k)} + \sigma^2 I \tag{4}$$

where $\Psi^{(k)}$ denotes a semi-positive matrix of rank k. Note that k ranges over the set of all possible numbers of Degrees of Freedom (DoF), i.e. $k = 0, 1, \ldots, p-1$. Using linear algebra, we can express $R^{(k)}$ as: $R^{(k)} = \sum_{i=1}^{k}(\lambda_i - \sigma^2)V_i V_i^H \sigma^2$, where $\sigma_1, \ldots, \sigma_k$ and $V_1, \ldots, V_k$ are the eigenvalues and eigenvectors, respectively, of $R^{(k)}$.

The number of signals is determined from the estimated covariance matrix $\hat{R}$ [5] defined by

$$\hat{R} = \frac{1}{N}\sum_{i=1}^{N} x(t_i)x(t_i)^H \tag{5}$$

If $\hat{\lambda}_1, \hat{\lambda}_2, \ldots, \hat{\lambda}_q$ are the eigenvalues of $\hat{R}$ in the decreasing order then,

$$AIC(k) = -2log\left(\frac{\Pi_{i=k+1}^{p}\hat{\lambda}_i^{\frac{1}{p-k}}}{\frac{1}{p-k}\sum_{i=k+1}^{p}\hat{\lambda}_i}\right)^{(p-k)N} + 2k(2p-k) \tag{6}$$

The number of DoF, possibly the number of significant eigenvalues, is determined as the value of $k \in 0, 1, \ldots, p-1$ which minimizes the value of AIC.

The number of significant eigenvalues (SE) is determined by the value of p and q, and is given by,

$$SE = \begin{cases} p \;\; noise \\ \\ q \;\; signal \end{cases} \tag{7}$$

where p is the dimension of the covariance matrix $R^{(k)}$.

Inspired by Akaike's [8] groundbreaking work, Schwartz [9] and Rissanen [10] approached the problem from distinct perspectives. Schwartz's method is rooted in Bayesian principles, where he presumed that each competing model could be assigned a prior probability. He advocated selecting the model that maximizes the posterior probability. Conversely, Rissanen's method is founded on information-theoretic principles. Viewing each model as a potential encoder for the observed sequence, Rissanen proposed selecting the model that results in the shortest code length for the observed data. Interestingly, in the large-sample limit, both Schwartz's and Rissanen's approaches converge to the same criterion, which is given by,

$$MDL = -\sum_{n=1}^{N} log(g_{\hat{\theta}}(x_n)) + 2Ulog(N) \tag{8}$$

The estimated eigenvalues of the covariance matrix $\hat{R}$ lead to the following forms of the resulting cost functions AIC and MDL,

$$AIC(k) = -2log\left(\frac{\Pi_{i=k+1}^{p}\hat{\lambda}_i^{\frac{1}{p-k}}}{\frac{1}{p-k}\sum_{i=k+1}^{p}\hat{\lambda}_i}\right)^{(p-k)N} + 2k(2p-k) \tag{9}$$

$$MDL(k) = -log\left(\frac{\Pi_{i=k+1}^{p}\hat{\lambda}_i^{\frac{1}{p-k}}}{\frac{1}{p-k}\sum_{i=k+1}^{p}\hat{\lambda}_i}\right)^{(p-k)N} + \frac{k}{2}(2p-k)log(N) \tag{10}$$

III. Dimension Estimation Detector

The system model that will be utilized throughout this work is described in this section. The goal of Handover Detector is to select one of the two following hypotheses,

$$\lambda_{threshold}(x_n) = \begin{cases} W_p - W_n < \lambda_{th} & \text{Handover } (H_0) \\ W_p - W_n \geq \lambda_{th} & \text{No Handover } (H_1) \end{cases} \tag{11}$$

where $\lambda_{threshold}(x_n)$ is the estimated decision, and λ_{th} is the decision threshold and is determined by using the Probability of False Alarm P_{FA} [11]. The threshold λ_{th} for a specified False Alarm Probability is determined by solving the equation

$$P_{FA} = P(H_0|H_1) = P(\lambda_{threshold}(x) < \lambda_{th}|H_1) \tag{12}$$

That is the probability of detecting a Handover under the hypothesis $(H1)$, and the Probability of Detection P_D expressed as,

$$P_D = 1 - P_{MD} = 1 - P(H_1|H_0) \tag{13}$$

where P_{MD} indicates the probability of a missed detection of Handover.

In [12], the authors illustrate that the number of degrees of freedom, potentially representing the number of significant eigenvalues, is identified as the value of $k \in \{0, 1, \ldots, p-1\}$ that minimizes the AIC and/or MDL values. As discussed in [6], when the PU is absent, the received signal x is only the white noise samples, so the AIC curve, for example, monotonically increases. Consequently, $AIC(0) < AIC(k)$, $\forall k \in \{1, \ldots, p-1\}$, which can be rewired as $AIC(0) < AIC(1)$. On the other hand, when the PU is present, the AIC curve monotonically decreases from $AIC(0)$ to AIC_{min}. In the same way, we can write that $AIC(0) > AIC(1)$ if PU is present. Hence, the generalized blind DED using AIC criteria can be given by

$$\gamma_{AIC}(x) = \begin{cases} AIC(0) - AIC(1) < \gamma_{AIC} & \text{Handover } (H_0) \\ AIC(0) - AIC(1) > \gamma_{AIC} & \text{No Handover } (H_1) \end{cases} \tag{14}$$

In this scenario, MDL criteria also yield identical properties, and the corresponding DED static test is provided as follows,

$$\gamma_{MDL}(x) = \begin{cases} MDL(0) - MDL(1) < \gamma_{MDL} & \text{Handover } (H_0) \\ MDL(0) - MDL(1) > \gamma_{MDL} & \text{No Handover } (H_1) \end{cases} \tag{15}$$

We define here the two thresholds γ_{AIC} and γ_{MDL} to decide on the nature of the received signal. These thresholds depend only on P_{FA} and are calculated in the following section.

IV. FALSE ALARM PROBABILITY COMPUTATION

In this section, we will derive a theoretical probability of False Alarm using both AIC and MDL criteria. The analytical outcomes will be juxtaposed with simulation results to validate the theoretical expressions of thresholds and false alarm probabilities.

A. DED-AIC False Alarm Probability

Following the sensing steps detailed in Section III, the false alarm of the DED based on AIC criteria arises when the calculated AIC values validate the equation (14). The test static $\gamma_{AIC}(x)$ of the proposed detector is

$$\gamma_{AIC}(x) = AIC(0) - AIC(1) \tag{16}$$

Thus, the probability of False Alarm can be expressed as

$$P_{FA,AIC} \approx Pr(AIC(0) - AIC(1) > \gamma_{AIC}|H_0) \tag{17}$$

According to the AIC function defined in (9), we can obtain

$$\begin{aligned} P_{FA,AIC} = Pr\Bigg(&-2log\left(\frac{\Pi_{i=1}^{p}\hat{\lambda}_i^{\frac{1}{p}}}{\frac{1}{p}\sum_{i=1}^{p}\hat{\lambda}_i}\right)^{pN} \\ &+ 2log\left(\frac{\Pi_{i=2}^{p}\hat{\lambda}_i^{\frac{1}{p-1}}}{\frac{1}{p-1}\sum_{i=2}^{p}\hat{\lambda}_i}\right)^{(p-1)N} - 4p + 2 \\ &> \gamma_{AIC}|H_0\Bigg) \end{aligned} \tag{18}$$

Then,

$$\begin{aligned} P_{FA,AIC} = Pr\Bigg(&log\left(\frac{(\frac{1}{p}\sum_{i=1}^{p}\hat{\lambda}_i)^p}{(\frac{1}{p-1}\sum_{i=2}^{p}\hat{\lambda}_i)^{p-1}\hat{\lambda}_1}\right) \\ &> \frac{4p-2+\gamma_{AIC}}{2N}|H_0\Bigg) \end{aligned} \tag{19}$$

and at hypothesis H_0 we have,

$$\frac{1}{p}\sum_{i=1}^{p}\hat{\lambda}_i \approx \frac{1}{p-1}\sum_{i=2}^{p}\hat{\lambda}_i \approx \sigma^2 \tag{20}$$

Substituting (20) into (19) yields,

$$P_{FA,AIC} = Pr\left(\frac{\sigma^{2p}}{\sigma^{2p-2}\hat{\lambda}_1} > exp\left(\frac{4p-2+\gamma_{AIC}}{2N}\right)|H_0\right) \tag{21}$$

So,

$$P_{FA,AIC} = Pr\left(\frac{\hat{\lambda}_1}{\sigma^2} < exp\left(\frac{2-4p-\gamma_{AIC}}{2N}\right)|H_0\right) \tag{22}$$

Let $\mu = (\sqrt{N}+\sqrt{p})^2$ and $\nu = (\sqrt{N}+\sqrt{p})(\frac{1}{\sqrt{N}}+\frac{1}{\sqrt{p}})^{\frac{1}{3}}$.

Then, $\frac{N\frac{\hat{\lambda}_1}{\sigma^2}-\mu}{\nu}$ converges, with probability one, to the Tracy Widom distribution of order two. The false alarm probability can be rewritten as,

$$P_{FA,AIC} = Pr\left(\frac{N\frac{\hat{\lambda}_1}{\sigma^2}-\mu}{\nu} < \frac{Nexp(\frac{2-4p-\gamma_{AIC}}{2N})-\mu}{\nu}|H_0\right) \tag{23}$$

Let F_2 denote the CDF for the distribution of Tracy-Widom of order two [13] given by

$$F_2(t) = exp\left(-\int_t^{\infty}(u-t)h^2(u)du\right) \tag{24}$$

where $h(u)$ is the solution of the nonlinear Painlevé II differential equation [13],

$$h(u) = uh(u) + 2h^3(u) \tag{25}$$

Therefore, the probability of False Alarm of our algorithm using AIC criteria can be approximated as,

$$P_{FA,AIC} = F_2\left(\frac{Nexp(\frac{2-4p-\gamma_{AIC}}{2N})-\mu}{\nu}\right) \tag{26}$$

or, equivalently,

$$\frac{Nexp(\frac{2-4p-\gamma_{AIC}}{2N})-\mu}{\nu} = F_2^{-1}(P_{FA,AIC}) \tag{27}$$

we finally obtain the threshold

$$\gamma_{AIC} = 2 - 4p - 2Nln\left(\frac{\nu F_2^{-1}(P_{FA,AIC})+\mu}{N}\right) \tag{28}$$

In general, assessing the function F_2 presents challenges; however, it is computable using Matlab, which provides a convenient solution.

B. DED-MDL False Alarm Probability

Similar to the preceding derivation, when implementing the MDL criterion, the adjustment required involves only the step outlined in (19), as specified in (29).

$$\begin{aligned} P_{FA,MDL} = Pr\Bigg(&-log\left(\frac{\Pi_{i=1}^{p}\hat{\lambda}_i^{\frac{1}{p}}}{\frac{1}{p}\sum_{i=1}^{p}\hat{\lambda}_i}\right)^{pN} \\ &+log\left(\frac{\Pi_{i=2}^{p}\hat{\lambda}_i^{\frac{1}{p-1}}}{\frac{1}{p-1}\sum_{i=2}^{p}\hat{\lambda}_i}\right)^{(p-1)N} -(p-\frac{1}{2})log(N) \\ &> \gamma_{MDL}|H_0\Bigg) \end{aligned} \tag{29}$$

Then,

$$\begin{aligned} P_{FA,MDL} = Pr\Bigg(&log\left(\frac{(\frac{1}{p}\sum_{i=1}^{p}\hat{\lambda}_i)^p}{(\frac{1}{p-1}\sum_{i=2}^{p}\hat{\lambda}_i)^{p-1}\hat{\lambda}_1}\right) \\ &> \frac{(p-\frac{1}{2})Log(N)+\gamma_{MDL}}{N}|H_0\Bigg) \end{aligned} \tag{30}$$

Given the assumption provided by (20), where the received signal consists solely of noise samples, we can express (30) accordingly,

$$P_{FA,MDL} = Pr\left(\frac{\hat{\lambda}_1}{\sigma^2} < exp\left(\frac{\gamma_{MDL}+(p-\frac{1}{2})log(N)}{N}\right)|H_0\right) \tag{31}$$

		p=100	p=150	p=200
	$P_{FA,AIC}$	0.0531	0.0518	0.0504
Simulation Results	$P_{FA,MDL}$	0.0549	0.0533	0.0520
	γ_{AIC}	3.857e04	2.590e04	2.152e04
	γ_{MDL}	3.613e04	2.097e04	1.956e04
	$P_{FA,AIC}$	0.0500	0.0500	0.0500
Analytical Results	$P_{FA,MDL}$	0.0500	0.0500	0.0500
	γ_{AIC}	3.762e04	2.527e04	1.984e04
	γ_{MDL}	3.484e04	1.825e04	1.754e04

TABLE I
SIMULATION AND ANALYTICAL RESULTS COMPARISON

Utilizing the Tracy-Widom proposition, the false alarm probability of the DED algorithm employing MDL criteria can be reformulated as follows

$$P_{FA,MDL} = F_2\left(\frac{Nexp\left(\frac{\gamma_{MDL}+(p-\frac{1}{2})log(N)}{N}\right)-\mu}{\nu}\right) \quad (32)$$

where μ and ν are defined in the previous subsection, and the threshold of the DED-MDL algorithm is given by

$$\gamma_{MDL} = (p-\frac{1}{2})log(N) - Nln\left(\frac{\nu F_2^{-1}(P_{FA,MDL})+\mu}{N}\right) \quad (33)$$

V. NUMERICAL APPLICATIONS

The proposed Dimension Estimation Detector (DED) scheme was simulated in MATLAB and the performance metrics used are probability of detection, probability of missing detection and probability of False Alarm. The findings are smoothed out by running each simulation configuration multiple times.

When calculating the probabilities of False Alarm using the AIC and MDL criteria, the assumption provided by (20) under hypothesis H_0 was utilized, acknowledging its known inaccuracy. However, it was reasoned that despite this inaccuracy, it should be adequate to yield reliable theoretical outcomes for the probability of False Alarm. It's noteworthy that for the DED, the threshold remains unrelated to noise power and is determined solely based on N, p, and P_{FA}, disregarding signal and noise considerations, in both cases employing the AIC and MDL criteria.

The comparison outcomes for threshold and P_{FA}, assessed through AIC and MDL criteria, are presented in Table 1. The table demonstrates a strong alignment between the simulated False Alarm and threshold performance with the theoretical results, indicating a high level of accuracy.

Figure 1 depicts the detection comparison of our Handover detection technique. The figure shows the probability of detection versus the number of significant eigenvalues ranging between 0 and 100. We can see that the probability of Detection increases as the index k increases and We can see also that, if the index $(k < 95)$, the probability of detection based on AIC is better than the probability of detection based

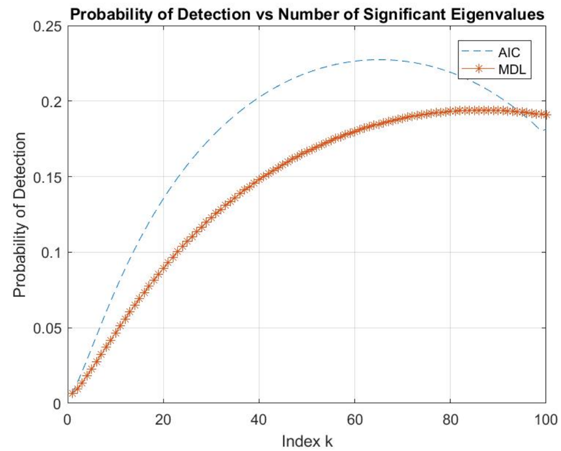

Fig. 1. Probability of Detection vs Index k

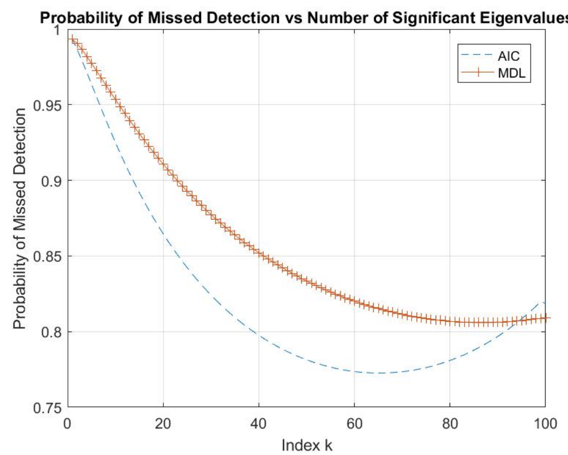

Fig. 2. Probability of Missed Detection vs Index k

on MDL, and as the number of significant eigenvalues is higher than 95, the detection using MDL is better than AIC.

Threshold values are computed according to the common framework and depend only on the Probability of False Alarme value.

On the other hand, by observing Figure 2, we can see another comparison between AIC and MDL of the probability of Missed Detection. The figure shows that the probability of Missed Detection decreases as the index k increases. We can see also that there are two cases, if $(k < 95)$ probability of Missed detection based on MDL is higher than Probability of Missed detection based on AIC, and on the other case, if k¿95 Probability of Missed detection based on AIC is higher than MDL.

VI. CONCLUSION

In conclusion, the concept of probability of detection plays a critical role in various fields, including surveillance, security, and scientific research. It quantifies the likelihood of identifying a target or event of interest within a given context or system. Throughout this article, we have explored a novel approach to manage handovers based on Dimension Estimation. We also estimated the performance in terms of the Probability of Detection and the probability of Missed Detection of the network channel, just by analyzing the received signal DF. After that, we realized the numerical applications of the proposed estimation of the Probability of Detection and the Probability of Missed Detection.

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