Improving Receiver Detection Performance Through NLOS/LOS Vision

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Abstract—**This paper explores the benefits of sensor-based line-of-sight/non-line-of-sight (LOS/NLOS) information on the detection performance of an on-off keying (OOK) communication link. Bayes risk and composite likelihood ratio test (LRT) methods are used to derive the optimal decision rule for minimizing probability of error in a dynamic LOS/NLOS channel. By exploring three varying degrees of knowledge, it is shown that one can achieve improved constant-false-alarm-rate (CFAR) detection performance in an ensemble of trials over the uniformly-most-powerful (UMP) test when *labeled* information about LOS is provided at the receiver. It is also shown that, in the presence of prior knowledge of signal presence, one can benefit from LOS statistics when minimizing probability of error.**

Index Terms—**Signal Detection, LOS/NLOS, GLRT, Dynamic Channel, Out-of-Band Knowledge**

I. Introduction

In modern communications systems there are often numerous opportunities to obtain external knowledge about the channel beyond that which is provided by the receiver itself, such as knowledge obtained through optical and radio frequency (RF) sensors operating outside of the main system frequency band; e.g., radar systems aided by optical sensors or cellular base stations aided by LOS infra-red sensors. Sensors of all varieties are abundant in the mobile devices we use and crucial to the functionality of wireless IoT devices, smart vehicles, and satellites. In this paper we explore the benefits that can be garnered from this external knowledge or "vision" through the lens of detection theory and hypothesis testing and apply these tools to a dynamic communications channel.

Arguably the simplest of classical signal detection problems is that of the constant DC value in additive white Gaussian noise (AWGN). The problem explored in this work generalizes this to arbitrary pulse shapes and introduces a stochastic element into the channel behavior while accounting for varying levels of information provided by the vision sensor. As with numerous other practical detection scenarios without fully-known distributions for each hypothesis, there are unknown parameters that must be accounted for when obtaining the optimal decision rule. Two approaches which address the unknown parameter detection problem from different angles are outlined in the literature; namely, the m-ary hypothesis approach and the composite hypothesis approach [1]. The latter is further broken down into the generalized likelihood ratio test (GRLT), Rao, and Wald tests which are asymptotically optimal for MLE estimates of the unknown parameter(s) with independent and identically-distributed (IID) data [2]–[4]. The GRLT, Rao, and Wald tests, however, do not take into account prior knowledge of the distribution of the parameter itself whereas the Bayesian composite hypothesis testing method does [5]–[7]. As this prior distribution is known in the problem at hand, it should logically be factored into the detection scheme.

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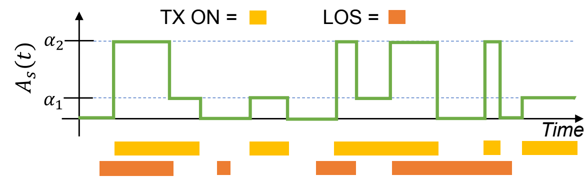

Fig. 1: Recieved signal amplitude over time.

Here we present an analysis of one such detection problem involving an unknown parameter whose state can be optionally obtained through a label. The parameter in question represents a Bernoulli channel state of either line-of-sight (LOS) or non-line-of-sight (NLOS), much like the characterization used in [8]. [9] provides another application in which a mixed NLOS/LOS environment is considered. The legitimacy of the uniformly-most-powerful (UMP) test is challenged for cases where the test statistic does not depend on the unknown parameter [10]. In the scenario presented, even though a UMP test does exist in a constant-false-alarm-rate (CFAR) detection paradigm, it is shown that, by adopting a dynamic detection scheme, one can achieve a higher probability of detection over an ensemble of trials for a given false alarm rate than that achieved through the UMP test. Further, given prior probabilities for the hypotheses, one can achieve a lower probability of error given knowledge of the parameter distribution than without.

II. System Model

We construct a simple detection scenario in which a receiver must determine the presence of a signal with known pulse shape in an AWGN channel. The amplitude of the received signal, however, is random and depends upon the channel state which can either be LOS or NLOS. Specifically, the channel state Ψ can take on one of two possible values: $\Psi(t) \in \{\text{NLOS}, \text{LOS}\}$. This provides a simple model for a dynamic wireless link which toggles intermittently between NLOS and LOS such that the state Ψ is a correlated Bernoulli random variable as in [8]. For the sake of the problem at hand, we will assume $\Psi(t)$ is governed by a Markov switching random process, also known as a continuous time Markov chain (CTMC).

$$\Psi(t)|\{t=t_0\} \sim \text{Bernoulli}(q)$$
$$P(\Psi(t)|\{t=t_0\}) = \left\{ \begin{array}{ll} 1-q, & \Psi=0 \text{ (NLOS)} \\ q, & \Psi=1 \text{ (LOS)} \end{array} \right\} \quad (1)$$

The marginal distribution of $\Psi(t)$ is shown in (1). Our model establishes α_1 and α_2 as the amplitudes the received signal will assume in the NLOS and LOS states, respectively, with with condition $\alpha_2 > \alpha_1$. Additionally, the signal is assumed to be present at times and absent at other times as in an on-off-keying (OOK) scenario for communications or a target in range/Doppler space for radar. This means that the received signal amplitude can take on three distinct values $A_s(t) \in \{0, \alpha_1, \alpha_2\}$ representing the no-signal, NLOS, and LOS cases. Figure 1 illustrates the behavior of the received signal amplitude $A_s(t)$ as a function of time in the midst of the intermittent channel state $\Psi(t)$ (shown in orange) and the OOK behavior at the transmitter (shown in yellow). One can notice how the channel state and signal state appear independent of one another, and indeed we assume that $A_s(t)$ and $\Psi(t)$ follow two independent random processes. The received signal has shape $P(t)$, and we assume that this shape is known at the receiver and that time alignment has been achieved; i.e. coherent reception is possible. The form of the received signal without noise is therefore $s(t) = A_s(t)P(t)$. The true received signal is corrupted in the channel by a white noise process $n(t)$ which is added to the received signal $s(t)$. The observation made by the receiver is then a vector of N samples, $\vec{r}(k)$, and we assume that the channel state $\Psi(t)$ does not change over the duration of the observation; i.e. the amplitude value $A_s(t)$ remains constant for the entire vector $\vec{r}(k)$, taking on a single value which we denote A_s. The decision regarding the presence of the signal is then made based upon the information obtained in $\vec{r}(k)$. The marginal probability distributions for a single noise sample n_k and a single signal sample s_k are shown in (2) for which σ_n^2 is the noise variance, P_k is a sample from the known signal shape, π_0 is the prior probability of the no-signal (only noise) state $(1 - Pr[A_s = 0])$, and q is the probability of LOS $(Pr[\Psi(t) = 1|\{t = t_k\}])$.

$$\vec{r}(k) = \vec{n}(k) + \vec{s}(k) = \vec{n}(k) + A_s\vec{P}(k),$$
where
$$n_k \sim \mathcal{N}(0, \sigma_n^2), \quad (2)$$
$$\text{and } s_k \sim f_{s_k}(s) = \left\{ \begin{array}{ll} \pi_0, & s=0 \\ (1-\pi_0)(1-q), & s=\alpha_1 P_k \\ (1-\pi_0)q, & s=\alpha_2 P_k \end{array} \right\}$$

The central question being explored is whether performance gains can be achieved when the receiver obtains knowledge of the channel state Ψ from an external sensor which we shall call "vision". The specifics of the sensor are not relevant to the problem at hand; the importance instead lies in the fact that knowledge is obtained about the wireless channel beyond that which the transmitter and receiver can perceive in their default RF domain.

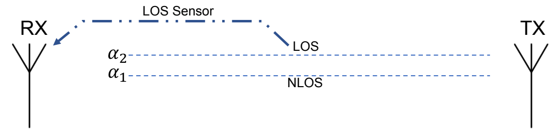

Fig. 2: Channel model.

A. Cases Involving Varying Levels of Knowledge

Figure 2 depicts the simple scenario laid out here where the receiver obtains knowledge of the LOS state by some external means. To provide a comprehensive analysis of the effects of this vision on detection performance, we establish 3 distinct cases representing varying degrees of knowledge about the channel state, ordered by decreasing quality: (1) labeled knowledge (Vision), (2) statistical knowledge, (3) blind. In the *labeled* case the receiver obtains, at any point in time, an exact label of LOS or NLOS corresponding to the channel state Ψ such that the observed state, denoted $\hat{\Psi}$, matches the true state at all times, $\hat{\Psi}(t) = \Psi(t)\ \forall\ t$. This case is termed the "vision" case because it represents the use of external sensor-based information. In the *statistical* case the receiver no longer has access to labels for the channel state; rather, it merely has knowledge of the statistics of the channel model. (2) provides the marginal probability mass function for the channel state Ψ which follows a Bernoulli distribution parameterized by q, the probability of LOS. Finally, the *blind* case represents a lack of any information regarding the channel state at the receiver beyond the *a priori* knowledge of the two possible amplitude values α_1 and α_2, the signal shape $P(t)$, and the noise variance σ_n^2. In the *blind* case the receiver has no notion of how often the channel is LOS vs NLOS, much less what the state is at any point in time.

One important characteristic distinguishing these cases is whether the information they provide is time-dependent. The vision case falls into this category as the labels provide an estimate of the channel state at any time t. The other two, however, give only model-specific information independent of time. This distinction is key to determining the achievable gains under different detection paradigms.

III. Detection Framework

To determine the presence of a signal with maximum reliability, one must construct a detector for which an input of N samples represented by the vector $\vec{r}(k)$ yields a decision upon whether the signal is present. Knowing this, there are two primary angles from which one can approach this detection problem. These two perspectives concern the number of hypotheses that are considered by the receiver, and in turn the methodology used to derive the optimal detection scheme. In one point of view, one can establish three hypotheses representing the no-signal, NLOS-signal, and LOS-signal states:

$$\begin{aligned} &\mathcal{H}_0 : A_s = 0 \text{ [No-Signal]} \\ &\mathcal{H}_1 : \Psi = 0 \wedge A_s = \alpha_1 \text{ [NLOS Signal]} \\ &\mathcal{H}_2 : \Psi = 1 \wedge A_s = \alpha_2 \text{ [LOS Signal]} \end{aligned} \quad (3)$$

In a second point of view, only two hypotheses are considered, one for the no-signal state and one for the signal-present state regardless of LOS:

$$\begin{aligned} \mathcal{H}_0 &: A_s = 0 \text{ [No-Signal]} \\ \mathcal{H}_1 &: A_s \neq 0 \text{ [Signal-Present]} \end{aligned} \tag{4}$$

Although these two models require different methodologies to arrive at the optimal detector, the ultimate decision rule that results must decide between the same two outcomes: signal-absent or signal-present. Intriguingly, it is shown in the following sections that these two models and approaches lead to the same optimal detection rule.

A. M-ary Detection using Bayes Risk

The 3-hypothesis model shown in (3) is an *M*-ary hypothesis testing problem, and it can be shown that having more than two hypotheses requires some *a priori* knowledge of the probabilities of these hypotheses occurring. If one takes the Neyman-Pearsonian approach, for example, comparing the likelihoods for each hypothesis requires more than one threshold; i.e. only two can be compared in a ratio test at one time. This leads us to formulate the Bayes Risk which considers the cost associated with every possible observation conditioned on the truth. Bayes Risk is defined in the most general case as follows:

$$\mathcal{R} = \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} C_{ij} P(\mathcal{H}_i|\mathcal{H}_j) P(\mathcal{H}_j). \tag{5}$$

where $P(\mathcal{H}_i|\mathcal{H}_j)$ is the probability of choosing $\mathcal{H}_i$ given that $\mathcal{H}_j$ matches reality. The coefficients C_{ij} can be seen as weights which determine the contribution to the overall risk when making a decision $\mathcal{H}_i$ conditioned on the truth, $\mathcal{H}_j$.

Minimization of the Bayes Risk encompasses any possible metric one might have for optimality as it allows for arbitary weight to be placed on Type-I and Type-II errors, otherwise known as *missed-detections* and *false-alarms* as they will henceforth be referred to. The interest in the problem at hand is in finding a detection rule which minimizes the probability of error or $\min_{\mathcal{H}_i}(P_e)$ where false-alarms and missed-detections are considered equally detrimental to the risk.

It has been shown that Bayes Risk is minimized if one decides $\mathcal{H}_i$ for which $c_i(X) = \sum_{j=0}^{N-1} C_{ij}\pi(\mathcal{H}_j|X)$ is minimal where $\pi(\mathcal{H}_j|X)$ is the posterior probability of $\mathcal{H}_j$ given an observation X. The optimal decision rule follows, upon definition of the weights C_{ij}. Adopting the $\min_{\mathcal{H}_i}(P_e)$ metric, the scenario at hand defines an error as mistaking the presence of a signal ($\mathcal{H}_1$ or $\mathcal{H}_2$) for the absence of a signal ($\mathcal{H}_0$) or equivalently in reverse. We can construct the C_{ij} matrix based off of this rule as follows:

$$C_{ij} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \tag{6}$$

where i indicates the decision index and j indicates the truth index. The symmetry of this matrix reflects the equal treatment of missed-detections and false-alarms, and the lack of risk associated with mistaking a LOS signal with an NLOS signal is represented with $C_{12} = C_{21} = 0$. Using this definition to minimize (5) leads to the following:

$$\underbrace{\text{argmin}}_{i}[c_i(X)] = \left\{ \begin{array}{ll} \sum_{j=0}^{2} \pi(\mathcal{H}_j|X) - \pi(\mathcal{H}_0|X) & i=0 \\ \sum_{j=0}^{2} \pi(\mathcal{H}_j|X) - \pi(\mathcal{H}_1|X) - \pi(\mathcal{H}_2|X) & 1 \text{ or } 2 \end{array} \right\} \tag{7}$$

The decision rule which minimizes $\mathcal{R}$ then follows:

$$\text{Choose } \mathcal{H}_i \text{ where} \quad i = \left\{ \begin{array}{ll} 0 & \pi(\mathcal{H}_0|X) > \pi(\mathcal{H}_1|X) + \pi(\mathcal{H}_2|X) \\ 1 \text{ or } 2 & \text{otherwise} \end{array} \right\} \tag{8}$$

This result resembles the classical *maximum a posteriori* (MAP) formulation for binary hypothesis testing with the key distinction being the union of $\mathcal{H}_1$ and $\mathcal{H}_2$. It is now straightforward to obtain the decision rule in terms of the system parameters by substituting the likelihoods and priors associated with the three hypotheses.

$$\text{Choose } \underbrace{\mathcal{H}_1 \text{ or } \mathcal{H}_2}_{\text{Signal Present}} \text{ if} \quad L(X|\mathcal{H}_1)\pi_1 + L(X|\mathcal{H}_2)\pi_2 > L(X|\mathcal{H}_0)\pi_0 \tag{9}$$

From (9) one can see the importance of knowledge of the prior probabilities $\{\pi_0, \pi_1, \pi_2\}$ in determining signal presence. Fortunately, although knowing the probability of the signal presence *a priori* might be impossible as in the case of radar, we have the privilege of knowing the probability of LOS, q, in the *vision* and *statistical* cases, though not the *blind*. Considering that $\pi_1 = (1-q)(1-\pi_0)$ and $\pi_2 = q(1-\pi_0)$, the ratio $\frac{\pi_2}{\pi_1} = \frac{q}{1-q}$ is known for these cases. This allows us to construct a decision rule where π_0 is the only unknown.

$$\begin{aligned} &\text{Choose } \underbrace{\mathcal{H}_1 \text{ or } \mathcal{H}_2}_{\text{Signal Present}} \text{ if} \\ &e^{-\frac{1}{2\sigma_n^2}\sum_{k=0}^{N-1}\left(\vec{r}[k]-\alpha_1\vec{P}[k]\right)^2}(1-q) + e^{-\frac{1}{2\sigma_n^2}\sum_{k=0}^{N-1}\left(\vec{r}[k]-\alpha_2\vec{P}[k]\right)^2} q \\ &> e^{-\frac{1}{2\sigma_n^2}\sum_{k=0}^{N-1}\vec{r}[k]^2} \frac{\pi_0}{1-\pi_0} \\ &\exp\left[-\frac{1}{2\sigma_n^2}\left(\alpha_1^2\sum_{k=0}^{N-1}\vec{P}[k]^2 - 2\alpha_1\sum_{k=0}^{N-1}\vec{r}[k]\vec{P}[k]\right)\right](1-q) + ... \\ &\exp\left[-\frac{1}{2\sigma_n^2}\left(\alpha_2^2\sum_{k=0}^{N-1}\vec{P}[k]^2 - 2\alpha_2\sum_{k=0}^{N-1}\vec{r}[k]\vec{P}[k]\right)\right] q > \underbrace{\frac{\pi_0}{1-\pi_0}}_{\eta} \end{aligned} \tag{10}$$

Now it can be seen that the sufficient statistic is a replica correlator, equivalent to a matched filter: $T(\vec{r}) = \sum_{k=0}^{N-1}\vec{r}[k]\vec{P}[k]$. The detection rule, however, cannot be isolated from the weight parameter q, indicating that knowledge of the probability of LOS is required for optimal detection performance.

B. Binary Composite Hypothesis Testing

As an alternative approach, one can consider only the two hypotheses shown in (4). A binary hypothesis testing scenario lends itself quite well to the Neyman-Pearsonian likelihood ratio test (LRT). Unlike the 3-ary Bayes risk approach, the binary approach requires treatment of the amplitude A_s as an unknown parameter and therefore falls into the category of detection of deterministic signals with unknown parameters. The LRT is optimal in that it maximizes the probability of detection (P_D) for a given probability of false alarm (P_{FA}) over all values of $A_s > 0$. It is therefore termed the UMP test. We can obtain the UMP detector by forming an LRT conditioned on A_s:

$$\begin{aligned}&\text{Choose } \mathcal{H}_1 \text{ if } LRT(\vec{r}) = \frac{L(\vec{r}; A_s, H_1)}{L(\vec{r}; H_0)} > \gamma,\\ &\text{which implies } \frac{\exp\left(-\frac{1}{2\sigma_n^2}\sum_{k=0}^{N-1}\left(\vec{r}[k] - A_s\vec{P}[k]\right)^2\right)}{\exp\left(-\frac{1}{2\sigma_n^2}\sum_{k=0}^{N-1}\vec{r}[k]^2\right)} > \gamma,\\ &\rightarrow \sum_{k=0}^{N-1}\vec{r}[k]\vec{P}[k] > \underbrace{\frac{A_s}{2}\sum_{k=0}^{N-1}\vec{P}[k]^2 - \frac{\sigma_n^2}{A_s}\log(\gamma)}_{\eta}\end{aligned} \tag{11}$$

The decision statistic obtained from the LRT is a replica correlator which notably does not depend on A_s. Further, although the threshold η does depend on A_s, this test is sufficient for a CFAR detection scheme even without knowledge of $\Psi(t)$ as the null (no-signal) hypothesis is independent of A_s.

If we return to the original interest in achieving $\min_{\mathcal{H}_i}(P_e)$ given knowledge of π_0, the LRT is not sufficient without knowledge of A_s due to the power of the test (P_D) being dependent upon A_s. Instead the Bayesian approach to composite hypothesis testing comes into play, taking into account prior knowledge of the distribution of A_s which we possess in all knowledge cases except the *blind* case.
The Bayes Factor for the scenario at hand has the following form:

$$\begin{aligned}&\text{Choose } \mathcal{H}_1 \text{ if}\\ &\frac{\pi(\vec{r}; \mathcal{H}_1)}{\pi(\vec{r}; \mathcal{H}_0)} = \frac{\int_{\Omega_{A_s}} L(\vec{r}|A_s; \mathcal{H}_1)p(A_s; \mathcal{H}_1)\mathrm{d}A_s}{\int_{\Omega_{A_s}} L(\vec{r}|A_s; \mathcal{H}_0)p(A_s; \mathcal{H}_0)\mathrm{d}A_s} > \underbrace{\frac{\pi_0}{1-\pi_0}}_{\eta},\\ &\text{where } p(A_s; \mathcal{H}_1) = (1-q)\delta(A_s - \alpha_1) + q\delta(A_s - \alpha_2),\\ &p(A_s; \mathcal{H}_0) = \delta(A_s),\\ &\delta(\cdot) \text{ is the Dirac Delta Function.}\end{aligned} \tag{12}$$

The Bernoulli form for the prior distribution on the amplitude A_s derives from the signal model shown in (2). The prior distribution for $\mathcal{H}_0$ is a point mass at zero representing the no-signal state. Applying these known priors yields a decision rule identical to that found in (10).

C. Performance Analysis

To evaluate the performance of this detection scheme we must derive expressions for probability of detection (P_D) and false-alarm (P_{FA}). One can either characterize the performance for a single observation or for an ensemble of observations, a distinction which emerges when time-dependent information about the channel is available as in the *vision* case. Here we desire to optimize ensemble performance and utilize the detection scheme which minimizes the average P_e. An exact form for P_D and P_{FA} given an arbitrary q value, however, is not tractable due to the exponential mixture form of the decision statistic in (10). An approximation is therefore employed which utilizes a piecewise-linear function in place of the weighted sum of complex exponentials:

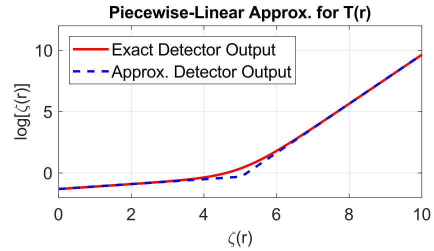

Fig. 3: Piecewise-linear approximation vs exact detector.

$$\begin{aligned}&T(\vec{r}) = c_1\exp\left(\Phi_1\zeta(\vec{r})\right) + c_2\exp\left(\Phi_2\zeta(\vec{r})\right), \text{ where}\\ &c_1 = (1-q)\exp\left(-\frac{\alpha_1^2\epsilon(P)}{2\sigma_n^2}\right), c_2 = q\exp\left(-\frac{\alpha_2^2\epsilon(P)}{2\sigma_n^2}\right),\\ &\Phi_1 = \frac{\alpha_1}{\sigma_n^2}, \Phi_2 = \frac{\alpha_2}{\sigma_n^2}, \epsilon(P) = \sum_{k=0}^{N-1}\vec{P}[k]^2, \zeta(\vec{r}) = \sum_{k=0}^{N-1}\vec{r}[k]\vec{P}[k]\end{aligned} \tag{13}$$

We can then form the following piecewise-linear approximation for the logarithm of $T(\vec{r})$ with boundary B:

$$\begin{aligned}&\ln(T(\vec{r})) \approx \begin{Bmatrix} \log(c_1) + \Phi_1\zeta(\vec{r}) & x \le B \\ \log(c_2) + \Phi_2\zeta(\vec{r}) & x > B \end{Bmatrix}\\ &c_1 e^{\Phi_1 B} = c_2 e^{\Phi_2 B} \rightarrow B = \frac{\ln(\frac{c_2}{c_1})}{\Phi_1 - \Phi_2}\end{aligned} \tag{14}$$

This yields an approximate decision rule as follows:

$$\begin{aligned}&\text{Choose } \mathcal{H}_1 \text{ if}\\ &\begin{Bmatrix} \{\zeta(\vec{r}) > \eta_1\} \cap \{\zeta(\vec{r}) \le B\} \\ \text{or} \\ \{\zeta(\vec{r}) > \eta_2\} \cap \{\zeta(\vec{r}) > B\} \end{Bmatrix}\\ &\text{where}\\ &\eta_1 = \frac{\sigma_n^2}{\alpha_1}\log\left(\frac{\pi_0}{(1-\pi_0)(1-q)}\right) + \frac{\alpha_1\epsilon(P)}{2}\\ &\eta_2 = \frac{\sigma_n^2}{\alpha_2}\log\left(\frac{\pi_0}{(1-\pi_0)q}\right) + \frac{\alpha_2\epsilon(P)}{2}\\ &B = \log\left(\frac{q}{1-q}\right)\frac{\sigma_n^2}{\alpha_1 - \alpha_2} + \frac{\epsilon(P)}{2}\left(\frac{\alpha_1^2 - \alpha_2^2}{\alpha_1 - \alpha_2}\right)\end{aligned} \tag{15}$$

The approximation forms two decision rules with corresponding optimal thresholds, each assuming dominance of one channel state or the other. In approximation, expressions for P_D and P_{FA} are realizable, and using the fact that the decision statistic $\zeta(\vec{r})$ is a random variable with the following distribution: $\zeta(\vec{r}) \sim \mathcal{N}\left(A_s\epsilon(P), A_s^2\sigma_n^2\epsilon(P)\right)$, one can obtain the ensemble P_D and P_{FA} expressions dependent on the two thresholds η_1 and η_2 and the boundary B as follows:

$$\begin{aligned}
P_D =& Pr\,[\text{ Choose signal-present } |\mathcal{H}_1] \\
P_D =& 1\{\eta_1 \le B\}\left(Pr\left[\zeta(\vec{r}) > \eta_1 | A_s = \alpha_1\right](1-q) + ...\right. \\
& Pr\left[\zeta(\vec{r}) > \eta_1 | A_s = \alpha_2\right] q) + ... \\
& 1\{\eta_1 > B\}\left(Pr\left[\zeta(\vec{r}) > \eta_2 | A_s = \alpha_1\right](1-q) + ...\right. \\
& Pr\left[\zeta(\vec{r}) > \eta_2 | A_s = \alpha_2\right] q) \\
\rightarrow P_D =& \\
1\{\eta_1 \le B\} & \left[Q\left(\frac{\eta_1 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_1 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] \\
+1\{\eta_1 > B\} & \left[Q\left(\frac{\eta_2 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_2 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] \\
P_{FA} =& Pr\,[\text{ Choose signal-present } |\mathcal{H}_0] \\
\rightarrow P_{FA} =& \\
1\{\eta_1 \le B\}Q & \left(\frac{\eta_1}{\sigma_n\sqrt{\epsilon(P)}}\right) + 1\{\eta_1 > B\}\,Q\left(\frac{\eta_2}{\sigma_n\sqrt{\epsilon(P)}}\right)
\end{aligned} \tag{16}$$

The piecewise-approximate detector has piecewise expressions for P_D and P_{FA} where the boundary condition is a comparison between one of the thresholds (η_1 or η_2) and B, all of which depend on the estimate for probability of LOS, $\hat{q}$, the prior probability of signal presence, π_0, and otherwise known parameters.

IV. Case-Based Analysis

The generalized detection scheme shown in (15) assumes some knowledge of q at the receiver, denoted $\hat{q}$, and it is this knowledge which differs among the three cases presented. The weights for the terms in the P_D and P_{FA} expressions depend on the true value of q while the thresholds η_1 and η_2 as well as the boundary B depend on the known value at the receiver, $\hat{q}$. Each knowledge case modifies its definition of $\hat{q}$, thereby altering the chosen thresholds.

A. Labeled Knowledge (Vision)

In the case where external knowledge of the LOS state Ψ is available, the knowledge at the receiver is binary in nature, meaning that $\hat{q}$ is either equal to 1 when the label is LOS or 0 when the label is NLOS. The expressions for P_D and P_{FA} for the vision case are then as follows:

$$\begin{aligned}
P_{D-V} &= Q\left(\frac{\eta_1 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_2 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q \\
P_{FA-V} &= Q\left(\frac{\eta_1}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_2}{\sigma_n\sqrt{\epsilon(P)}}\right)q
\end{aligned} \tag{17}$$

P_D and P_{FA} for the vision case are exact results and do not rely on the piecewise-linear approximation because only one term in the weighted sum of exponentials need be considered at a time.

B. Statistical Knowledge

In the case where the receiver no longer has access to the labeled LOS state, $\hat{q}$ is simply equal to the true probability of LOS for the channel. This yields the following expressions for P_D and P_{FA}:

$$\begin{aligned}
& P_{D-S} = \\
& 1\{\eta_1 \le B\}\left[Q\left(\frac{\eta_1 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_1 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] + \\
& 1\{\eta_1 > B\}\left[Q\left(\frac{\eta_2 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_2 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] \\
& P_{FA-S} = \\
& 1\{\eta_1 \le B\}Q\left(\frac{\eta_1}{\sigma_n\sqrt{\epsilon(P)}}\right) + 1\{\eta_1 > B\}\,Q\left(\frac{\eta_2}{\sigma_n\sqrt{\epsilon(P)}}\right)
\end{aligned} \tag{18}$$

For the *statistical* case this result is an approximation as the entire distribution with both LOS and NLOS terms must be considered.

C. Blind

In the absence of even statistical knowledge of the channel, the receiver's knowledge of LOS is entirely non-existent. The best strategy is therefore to establish an uninformative prior distribution on the parameter $\hat{q}$. Considering that the distribution for q is known to be Bernoulli even in the blind case, a good choice for the prior on $\hat{q}$ is the Beta$\left(\frac{1}{2}, \frac{1}{2}\right)$ distribution. The ensemble performance can then be found by marginalizing the original Bayes Factor from (12) over the entire space of $\hat{q}$ such that its dependence is removed:

$$\begin{aligned}
& \text{Choose } \mathcal{H}_1 \text{ if} \\
& \frac{\pi(\vec{r};\mathcal{H}_1)}{\pi(\vec{r};\mathcal{H}_0)} = \frac{\int_{\hat{q}=0}^{1}\int_{\Omega_{A_s}} L(\vec{r}|A_s;\mathcal{H}_1)p(A_s|\hat{q};\mathcal{H}_1)\mathrm{d}A_s\mathrm{d}\hat{q}}{\int_{\hat{q}=0}^{1}\int_{\Omega_{A_s}} L(\vec{r}|A_s;\mathcal{H}_0)p(A_s|\hat{q};\mathcal{H}_0)\mathrm{d}A_s\mathrm{d}\hat{q}} > \underbrace{\frac{\pi_0}{1-\pi_0}}_{\eta}, \\
& \text{where } p(A_s|\hat{q};\mathcal{H}_1) = (1-\hat{q})\delta(A_s - \alpha_1) + \hat{q}\delta(A_s - \alpha_2), \\
& p(A_s|\hat{q};\mathcal{H}_0) = \delta(A_s), \\
& \delta(\cdot) \text{ is the Dirac Delta Function.}
\end{aligned} \tag{19}$$

This yields an identical decision rule to (15) but with $q = 0.5$. Therefore, in the absence of statistical knowledge, the receiver should assume equal weighting between LOS and NLOS channel states. The expressions for P_D and P_{FA} for the blind case are then as follows:

$$\begin{aligned}
& P_{D-B} = \\
& 1\{\eta_1 \le B\}\left[Q\left(\frac{\eta_1 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_1 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] \\
& +1\{\eta_1 > B\}\left[Q\left(\frac{\eta_2 - \alpha_1\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)(1-q) + Q\left(\frac{\eta_2 - \alpha_2\epsilon(P)}{\sigma_n\sqrt{\epsilon(P)}}\right)q\right] \\
& P_{FA-B} = \\
& 1\{\eta_1 \le B\}Q\left(\frac{\eta_1}{\sigma_n\sqrt{\epsilon(P)}}\right) + 1\{\eta_1 > B\}\,Q\left(\frac{\eta_2}{\sigma_n\sqrt{\epsilon(P)}}\right) \\
& \text{With } \hat{q} = \frac{1}{2}.
\end{aligned} \tag{20}$$

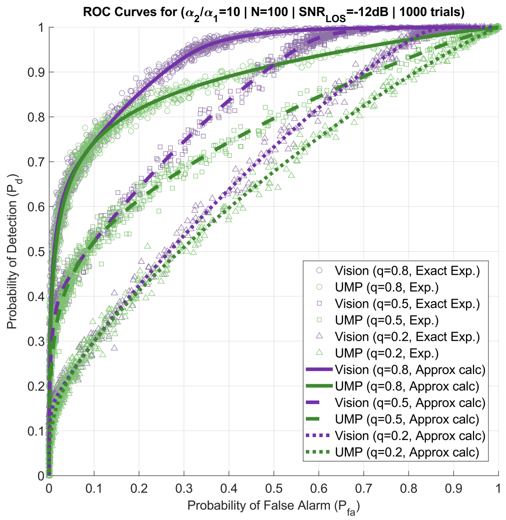

Fig. 4: ROC curve (CFAR) performance: vision vs UMP test.

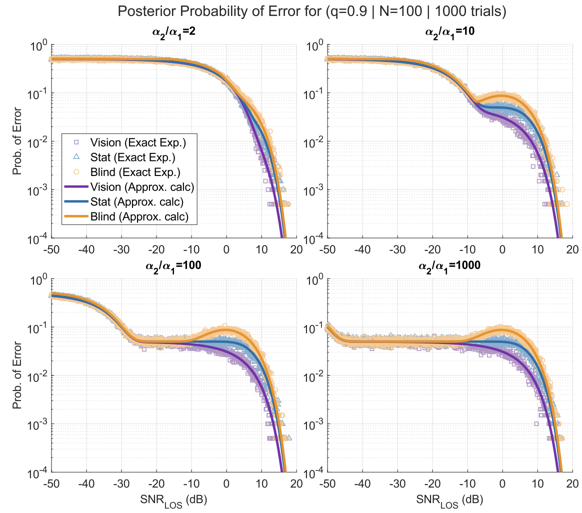

Fig. 5: Prob. of error performance: vision vs statistical vs blind

V. Numerical Results and Discussion

Here these performance results are tested under both CFAR and $\min_{\mathcal{H}_i}(P_e)$ detection paradigms in a Monte Carlo simulation. Beginning with the CFAR detection simulation, $T = 1000$ trials are performed in which $N = 100$ samples are collected from a received signal with arbitrary known shape. For each trial, a signal-present scenario and a signal-absent scenario are tested, and the exact decision rule shown in (10) is used to determine the receiver's hypothesis of choice. This process is performed over a range of prior π_0 values producing the receiver operating characteristic (ROC) shown in Figure 4. Note that the *statistical* and *blind* cases produce performance identical to the UMP test from a ROC perspective, and thus only a comparison between *vision* and UMP is necessary.

The probability of error simulation is performed in a similar fashion, but the trials are performed while sweeping over SNR values and a fixed value of $\pi_0 = 0.5$.

One can see from the ROC curves that the *vision* case always provides a higher P_D for a given P_{FA} than the UMP test, and the gain achieved depends upon the probability of LOS, q. This sets the *vision* case apart from the other knowledge cases. The benefit provided by the *statistical* case over the *blind* case is demonstrated in the prob. of error curves wherein prior knowledge of signal presence is available.

VI. Conclusions and Future Work

We have shown that information provided through sensors which is supplementary to that obtained by the receiver itself can, under the right circumstances, improve the detection performance for the receiver when a dynamic detection scheme is used. Moreover, out of three knowledge cases presented, *vision*, *statistical*, and *blind*, the *vision* case leads to better ensemble performance compared to the UMP test while the others do not. By dynamically changing the detection threshold used depending on the known channel state, one can allow higher false alarm rates in NLOS conditions while lowering false alarm rates in LOS conditions to achieve the desired average false alarm rate. Possession of statistical knowledge at the receiver, although not helpful in a CFAR paradigm, dominates the *blind* case when prior information about signal presence is provided.

The results obtained point to the broader advantage provided by sensor-based information for both CFAR and $\min_{\mathcal{H}_i}(P_e)$ detectors. Therefore, future work should examine the impact of imperfect sensor-based information, a scenario more representative of real systems. There is also ample room to explore the impact of *vision* for more sophisticated channels such as those with Rayleigh and Ricean fading.

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