

## S-72.311 ADVANCED ERROR CONTROL SCHEMES

Home assignment #1, submission date: March 13<sup>th</sup> 2001

1. (Van Trees, problem 2.2.1) Consider the following binary hypothesis testing problem:

$$H_1 : r = s + n$$

$$H_0 : r = n,$$

where  $s$  and  $n$  are independent random variables.

$$p_s(S) = ae^{-aS} \quad S \geq 0,$$

$$0 \quad S < 0,$$

$$p_n(N) = be^{-bN} \quad N \geq 0,$$

$$0 \quad N < 0.$$

- a) Prove that the likelihood ratio test reduces to

$$\text{choose } H_1 \text{ if } R > \gamma$$

$$\text{choose } H_0 \text{ if } R < \gamma.$$

- b) Find  $\gamma$  for the optimum Bayes test as a function of the costs and a priori probabilities.
- c) Now assume that we need a Neyman-Pearson test. Find  $\gamma$  as a function of  $P_F$ , where

$$P_F \triangleq \Pr[\text{say } H_1 \mid H_0 \text{ is true}].$$

2. (Van Trees, problem 2.2.6) The observation  $r$  is defined in the following manner:

$$r = bm_1 + n : H_1,$$

$$r = n : H_0,$$

where  $b$  and  $n$  are independent zero-mean Gaussian variables with variances  $\sigma_b^2$  and  $\sigma_n^2$  respectively.

- a) Find the LRT and draw a block diagram of the optimum processor.

- b) Draw the ROC.
- c) Assume that the two hypotheses are equally likely. Use the criterion of minimum probability of error. What is the  $\Pr(\varepsilon)$ ?
3. (Van Trees, problem 2.2.12, parts a and b) Randomized tests. Our basic model of the decision problem in the text (p. 24) did not permit randomized decision rules. We can incorporate them by assuming that at each point  $\mathbf{R}$  in  $Z$  we say  $H_1$  with probability  $\phi(\mathbf{R})$  and say  $H_0$  with probability  $1 - \phi(\mathbf{R})$ . The model in the text is equivalent to setting  $\phi(\mathbf{R}) = 1$  for all  $\mathbf{R}$  in  $Z_1$  and  $\phi(\mathbf{R}) = 0$  for all  $\mathbf{R}$  in  $Z_0$ .
- a) We consider the Bayes criterion first. Write the risk for the above decision model.
- b) Prove that a LRT minimizes the risk and a randomized test is *never* necessary.
4. (Van Trees, problem 2.2.13) The random variable  $\Lambda(\mathbf{R})$  is defined by (13) and has a different probability density on  $H_1$  and  $H_0$ . Prove the following:
- a)  $E[\Lambda^n | H_1] = E[\Lambda^{n+1} | H_0]$ ,
- b)  $E[\Lambda | H_0] = 1$ ,
- c)  $E[\Lambda | H_1] - E[\Lambda | H_0] = \text{var}[\Lambda | H_0]$ .
5. (Van Trees, problem 2.2.14) Consider the random variable  $\Lambda$ . In (94) we showed that

$$p_{\Lambda|H_1}(X | H_1) = X p_{\Lambda|H_0}(X | H_0).$$

- a) Verify this relation by direct calculation of  $p_{\Lambda|H_1}[\cdot]$  and  $p_{\Lambda|H_0}[\cdot]$  for the densities in Example 1 [p. 27, (19) and (20)].
- b) On page 37 we saw that the performance of the test in Example 1 was completely characterized by  $d^2$ . Show that

$$d^2 = \ln[1 + \text{var}(\Lambda | H_0)].$$