Published in final edited form as:

J Opt Soc Am A Opt Image Sci Vis. 2016 March ; 33(3): 286–292.

Shannon information for joint estimation/detection tasks and complex imaging systems

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Abstract

Shannon information is defined for imaging tasks where signal detection is combined with parameter estimation. The first task considered is when the parameters are associated with the signal and parameter estimates are only produced when the signal is present. The second task examined is when the parameters are associated with the object being imaged, and parameter estimates are produced whether the signal is present or not. In each case, the Shannon information expression has a simple additive form.

1. INTRODUCTION

Shannon information [1–5] has been used as a figure of merit for the optimization of imaging systems in the contexts of signal detection or parameter estimation [6–9]. In these studies, the task-specific information (TSI) is computed for a set of imaging system parameters and a population of objects being imaged. For detection tasks, the TSI is the Shannon information between the binary state variable, which specifies the presence to absence of a signal and the data vector produced by the imaging system. For estimation tasks, the TSI is the Shannon information between the object parameters of interest and the imaging system data vector. In both cases, the TSI is then a function of the system parameters, and the goal is to maximize this function [10].

For detection tasks, receiver operating characteristic (ROC) analysis [11–18] is often used to measure the performance of an imaging system combined with an observer, i.e., a detection algorithm or a person. The ideal observer is a mathematical observer that has full knowledge of the statistics of the data and uses that knowledge to perform the detection task. The ideal observer minimizes the probability of error for all values of the prevalence (the probability that the signal is present). This observer also has the best possible ROC curve and maximizes the area under this curve (AUC). Since the AUC is directly measurable for any observer using a two-alternative forced-choice (2AFC) test, or any rating scale ROC method, the ideal-observer AUC is also used as a figure of merit for the imaging system on a specified detection task. We have recently found a connection between TSI for the detection task and the ideal-observer ROC curve via a Shannon information ROC (SIROC) curve [10].

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OCIS codes: (110.2960) Image analysis; (110.3000) Image quality assessment

We have found that ROC analysis for the ideal observer is mathematically equivalent to the computation of the Shannon information for the same task.

In previous publications, we defined the estimation ROC (EROC) curve for joint estimation/detection tasks [19–21]. This is a generalization of the localization ROC (LROC) curve to more general parameter estimation problems. We also showed that there is an ideal EROC observer, i.e., a mathematical observer that has the best EROC curve and maximizes the area under this curve. This observer actually performs the parameter estimation first, and then uses that estimate to decide whether the signal is present or not. This is why we are calling the joint task an estimation/detection task.

We wish to extend TSI optimization to combined estimation/detection tasks. Joint tasks are important as they allow for detection and localization tasks, such as the detection and location of tumors. There are two types of tasks we will be considering. In Application I, the parameters are associated with the signal, and we only produce an estimate when we decide that there is a signal present. An example of this situation is the estimation of parameters describing a tumor in medical imaging. In Application II, the parameters are associated with the object being imaged whether the signal is present or not. This will be the case, for example, in x-ray computed tomography (CT) systems for luggage where object reconstruction is desired for all bags. In the simulation section, we will see that this joint task approach can lead to different performance optimization.

2. APPLICATION I

In this application, the parameters to be estimated are associated with the signal to be detected. Therefore, we want to use the data to detect if the signal is present or absent. If we decide that it is present, then we want to estimate the signal parameters of interest. If we decide the signal is absent, then no further action is needed. In medical imaging, for example, the signal could be a localized abnormality, and we may want to detect it and estimate its location, size, and shape. This is the scenario analyzed by the EROC curve. We are essentially looking for a Shannon information analog for this curve.

Let $S_0 = \{0\}$ and $S_1 = \{1\}$ be single element sets, indicating whether the signal is absent or present. Let Θ be the Q -dimensional manifold of possible values for a vector parameter θ . The state space for the input to the imaging system is then $X = S_0 \cup (S_1 \times \Theta)$. An element x of the space X will be called a prior state. Thus, a prior state x is either 0 or the pair $(1, \theta)$. The probability that the signal is absent is P_0 , and the probability that the signal is present is $P_1 = 1 - P_0$. The prior probability density function (PDF) for θ will be denoted by $pr_{\theta}(\theta)$.

Let $\mathbf{y} \in Y \subseteq \mathbb{R}_M$ be the imaging system data vector, where Y is an M -dimensional subset of $\mathbb{R}_M$ containing all possible data vectors. Let $pr_0(\mathbf{y})$ be the PDF for the data when the signal is absent, and let $pr(\mathbf{y}, \theta)$ be the joint PDF on the data and the parameter vector when the signal is present. We will also use the conditional PDF $pr(\mathbf{y}|\theta)$ defined by $pr(\mathbf{y}, \theta) = pr(\mathbf{y}|\theta)pr_{\theta}(\theta)$. The marginal PDF for $\mathbf{y}$ is then given by

$$pr_y(\mathbf{y}) = P_0 pr_0(\mathbf{y}) + P_1 \int_{\Theta} pr(\mathbf{y}, \boldsymbol{\theta}) d^Q \theta. \quad (1)$$

We will also write this as $pr_y(\mathbf{y}) = P_0 pr_0(\mathbf{y}) + P_1 pr_1(\mathbf{y})$.

We compute the SI for this application using $I = H(\mathbf{y}) - H(\mathbf{y}|x)$. The entropy $H(\mathbf{y})$ is given by

$$H(\mathbf{y}) = - \int_{\mathbf{y}} [P_0 pr_0(\mathbf{y}) + P_1 pr_1(\mathbf{y})] \ln [P_0 pr_0(\mathbf{y}) + P_1 pr_1(\mathbf{y})] d^M y. \quad (2)$$

The negative of the conditional entropy $H(\mathbf{y}|x)$ is

$$-H(\mathbf{y}|x) = P_0 \int_{\mathbf{y}} pr_0(\mathbf{y}) \ln [pr_0(\mathbf{y})] d^M y + P_1 \int_{\Theta} \int_{\mathbf{y}} pr(\mathbf{y}, \boldsymbol{\theta}) \ln [pr(\mathbf{y}, \boldsymbol{\theta})] pr_{\theta}(\boldsymbol{\theta}) d^M y d^Q \theta. \quad (3)$$

The second integral in this expression may be written as

$$P_1 \int_{\Theta} \int_{\mathbf{y}} pr(\mathbf{y}, \boldsymbol{\theta}) \ln \left[\frac{pr(\mathbf{y}, \boldsymbol{\theta})}{pr_1(\mathbf{y})} \right] pr_{\theta}(\boldsymbol{\theta}) d^M y d^Q \theta + P_1 \int_{\mathbf{y}} pr_1(\mathbf{y}) \ln [pr_1(\mathbf{y})] d^M y. \quad (4)$$

The first of these integrals can also be written as

$$P_1 \int_{\Theta} \int_{\mathbf{y}} pr(\mathbf{y}, \boldsymbol{\theta}) \ln \left[\frac{pr(\mathbf{y}, \boldsymbol{\theta})}{pr_1(\mathbf{y}) pr_{\theta}(\boldsymbol{\theta})} \right] d^M y d^Q \theta = I(\mathbf{y}, \boldsymbol{\theta}), \quad (5)$$

which is P_1 times the SI between $\mathbf{y}$ and $\boldsymbol{\theta}$. This is the SI for the estimation task when the signal is known to be present and will be denoted by I_e . The remaining terms in the expansion $I = H(\mathbf{y}) - H(\mathbf{y}|x)$ give us the SI for the pure detection task, which we will call I_d .

$$I_d = P_0 \left\langle \ln \left[\frac{pr_0(\mathbf{y})}{P_0 pr_0(\mathbf{y}) + P_1 pr_1(\mathbf{y})} \right] \right\rangle_0 + P_1 \left\langle \ln \left[\frac{pr_1(\mathbf{y})}{P_0 pr_0(\mathbf{y}) + P_1 pr_1(\mathbf{y})} \right] \right\rangle_1. \quad (6)$$

The final result is then

$$I = I_d + P_1 I_e, \quad (7)$$

so that the SI for the joint task is a linear combination of the SI for the detection task and the SI for the estimation task.

3. APPLICATION II

In this application, we want to estimate object parameters whether the signal is present or not. In imaging applications, we may want a reconstructed image as well as a decision as to whether or not the signal is present. In tomographic imaging, an image reconstruction is an estimate of the vector of voxel values for the physical quantity being imaged. In CT scans, for example, we want an estimate of the integrated x-ray attenuation in each voxel.

As before, the absence or presence of a signal is associated with the single element sets $S_0 = \{0\}$ and $S_1 = \{1\}$. For $i = 0, 1$, let Θ_i be the Q_i -dimensional manifold of possible values for a vector parameter θ_i . We allow these two manifolds to be different because there may be more parameters to estimate when the decision is made that the signal is present. The state space for the input to the imaging system is now $X = (S_0 \times \Theta_0) \cup (S_1 \times \Theta_1)$. An element x of the space X will again be called a prior state. Thus, a prior state x is either the pair $(0, \theta_0)$ or the pair $(1, \theta_1)$. The prior PDFs for the parameter vectors will be denoted by $pr_0(\theta_0)$ and $pr_1(\theta_1)$ for the signal absent and signal present cases, respectively.

Let $y \in Y \subseteq \mathbb{R}_M$ be the imaging system data vector, where Y is again an M -dimensional subset of $\mathbb{R}_M$ containing all possible data vectors. Let $pr_0(y, \theta_0)$ be the joint PDF for the data and parameter vector when the signal is absent, and let $pr_1(y, \theta_1)$ be the joint PDF on the data and the parameter vector when the signal is present. We will also use the conditional PDFs $pr_i(y|\theta_i)$ defined by $pr_i(y, \theta_i) = pr_i(y|\theta_i)pr_i(\theta_i)$. The marginal PDF for y is now given by

$$pr_y(y) = P_0 \int_{\Theta_0} pr_0(y, \theta_0) d^{Q_0} \theta_0 + P_1 \int_{\Theta_1} pr_1(y, \theta_1) d^{Q_1} \theta_1. \quad (8)$$

We will also write this as $pr_y(y) = P_0 pr_0(y) + P_1 pr_1(y)$.

We will now compute the SI for this application by again using $I = H(y) - H(y|x)$. The entropy $H(y)$ is given as above by

$$H(y) = - \int_Y [P_0 pr_0(y) + P_1 pr_1(y)] \ln [P_0 pr_0(y) + P_1 pr_1(y)] d^M y. \quad (9)$$

The negative of the conditional entropy $H(y|x)$ is now

$$-H(y|x) = P_0 \int_{\Theta_0} \int_Y pr_0(y|\theta_0) \ln [pr_0(y|\theta_0)] pr_{0\theta}(\theta_0) d^M y d^{Q_0} \theta_0 + P_1 \int_{\Theta_1} \int_Y pr_1(y|\theta_1) \ln [pr_1(y|\theta_1)] pr_{1\theta}(\theta_1) d^M y d^{Q_1} \theta_1. \quad (10)$$

Each integral in this expression may be written as

$$P_i \int_{\Theta_i} \int_{\mathbf{y}} pr_i(\mathbf{y}|\boldsymbol{\theta}_i) \ln \left[\frac{pr(\mathbf{y}|\boldsymbol{\theta}_i)}{pr_1(\mathbf{y})} \right] pr_{i\theta}(\boldsymbol{\theta}_i) d^M y d^{Q_i} \theta_i + P_i \int_{\mathbf{y}} pr_i(\mathbf{y}) \ln[pr_i(\mathbf{y})] d^M y. \quad (11)$$

As before, the first of these integrals can also be written as

$$P_i \int_{\Theta_i} \int_{\mathbf{y}} pr_i(\mathbf{y}, \boldsymbol{\theta}_i) \ln \left[\frac{pr_i(\mathbf{y}, \boldsymbol{\theta}_i)}{pr_i(\mathbf{y}) pr_{i\theta}(\boldsymbol{\theta}_i)} \right] d^M y d^{Q_i} \theta_i = I(\mathbf{y}, \boldsymbol{\theta}_i), \quad (12)$$

which is P_i times the SI between $\mathbf{y}$ and $\boldsymbol{\theta}_i$. This is the SI for the estimation task when the signal is known to be absent ($i=0$), or known to be present ($i=1$), and will be denoted by I_{je} . The remaining terms in the expansion $I = H(\mathbf{y}) - H(\mathbf{y}|x)$ give us again the SI for the pure detection task, I_d . The final result for this application is then

$$I = I_d + P_0 I_{0e} + P_1 I_{1e}, \quad (13)$$

so that the SI for the joint task is a linear combination of the SI for the detection task and the SIs for the estimation tasks. Note that the last two terms together form the expected value of the SI for the estimation task over the ensemble of input states:

$$\langle I_e \rangle = P_0 I_{0e} + P_1 I_{1e}. \quad (14)$$

This last result can be easily generalized to compute the Shannon information for the multiple estimation/classification problem (i.e., the Shannon MECI). In this case,

$$I = I_c + \sum_{j=1}^J P_j I_{je}, \quad (15)$$

where I_c is the Shannon information for the pure classification problem, J is the number of classes, and I_{je} is the Shannon information for the parameter estimation problem when the data vector is known to be generated from class j .

4. SIMULATIONS

In this section, we look at the response of joint estimation and detection information (JEDI) as we vary parameters for the two applications discussed in the previous sections. In order to analyze JEDI behavior for the scenario discussed in Application I, we use two Gaussian distributions to represent object detection and vary distribution parameters. After studying Application I, we move on to analyzing Application II by considering a pinhole imaging device and how altering system parameters effect JEDI.

A. Simulation Study with 1D Gaussian Models

To explore JEDI, we first used two one-dimensional Gaussian models. The signal absent distribution is a standard normal distribution, and the signal present is a Gaussian distribution with a mean and variance used as parameters. In other words, we use the two hypotheses $H_0: x \sim \mathcal{N}(0, 1)$ and $H_1: x \sim \mathcal{N}(m, \sigma^2)$. The mean and standard deviation are varied along some interval uniformly. We will also use as a parameter the relative prevalence of a signal absent $t = \frac{P_0}{P_1}$. This allows us to analyze JEDI information developed in Application I.

1. Information as It Varies with Threshold—We first examine the JEDI curve for a change in t . From Eq. (5), we expect I_e to be constant for a shift in t . We also expect the I_d to be zero when t is zero or infinity; in between these bounds, we will quickly reach a peak and then decay back to zero, as can be seen in Eq. (6). JEDI is then found by combining detection and estimation information in accordance with Eq. (7). JEDI will be equivalent to estimation information when $t = 0$. The results for the simulation are shown in Fig. 1. For the simulation, we randomly sampled $H_1: m \sim U[-2.5, 2.5]$, $\sigma^2 \sim U[0.0001, 5.0001]$. We then ran Monte Carlo integration to find the expectations for both signals present and signal absent distributions to solve for JEDI in accordance with Eq. (7). We can see that JEDI, detection information, and estimation information all follow their expected trends.

2. Information as the Signal Present Varied—For the next two simulations we set the threshold to $t = 1$, allowing the prior probabilities to be equal, and then examine the effect of changing the range of possible means or standard deviations for the signal present distribution. As the difference between signal present and signal absent parameters are made larger, we can expect the information to increase.

In order to measure the effect of changing possible means, the variable mean range, m_r , is established. We then define the characteristics of the signal present by randomly sampling $H_1: m \sim U[-\frac{m_r}{2}, \frac{m_r}{2}]$, $\sigma^2 \sim U[0.0001, 5.0001]$. By plotting m_r against the information metrics, we can see how introducing more variability in the means effects JEDI. In Fig. 2 we see that as the range of possible means increases, the separation between signal absent and signal present also increases. This leads to an increase in detection information, but eventually the benefit of signal present and absent separation decreases resulting in saturation of detection information. Estimation information also benefits from the increase of m_r . The JEDI curve ends up being between the two curves.

To complete the analysis of JEDI from Application I, we then look at the effect of changing the range of possible standard deviations. The variable standard deviation range, σ_r^2 , will be used to observe the effect. We then define the characteristics of signal present by randomly sampling $H_1: m \sim U[-2.5, 2.5]$, $\sigma^2 \sim U[10^{-4}, \sigma_r^2 + 10^{-4}]$, and by varying σ_r^2 we can plot how information is affected by the range of standard deviations. The results are shown in Fig. 3. The smaller the range of standard deviations, the easier it is to estimate the actual signal so the estimation information curve increases as σ_r^2 goes to zero. The detection information benefits from the increased standard deviation range, because it separates the signal absent

and signal present distributions. As the upper limit on the range of variances is increased, more of the samples from the signal present will be distributed further from signal absent samples. This results in an increased signal detection. The trade-off between the two results in a non-monotonic JEDI curve.

From Figs. 2 and 3, we can see that the more we separate the distributions between signal present and signal absent, the better detection response we get. When performing the joint task of estimation and detection, we can see from Fig. 2 that we want to maximize the mean range of signal present relative to signal absent. For the standard deviation range, we would want to minimize the spread of signal present distributions in order to maximize Shannon estimation information, but this would negatively affect detection information. This demonstrates that different design decisions for system optimization would be made for a joint task detection system versus a pure detection task system.

B. Simulation Study Using Pinhole Imaging

In order to look at JEDI for Application II, a simulated imaging system was developed. For this system, a filtered Gaussian background was made by filtering Gaussian white noise backgrounds with a centered Gaussian filter with variance σ_f^2 . The signal is a disk with a random radius (r) and magnitude (A). The disk size is selected using a Gaussian distribution with mean m_r and variance σ_r^2 . The center of the signal is determined such that the entire signal will fit within the predefined object space and is placed randomly using a uniform distribution. The amplitude is also determined by a Gaussian distribution with mean m_A and variance σ_A^2 . This object is then placed into a model of a pinhole single-photon emission computed tomography (SPECT) imaging system by convolving the resulting object with a Gaussian point spread function with variance σ_{sys}^2 . This image is then multiplied by the gain G of the pinhole. Measurement noise is then added as a Gaussian distribution with variance σ_m^2 . Figure 4 shows an example of the images generated from the system described above.

1. Information as It Varies with Pinhole Parameters—We start exploring the meaning of JEDI by adjusting the pinhole parameters by changing the system magnification parameter σ_{sys} without altering exposure.

The results in Fig. 5 show the significance of joint task considerations. The choice of detection information, estimation information, or Shannon information will determine different values for the optimal magnification parameter. To optimize these results, you could pick the σ_{sys} which will maximize JEDI as the optimal magnification parameter, choosing a trade-off between estimation and detection. The designer could also decide to create a system which alters configuration for a detection and estimation mode, applying the optimal magnification parameter in each mode. In the event of a time or photon budget, there will be a constraint on the time or number of photons in each system, in which case the JEDI will allow you to pick a trade-off between detection and estimation.

We can also consider the effect of adjusting the exposure (G) and see the effect of increasing exposure time on a fixed pinhole. Figure 6 shows the results of changing the exposure time.

If we are just considering the detection task, then exposure would be considered a relatively unimportant trait for this range of exposure but considering the joint task there is a benefit.

Finally, we could consider a fixed imaging system where we instead change the pinhole size. This is accomplished by redefining G to be a function of σ_{sys} . For Eq. (16), we set $C = 1$. In Fig. 7, we see the results;

$$G = C \sigma_{\text{sys}}^2. \quad (16)$$

2. Information as It Varies with Threshold—Next we can compare adjusting the threshold as in the previous section on Application I by using $t = \frac{P_0}{P_1}$. By varying the threshold of the imaging system, identical results to Application I case are expected. The estimation information does not vary with the relative prevalence of signal absent and signal present. Detection information rises to a maximum, and then comes down. JEDI is a weighted average of estimation and detection information. The results are shown in Fig. 8 and match closely with the results in Fig. 1.

3. Information as It Varies with System Noise—Next we can explore system noise parameters. First we will examine the effect of changing σ_f^2 , and then we can change the m_{bg} . First we set the probabilities, $P_0 = P_1 = 0.5$. Then by varying the background filter variance, we can control the background covariance. As we increase σ_f^2 , the background will become more correlated. A more correlated background will have little effect on the ability to estimate our signal parameters but will make detecting the signal much harder. Correlated background can result in spurious signal detection when correlated values are mistaken as a signal. Estimation, however, will not be effected as it is a measure of our ability to reconstruct the image. In Fig. 9, we see that estimation is mostly unchanged and detection information decreases with σ_f .

In Fig. 10, we vary mean background m_{bg} . As the background increases, the signal becomes harder to detect, but the ability to estimate the image does not change. In this case, we see that m_{bg} only matters when we consider the joint task.

4. Information as It Varies with Signal Parameters—For the last simulations, we can evaluate the effect of signal adjustments on the information available in the imaging system. We observe the effect of mean signal amplitude, m_A , and mean signal radius, m_r .

In the case of amplitude, we see that the strength of the signal has a small effect on detection within a certain range but that estimation becomes much stronger as the object amplitude becomes larger. These results are given in Fig. 11.

Next we fix the amplitude of the signal and adjust its radius. In Fig. 12 we see that as the signal radius grows, it will increase information but only to a certain extent. Depending on the choice of detection, estimation, or joint information, this system is optimized for different signal sizes.

5. CONCLUSION

We have shown how Shannon TSI may be defined for two types of combined estimation/detection tasks. The results are easily generalized to tasks that combine N-class classification with parameter estimation for objects in some or all of the classes. The result is always a linear combination of the TSI for the classification task and the TSIs for each estimation task. This simple decomposition is unique to Shannon information and does not apply to other measures of information, such as those defined using Renyi divergences or f -divergences. The simulations have shown how the relative contributions to Shannon JEDI from the detection and estimation components can change as the prior probability density for the parameter vector is changed. In a future publication we will show how these results lead to generalizations of the planar EROC curve to 3D and 4D EROC curves. The exact relation between these curves and the Shannon JEDI is the subject of ongoing study. We will also consider complex imaging systems and joint tasks where a measure theoretic definition of JEDI is required [5]. This will be a subject of a future publication.

Acknowledgments

Funding. National Institutes of Health (NIH) (P41-EB002035), (R01-EB000803); U.S. Department of Homeland Security (DHS) (HSHQDC-14-C-BOOIO).

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Fig. 1.
Information as it varies with threshold for the 1D Gaussian.

Fig. 2.
Information as it varies with the range of means for the 1D Gaussian.

Fig. 3.

Information as it varies with the range of standard deviations for the 1D Gaussian.

Fig. 4.
Sample image for the pinhole.

Fig. 5.
Information change as the magnification parameter is adjusted.

Fig. 6.
Information change as the gain is adjusted.

Fig. 7.
Information change as the fixed imaging pinhole is adjusted.

Fig. 8.
Information as it varies with threshold for the SPECT system.

Fig. 9.

Information as the background filter size is adjusted for the SPECT system.

Fig. 10.
Information as it varies with mean background for the SPECT system.

Fig. 11.
Information as it varies with mean signal amplitude for the SPECT system.

Fig. 12.
Information as it varies with mean signal radius for the SPECT system.