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INFORMATION INTEGRATION FROM HUMAN AND SENSING DATA FOR COGNITIVE RADAR (Preprint)

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14. ABSTRACT Cognitive radar, according to IEEE Standard Radar Definitions 686 [1], is a ‘radar system that in some sense displays intelligence, adapting its operation and its processing in response to a changing environment and target scene’. In particular, both the active and passive sensors embedded in a cognitive radar allow it to perceive/learn the dynamically changing environments, e.g., targets, clutter, RF interference and terrain map. To attain optimized performance for tasks such as detection, tracking and classification, the controller in a cognitive radar adapts the radar architecture and adjusts the resource allocation policy in real time [2, 3, 4]. For a wide range of applications, different techniques and methods of adaptation have been proposed, e.g., adaptive revisit time scheduling, waveform selection, antenna beam pattern, and spectrum sharing, to advance the mathematical foundations, assessment and evaluation in the context of cognitive radar [5, 6, 7, 8, 9, 10].					
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Chapter 11

Information Integration from Human and Sensing Data for Cognitive Radar

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Cognitive radar, according to IEEE Standard Radar Definitions 686 [1], is a ‘radar system that in some sense displays intelligence, adapting its operation and its processing in response to a changing environment and target scene’. In particular, both the active and passive sensors embedded in a cognitive radar allow it to perceive/learn the dynamically changing environments, e.g., targets, clutter, RF interference and terrain map. To attain optimized performance for tasks such as detection, tracking and classification, the controller in a cognitive radar adapts the radar architecture and adjusts the resource allocation policy in real time [2, 3, 4]. For a wide range of applications, different techniques and methods of adaptation have been proposed, e.g., adaptive revisit time scheduling, waveform selection, antenna beam pattern, and spectrum sharing, to advance the mathematical foundations, assessment and evaluation in the context of cognitive radar [5, 6, 7, 8, 9, 10].

While cognitive approaches and techniques have led to great progress in improving the radar performance in a number of areas, one key challenge of cognitive radar design and implementation is its interaction with the end users, i.e., how to bring humans in the loop for decision making and control. In critical situations such as national security and natural disaster forecasting, incorporating human cognitive strengths and expertise is imperative to improve decision quality and enhance situational awareness (SA). For instance, in electronic warfare (EW) systems, the detection of an adversary radar is required before designing appropriate countermeasures. In such scenarios where the course and success of the campaign depends on a small detail being observed or missed, automatic sensor-only decision making may not be sufficient and it is necessary to incorporate human(s) in the loop of decision making, command and control.

In many applications, humans serve as sensors as well, e.g., scouts monitoring a phenomenon of interest (PoI) to gather intelligence. In next generation cognitive radar systems, it is desirable to establish a framework to capture attributes suggested

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by human-based sources of information so that information from both the physical sensors and humans can be employed for inference. However, unlike traditional physical sensors/machines⁴ that take objective measurements, humans are subjective in expressing their opinions or decisions. Modeling and analysis of human decision making need to take several factors into account including cognitive biases of humans, mechanisms to handle uncertainties and noise as well as unpredictability of humans, in contrast to decision making processes consisting of only machine agents.

There have been research efforts that exploit the theory of signal processing and information fusion to analyze and incorporate human-specific factors in decision making. The authors in [11] employed quantization of prior probabilities to model the fact that humans make categorical perceptions instead of continuous observations for collaborative decision making in a Bayesian framework. In [12, 13], the authors have studied the group decision making performance when the human agents are assumed to use random thresholds to make threshold-based binary decisions. Considering that humans are affected by the starting point beliefs, the impact of selecting, ordering and presentation of data on human-decision making performance has been studied in [14]. In the collaborative human decision making paradigm, different schemes and fusion rules have been developed to ameliorate the unreliability and uncertainty of human crowd workers [15, 16]. Moreover, in [17, 18], the authors have included prospect theory (PT) to characterize human cognitive biases such as risk aversion and have studied human decision making behavior in realistic environments. Information fusion of human based and machine based sources of information has also been explored in [19, 20] for different scenarios. In [19], the authors show that human cognitive strengths can utilize multimedia data for better interpretation of data. A user refinement stage has been exploited together with the Joint Director of Labs (JDL) fusion model to incorporate human behavioral factors and judgement in decision making [20].

Battlefield of the future will require seamless integration of the human and the machine expertise where they simultaneously work within the same environment model to understand and solve problems. According to [21], humans surpass machines in their ability to improvise and use flexible procedures, exercise judgement and reason inductively. On the other hand, machines outperform humans in responding quickly, storing a large amount of information, performing routine tasks, and reason deductively (including computational ability). Advanced cognition in future radar systems seeks to build an augmented human-machine symbiosis and merge the best of the human with the best of the machine [22]. In this chapter, we provide an overview of these challenges and focus on three specific problems: i) integration of human decisions with decisions from physical sensors, ii) usage of the behavioral economics concept PT to model human cognitive biases in binary decision making, and iii) human-machine collaboration for semi-autonomous binary decision making under correlated observations.

The rest of this chapter is organized as follows. In Section 11.1, we present a work that shows how the presence of human sensors can be incorporated in the statistical signal processing framework. We also derive the asymptotic performance of

⁴The terms ‘sensors’ and ‘machines’ will be used interchangeably throughout this chapter.

such a human-machine integrated system when the humans possess auxiliary/side information that is not available to the machine. We employ the behavioral economics concept prospect theory to model human cognitive biases and study the behavior of human decision making under the binary hypothesis testing framework in Section 11.2. A novel human-machine collaboration paradigm is discussed in Section 11.3 to solve the binary hypothesis testing problem, where the dependency of the human's knowledge and the machine's observation is characterized using Copula theory. Finally, we provide a summary of the current challenges and some research directions related to this problem domain in Section 11.4 before concluding in Section 11.5.

Throughout this chapter, we use an arrow on top of a lowercase letter to denote vectors, e.g., $\vec{x}$. We represent the set of real numbers by $\mathbb{R}$. We denote the transpose by $(\cdot)^T$ and we use $Pr(\cdot)$ to denote probability. $N(\mu, \sigma^2)$ denotes the Gaussian distribution with mean μ and variance σ^2 .

11.1 Integration of Human Decisions with Physical Sensors in Binary Hypothesis Testing

In this section, we investigate the problem of decision making using data collected by physical sensor/device and sources of information from humans. Consider that we have $L = L_1 + L_2$ agents (L_1 physical sensors and L_2 human sensors) that collaboratively perform a binary hypothesis testing task, where the hypotheses are denoted by H_0 and H_1 , respectively. We assume that the conditional probability density functions (PDFs) of the observation x under H_j are denoted as $f_j(x)$ for $j = 0, 1$. The observations at the i^{th} agent are represented by x_i , $i = 1, \dots, L$, which are assumed to be independent and identically distributed (iid) under H_0 and H_1 .

11.1.1 Decision fusion for physical sensors and human sensors

First, we provide some background on the fusion of binary decisions made by physical sensors only [23]. We consider that the i^{th} sensor's binary decision d_i is modeled as

$$d_i = \begin{cases} 1, & \text{if } x_i \geq \tau_i \\ 0, & \text{if } x_i < \tau_i \end{cases} \quad (11.1)$$

for $i = 1, \dots, L_1$. The fusion center (FC) makes the final decision regarding the true hypothesis based on the decision vector $\vec{d} = [d_1, \dots, d_{L_1}]$. Let $p_{d,i}$ and $p_{f,i}$ represent the probability of detection and probability of false alarm of the i^{th} sensor when providing its decision d_i . To determine the true hypothesis at the FC based on some observed evidence, it was shown in [23] that the likelihood ratio test (LRT) is optimal as it has the minimum average probability of error:

$$\frac{Pr(\vec{d}|H_1)}{Pr(\vec{d}|H_0)} = \frac{\prod_{i=1}^{L_1} p_{d,i}^{d_i} (1 - p_{d,i})^{1-d_i}}{\prod_{i=1}^{L_1} p_{f,i}^{d_i} (1 - p_{f,i})^{1-d_i}} \underset{H_0}{\overset{H_1}{\geq}} \eta_0 \quad (11.2)$$

where η_0 is an appropriate threshold. In such a distributed detection setup, the authors in [24] proved that it is asymptotically optimal for the physical sensors to use the same decision threshold in order to achieve the best detection accuracy. As a result, we assume that $\tau_i = \tau$, $p_{f,i} = p_f$ and $p_{d,i} = p_d$ for $i = 1, \dots, L_1$. In this case, the log likelihood ratio (LLR) can be computed as $G_1 \sum_i d_i + G_0$ with $G_1 = \log \frac{p_d(1-p_f)}{p_f(1-p_d)}$ and $G_0 = L_1 \log \frac{1-p_d}{1-p_f}$. The decision rule (11.2) for final decision making becomes

$$d = \begin{cases} 1, & \text{if } \sum_i d_i \geq \eta_1 \\ 0, & \text{otherwise} \end{cases} \quad (11.3)$$

where $\eta_1 = \frac{\log \eta_0 - G_0}{G_1}$. As $\Lambda_1(\vec{d}) = \sum_i d_i$ follows Binomial distribution under both hypotheses, the probabilities of false alarm and detection for the decision rule (11.3) can be computed as [25]

$$P_{f,1} = Pr(\Lambda_1 \geq \eta_1 | H_0) = 1 - \sum_{k=0}^{\lfloor \eta_1 \rfloor} \binom{L_1}{k} p_f^k (1-p_f)^{L_1-k} \quad (11.4)$$

$$P_{d,1} = Pr(\Lambda_1 \geq \eta_1 | H_1) = 1 - \sum_{k=0}^{\lfloor \eta_1 \rfloor} \binom{L_1}{k} p_d^k (1-p_d)^{L_1-k} \quad (11.5)$$

respectively, where the second subscript ‘1’ in $P_{f,1}$ and $P_{d,1}$ refers to case 1 that is composed of L_1 physical sensors. We consider that L_1 is large enough so that $\Lambda_1(\vec{d})$ can be approximated by a Gaussian random variable and the probabilities of false alarm and detection can be computed as

$$P_{f,1} \approx Q\left(\frac{\eta_1 - L_1 p_f}{\sqrt{L_1 p_f(1-p_f)}}\right), \quad P_{d,1} \approx Q\left(\frac{\eta_1 - L_1 p_d}{\sqrt{L_1 p_d(1-p_d)}}\right) \quad (11.6)$$

respectively, where $Q(x)$ is the complement of the cumulative distribution function of the standard normal distribution with $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-u^2/2} du$.

Under the Neyman–Pearson criterion, the aim is to maximize the probability of detection under a false alarm constraint. If the FC chooses the decision threshold that satisfies $P_{f,1} \leq \omega_f$, the corresponding $P_{d,1}$ can be approximated as [25]

$$P_{d,1} \approx Q\left(\frac{\sqrt{p_f(1-p_f)}Q^{-1}(\omega_f) + \sqrt{L_1}(p_f - p_d)}{\sqrt{p_d(1-p_d)}}\right) \quad (11.7)$$

where $Q^{-1}(\cdot)$ is the inverse function of $Q(x)$. As both p_f and p_d in (11.7) are determined by τ such that $p_f = \int_\tau^\infty f_0(x)dx$ and $p_d = \int_\tau^\infty f_1(x)dx$, the optimal τ that maximizes $P_{d,1}$ is expressed as

$$\arg \max_{\tau} Q\left(\frac{\sqrt{p_f(\tau)(1-p_f(\tau))}Q^{-1}(\omega_f) + \sqrt{L_1}(p_f(\tau) - p_d(\tau))}{\sqrt{p_d(\tau)(1-p_d(\tau))}}\right) \quad (11.8)$$

In case that the physical sensors are not able to collect sufficiently informative observations, or when the system demands a higher level of detection accuracy such

as adversarial target detection and medical diagnosis, incorporation of human sensors based sources of information is desirable. To characterize the cognitive biases and uncertainties of each human in decision making, we consider that human sensors employ random thresholds to make binary decisions as discussed in [12].

Consider that L_2 human agents have the same iid observations as the physical sensors x_i for $i = L_1 + 1, \dots, L_2$, and the i^{th} human's decision rule is to compare the observation to a random threshold ς_i

$$t_i = \begin{cases} 1, & \text{if } x_i \geq \varsigma_i \\ 0, & \text{if } x_i < \varsigma_i \end{cases} \quad (11.9)$$

for $i = L_1 + 1, \dots, L_1 + L_2$. Unlike physical sensors that can be programmed to use fixed thresholds, we consider that humans use random decision thresholds because of their individual cognitive biases and uncertainties, where the PDF of ς_i is given by, $f_{\varsigma_i}(\varsigma_i)$, which can be estimated by collecting experimental data. For the i^{th} human that employs (11.9), the expected values of probabilities of detection and false alarm can be computed as $\theta_{t,i} = \Pr(\tilde{x}_i \geq 0|H_0)$ and $\gamma_{t,i} = \Pr(\tilde{x}_i \geq 0|H_1)$, respectively, with $\tilde{x}_i = x_i - \varsigma_i$. If the statistical distribution of ς_i is available, the PDF of $\tilde{x}_i$ under both H_0 and H_1 can be expressed as $f_{\tilde{x}_i}(\tilde{x}_i|H_j) = \int_{-\infty}^{\infty} f_i(\tilde{x}_i + \varsigma_i)f_{\varsigma_i}(\varsigma_i)d\varsigma_i$ for $j = 0, 1$. Hence, we have $\theta_{t,i} = \int_0^{\infty} f_{\tilde{x}_i}(\tilde{x}_i|H_0)d\tilde{x}_i$ and $\gamma_{t,i} = \int_0^{\infty} f_{\tilde{x}_i}(\tilde{x}_i|H_1)d\tilde{x}_i$. Define $\vec{t} = [t_{L_1+1}, \dots, t_{L_1+L_2}]$ and the LLR at the FC is given by

$$\Lambda_2(\vec{d}, \vec{t}) = G_1 \sum_{i=1}^{L_1} d_i + G_0 + \sum_{i=L_1+1}^{L_1+L_2} t_i \tilde{G}_{1,i} + \tilde{G}_0 \quad (11.10)$$

where $\tilde{G}_{1,i} = \log \frac{\gamma_{t,i}(1-\theta_{t,i})}{\theta_{t,i}(1-\gamma_{t,i})}$ and $\tilde{G}_0 = \sum_{i=L_1+1}^{L_1+L_2} \log \frac{1-\gamma_{t,i}}{1-\theta_{t,i}}$. When the final decision d is made by comparing (11.10) to a suitably designed threshold η_2 , the probabilities of detection and false alarm are given by $P_{d,2} = \Pr(\Lambda_2(\vec{d}, \vec{t}) \geq \eta_2|H_1)$ and $P_{f,2} = \Pr(\Lambda_2(\vec{d}, \vec{t}) \geq \eta_2|H_0)$, respectively, where the second subscript '2' in $P_{f,2}$ and $P_{d,2}$ refers to case 2 that is composed of L_1 physical sensors and L_2 human sensors.

By utilizing the statistical information of the human sensors' threshold (i.e., the PDFs of ς_i), it is possible to design the optimal threshold τ for the physical sensors so that the decision accuracy of the entire system can be maximized. With a total of $L =$

$L_1 + L_2$ sensors, the LLR at the FC is $\Lambda_2(\vec{d}, \vec{t}) = G_1 \sum_{i=1}^{L_1} d_i + G_0 + \sum_{i=L_1+1}^{L_1+L_2} t_i \tilde{G}_{1,i} + \tilde{G}_0$.

Let $\tilde{\Lambda}_2(\vec{d}, \vec{t}) = G_1 \sum_{i=1}^{L_1} d_i + \sum_{i=L_1+1}^{L_1+L_2} t_i \tilde{G}_{1,i}$ and note that $\sum_i d_i$ can be approximated

by Gaussian random variables under both hypotheses. Define $\tilde{\Lambda}_{2,1}(\vec{d}) = G_1 \sum_i d_i$ and $\tilde{\Lambda}_{2,2}(\vec{t}) = \sum_{i=L_1+1}^{L_1+L_2} t_i \tilde{G}_{1,i}$. For ease of presentation, we assume that the PDF of threshold ς_i employed by all the human agents are the same, then, we have $\tilde{G}_{1,i} = \tilde{G}_1$, $\theta_{t,i} = \theta_t$, and $\gamma_{t,i} = \gamma_t$ for $i = L_1 + 1, \dots, L_1 + L_2$. As the locals decisions of the human sensors are independent, $\tilde{\Lambda}_{2,2}/\tilde{G}_1$ represents a sum of iid Bernoulli random variables. Exploiting Gaussian approximation, we get $\tilde{\Lambda}_{2,2}(\vec{t})|H_1 \sim N(L_2 \tilde{G}_1 \gamma_t, L_2 \tilde{G}_1^2 \gamma_t(1 - \gamma_t))$ and $\tilde{\Lambda}_{2,2}(\vec{t})|H_0 \sim N(L_2 \tilde{G}_1 \theta_t, L_2 \tilde{G}_1^2 \theta_t(1 - \theta_t))$. Hence, $\tilde{\Lambda}_2$ approximately follow the Gaussian distributions with $\tilde{\Lambda}_2|H_j \sim N(\mu_j(\tau), \sigma_j^2(\tau))$ for $j = 0, 1$ where $\mu_0(\tau) =$

$L_1 G_1(\tau) p_f(\tau) + L_2 \tilde{G}_1 \theta_t$, $\mu_1(\tau) = L_1 G_1 p_d(\tau) + L_2 \tilde{G}_1 \gamma_t$, $\sigma_0^2(\tau) = L_1 G_1^2(\tau) p_f(\tau)(1 - p_f(\tau)) + L_2 \tilde{G}_1^2 \theta_t(1 - \theta_t)$ and $\sigma_1^2(\tau) = L_1 G_1^2(\tau) p_d(\tau)(1 - p_d(\tau)) + L_2 \tilde{G}_1^2 \gamma_t(1 - \gamma_t)$. Moreover, define $\tilde{\eta}_2 = \eta_2 - G_0 - \tilde{G}_0$ and we get

$$P_{d,2}(\tau) \approx Q\left(\frac{\tilde{\eta}_2 - \mu_1(\tau)}{\sigma_1(\tau)}\right), \quad P_{f,2}(\tau) \approx Q\left(\frac{\tilde{\eta}_2 - \mu_0(\tau)}{\sigma_0(\tau)}\right) \quad (11.11)$$

The optimal τ^* for optimized system performance can be obtained as

$$\tau^* = \arg \max_{\tau} P_{d,2} \text{ given that } P_{f,2} \leq \omega_f,$$

where ω_f is the constraint on probability of false alarm.

11.1.2 Asymptotic system performance when humans possess side information

In Subsection 11.1.1, the evaluation of system performance is obtained by the Gaussian approximation under certain regularity conditions on τ as $N \rightarrow \infty$. To avoid such an approximation, we evaluate the asymptotic performance of this system via Chernoff information, which could be used to approximate the probability of error for a likelihood ratio (LR) based decision fusion rule.

The Chernoff distance (Chernoff information) between two PDFs $f(z|H_0)$ and $f(z|H_1)$ is defined as

$$C \triangleq - \min_{0 \leq \lambda \leq 1} \log \int_z \left(\frac{f(z|H_1)}{f(z|H_0)} \right)^\lambda f(z|H_0) dz \quad (11.12)$$

where $f(z|H_0)$ and $f(z|H_1)$ are the conditional joint PDFs of z under hypotheses H_0 and H_1 , respectively. The probability of error at the FC can be expressed as $p_e \approx 2^{-nC}$, where n represents the number of data samples. Intuitively, p_e decreases exponentially as the number of data samples n increases, and C represents the decay rate. It is desired to have a larger Chernoff information in order to minimize p_e .

We consider that the PDFs of the humans' decision thresholds follow the same distribution $f_\zeta(\zeta)$. We denote θ_t and γ_t as the expected values of probabilities of false alarm and detection when t_i is made based on (11.9). In this situation, the normalized Chernoff information of the L_2 human sensors' decision $\vec{t}$ is given by [26]

$$\frac{1}{L_2} C_h = - \min_{0 \leq \lambda \leq 1} \log \left(\left(\frac{\gamma_t}{\theta_t} \right)^\lambda \theta_t + \left(\frac{1 - \gamma_t}{1 - \theta_t} \right)^\lambda (1 - \theta_t) \right) \quad (11.13)$$

However, in many situation awareness tasks, humans may possess additional information regarding the PoI in addition to the common attributes x observed by both the physical sensors and human sensors. For instance, humans are able to observe some phenomena such as the activities of animals, which can not be easily observed by physical sensors, before a natural disaster. We name this kind of information as human sensors' side information. In particular, assume that in addition to the common observation x_i , humans sensors possess side information w_i related to the PoI for $i = L_1 + 1, \dots, L_2$. To model the error behavior exhibited in

side information, w_i is modeled as an independent Bernoulli random variable with $Pr(w_i = 1|H_0) = \theta_{w,i}$ and $Pr(w_i = 1|H_1) = \gamma_{w,i}$. We further assume that $\theta_{w,i} = \theta_w$ and $\gamma_{w,i} = \gamma_w$ for $i = L_1 + 1, \dots, L_2$.

The overall decision v_i of the i^{th} human sensor is made based on t_i in (11.9) and the side information w_i . In the following, we consider two operations, i.e., OR rule and AND rule, that humans may use to incorporate t_i and w_i into the overall decision v_i .

OR operation[25]

The decision rule when employing the OR operation to incorporate side information is given as follows.

$$v_i = \begin{cases} 1 & x_i \geq \tau_i \text{ or } w_i = 1 \\ 0 & \text{otherwise} \end{cases} \quad (11.14)$$

for $i = L_1 + 1, \dots, L_2$. When the FC performs LR based fusion with the humans' local decisions $\vec{v} = [v_{L_1+1}, \dots, v_{L_2}]^T$, the PDF of $\vec{v}$ under H_1 and H_0 needs to be computed.

$$f(\vec{v}|H_1) = \prod_{i=L_1+1}^{L_2} \gamma_w v_i + (1 - \gamma_w)(\gamma_t^{v_i}(1 - \gamma_t)) \quad (11.15)$$

$$f(\vec{v}|H_0) = \prod_{i=L_1+1}^{L_2} \theta_w v_i + (1 - \theta_w)(\theta_t^{v_i}(1 - \theta_t)) \quad (11.16)$$

The asymptotic performance of the L_2 human sensors can be computed via Chernoff information. When employing the OR operation to incorporate side information, the normalized Chernoff information of the L_2 human decisions can be written as

$$\frac{1}{L_2} C_h^{OR} = - \min_{0 \leq \lambda \leq 1} \log(T_1^{OR}(1 - \theta_w)(1 - \theta_t) + T_2^{OR}(\theta_w + (1 - \theta_w)\theta_t)) \quad (11.17)$$

where $T_1^{OR} = \left(\frac{(1 - \gamma_w)(1 - \gamma_t)}{(1 - \theta_w)(1 - \theta_t)} \right)^\lambda$ and $T_2^{OR} = \left(\frac{\gamma_w + (1 - \gamma_w)\gamma_t}{\theta_w + (1 - \theta_w)\theta_t} \right)^\lambda$.

AND operation [27]

The decision rule when utilizing the AND operation to incorporate human decision t_i and side information w_i is given by

$$v_i = \begin{cases} 1 & x_i \geq \tau_i \text{ and } w_i = 1 \\ 0 & \text{otherwise} \end{cases} \quad (11.18)$$

for $i = L_1 + 1, \dots, L_2$. The PDF of $\vec{v} = [v_{L_1+1}, \dots, v_{L_2}]^T$ under H_1 and H_0 can be expressed as

$$f(\vec{v}|H_1) = \prod_{i=L_1+1}^{L_2} \gamma_w \gamma_t^{v_i} (1 - \gamma_t)^{1-v_i} + (1 - \gamma_w)(1 - v_i) \quad (11.19)$$

$$f(\vec{v}|H_0) = \prod_{i=L_1+1}^{L_2} \theta_w \theta_t^{v_i} (1 - \theta_t)^{1-v_i} + (1 - \theta_w)(1 - v_i) \quad (11.20)$$

Similar to the results for the OR operation, the normalized Chernoff information of the L_2 human decisions for the AND operation is given by

$$\frac{1}{L_2} C_h^{AND} = - \min_{0 \leq \lambda \leq 1} \log (T_1^{AND} (\theta_w (1 - \theta_t) + 1 - \theta_w) + T_2^{AND} \theta_w \theta_t) \quad (11.21)$$

where $T_1^{AND} = \left(\frac{\gamma_w (1 - \gamma_t) + 1 - \gamma_w}{\theta_w (1 - \theta_t) + 1 - \theta_w} \right)^\lambda$ and $T_2^{AND} = \left(\frac{\gamma_w \gamma_t}{\theta_w \theta_t} \right)^\lambda$.

In the above two cases, we can derive the optimal λ^* by setting $\frac{\partial C_h^{OR}}{\partial \lambda} = 0$ and $\frac{\partial C_h^{AND}}{\partial \lambda} = 0$, respectively. Given the PDF $f_\zeta(\zeta)$ of the human thresholds, we can find the conditions under which incorporating the side information improves the detection performance, i.e., when $\gamma_w \in \{\gamma_w | C_h^{OR}(\gamma_w) \geq C_h\}$ for the OR operation or $\gamma_w \in \{\gamma_w | C_h^{AND}(\gamma_w) \geq C_h\}$ for the AND operation, the side information helps improve the quality of human sensors' decisions.

Recall that when the physical sensors use the same decision threshold τ in (11.1), the likelihood function of $\vec{d} = [d_1, \dots, d_{L_1}]$ under H_1 and H_0 is expressed as

$$f(\vec{d}|H_1) = \prod_{i=1}^{L_1} p_d^{d_i} (1 - p_d)^{1-d_i}, \quad f(\vec{d}|H_0) = \prod_{i=1}^{L_1} p_f^{d_i} (1 - p_f)^{1-d_i} \quad (11.22)$$

The normalized Chernoff information of the L_1 physical sensors' decisions is given by

$$\frac{1}{L_1} C_p = - \min_{0 \leq \lambda \leq 1} \log \left(\left(\frac{p_d}{p_f} \right)^\lambda p_f + \left(\frac{1 - p_d}{1 - p_f} \right)^\lambda (1 - p_f) \right) \quad (11.23)$$

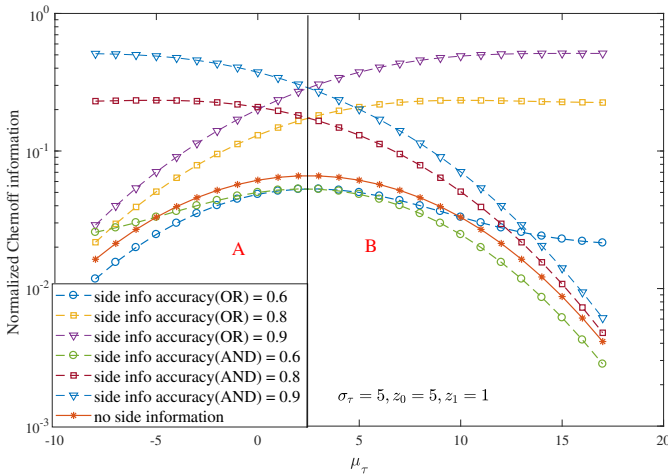


Figure 11.1 Normalized Chernoff information with different values of μ_τ and different accuracy of side information

Finally, the overall Chernoff information of the integrated system composed of L_1 physical sensors and L_2 human sensors can be approximately computed as $C_o^{OR} \approx C_p + C_h^{OR}$ when humans adopt the OR operation rule, and $C_o^{AND} \approx C_p + C_h^{AND}$ when humans adopt the AND operation rule.

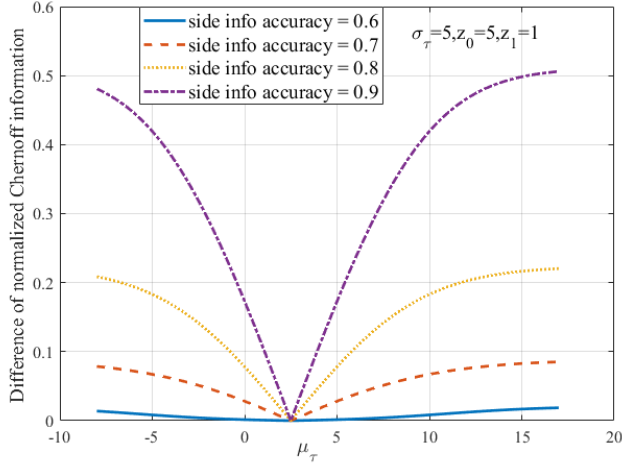


Figure 11.2 Difference of Chernoff information through AND operation and OR operation with different μ_τ and accuracy of side information

We present some simulation results for illustration. It is assumed that $z_i|H_j \sim \exp(x_j)$ for $i = 1, 2, \dots, L_1 + L_2$ and $j = 0, 1$, where $x \sim \exp(z)$ means that x follows an exponential PDF $f(x) = ze^{-zx}$ for $x \geq 0$ and the probability is 0 otherwise. In Figure 11.1 and Figure 11.2, we plot the performance for the system composed of only human sensors and without participation of physical sensors to show the impact of side information on humans' decisions more clearly. The thresholds of the human sensors are assumed to follow the Gaussian distribution with mean and standard deviation (μ_τ, σ_τ) . The impact of OR and AND operations on the asymptotic performance of this system is illustrated in Figure 11.1. It shows how the normalized Chernoff information changes with respect to the parameter of the PDF of threshold μ_τ and the accuracy of side information γ_w . It is observed that the system performs even worse than the system with no side information if $\gamma_w = 0.6$. This indicates that the accuracy of side information is not in the set $\{\gamma_w | Ch_h^{OR}(\gamma_w) \geq C_h\}$ or $\{\gamma_w | Ch_h^{AND}(\gamma_w) \geq C_h\}$, and therefore the side information will not improve the quality of humans' decisions. When γ_w increases beyond a specific threshold, the side information helps improve the human's performance. Furthermore, when μ_τ is in the region A shown in Figure 11.1, the OR operation is a better choice to incorporate side information. Otherwise, the AND operation performs better.

To further identify the regions A and B more clearly, the difference of the Chernoff information when the humans employ the OR operation and the AND operation $|Ch_h^{OR} - Ch_h^{AND}|$ is plotted in Figure 11.2. It is observed that the difference

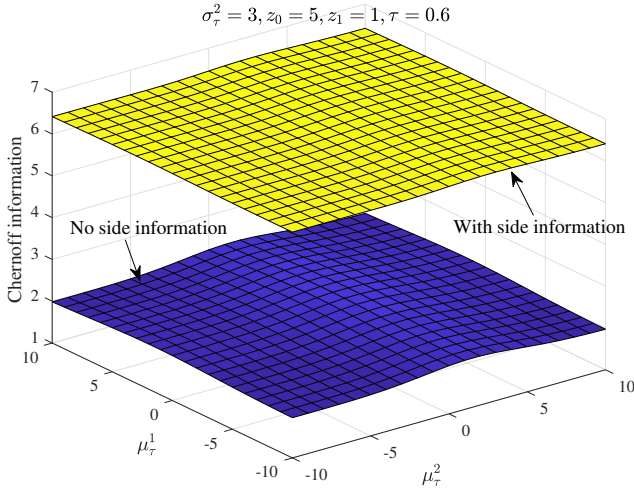


Figure 11.3 Comparison of the performance between the systems with side information and without side information.

decreases to 0 at a certain fixed μ_τ irrespective of how the accuracy of side information changes. Hence, the point that delineates the regions corresponding to the two rules, namely OR and AND rules, is a fixed point that depends on the statistical information of the humans' thresholds and has nothing to do with the accuracy of side information.

In Fig. 11.3, we compute the performance of the integrated system composed of $L_1 = 20$ physical sensors and $L_2 = 20$ human sensors. The observations x_i for $i = 1, \dots, 40$ are assumed to follow exponential distributions. Out of the 20 human sensors, we consider that the thresholds of 10 human sensors follow the Gaussian distribution $N(\mu_\tau^1, \sigma_\tau)$, and the thresholds of the other 10 human sensors follow $N(\mu_\tau^2, \sigma_\tau)$. It can be observed that the system incorporating side information significantly outperforms the system with no side information when the accuracy of side information is 0.8.

11.2 Prospect Theoretic Utility based Human Decision Making in Multi-agent Systems

In this section, we study how human cognitive biases may cause the random thresholds of humans to differ from one person to another in binary decision making. The Nobel-prize-winning prospect theory (PT) is utilized to characterize the human cognitive biases in decision making. PT provides a psychologically accurate framework to describe the way people choose between probabilistic alternatives that involve risk. There are two main properties of PT: (1) A human has asymmetric valuations

towards gains and losses, as one strongly prefers avoiding losses than achieving gains. (2) Humans are usually risk seeking in events that have small probabilities and are usually risk averse in events that have large probabilities.

According to prospect theory [28], quantitative outcomes x are represented through the lens of a monotonically increasing *value function* $v(x)$, illustrated in Figure 11.4(a), that is convex below a reference point ϵ for which $v(\epsilon) = 0$, and concave for gains above it. In turn, probabilities are represented by a inverse-S-shaped *weighting function* $w(p)$, depicted in Figure 11.4(b), that *overweights* small probabilities (e.g., $p < .2$), is *insensitive* toward moderate probabilities (e.g., $.2 \leq p < .7$), and *underweights* large probabilities (e.g., $p > .7$).

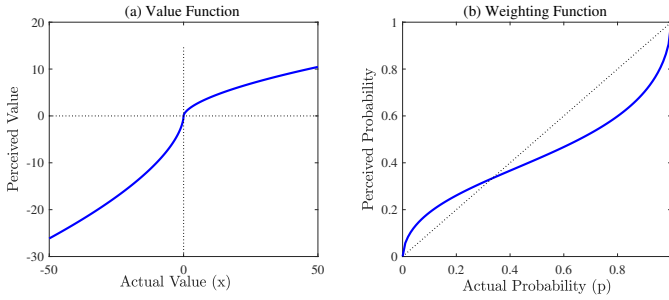


Figure 11.4 Value function and weighting function in prospect theory

Following Tversky and Kahneman (1992), we assume that the value function is:

$$v(x) = \begin{cases} x^\lambda, & \text{for } x \geq 0, \\ -\beta|x|^\lambda, & \text{for } x < 0, \end{cases} \quad (11.24)$$

where β is the loss aversion parameter and λ characterizes the phenomenon of diminishing marginal utility, which says that as the total number of units of gain (or loss) increases, the utility of an additional unit of gain (or loss) to a person decreases.

The probability weighting function is given by

$$w(p) = \frac{p^\alpha}{(p^\alpha + (1-p)^\alpha)^{\frac{1}{\alpha}}}, \quad (11.25)$$

where α characterizes the degree of distortion. Both the value function and the weighting function are used to determine the subjective utility U of a choice option with probabilistic outcomes, with the option maximizing U being preferred.

Some research efforts have been made to investigate how PT affects the behavior of humans in decision making. The authors in [29] studied a simplified form of PT to analyze the behavioral difference of pessimistic and optimistic human decision makers. It has been shown that the LRT may or may not be optimal in PT based binary hypothesis testing [30]. In these works, a human decision maker uses the following rule to decide which hypothesis is true out of H_0 and H_1

$$d = \begin{cases} 1; & \text{if } r \in X_1 \\ 0; & \text{otherwise} \end{cases} \quad (11.26)$$

where r is the observation regarding the PoI and R_1 denotes the acceptance region of H_1 . The expected behavioral risk under Bayesian formulation is computed by applying the value and weighting functions from PT in the following

$$b(R_1) = \sum_{i=0}^1 \sum_{j=0}^1 w(Pr(\text{Declare } H_i | H_j \text{ is true})) \cdot v(c_{ij}) \quad (11.27)$$

where c_{ij} represents the cost of deciding H_i when the true hypothesis is H_j for $i, j = 0, 1$. When the human is subject to cognitive biases, the optimal R_1^* is designed to minimize the human's behavioral Bayesian risk $R_1^* = \arg \min_{R_1 \in X} b(R_1)$.

In the above Bayesian formulation, the human is assumed to design the decision rule (i.e., the acceptance region of H_1) beforehand and employs the same decision rule no matter what the observation is. However, this method is not reasonable from a psychology point of view. In decision making, psychologists show that instead of averaging over all possible observations and constructing a fixed decision rule, decision makers first make some observations and based on these observations, they choose the action that yields the highest expected utility [31, 32, 33]. In the following, we proceed with the utility based approaches to analyze the behavior of human decision making under cognitive biases modeled by PT.

11.2.1 Subjective utility based hypothesis testing

We first provide some background on the utility based method for binary hypothesis testing problems under expected utility theory, where the decision makers are considered to be rational. Rather than minimizing the Bayesian risk in (11.27), the goal for the decision maker is to choose the hypothesis that yields the largest expected utility. Let U_{ij} denote the utility of declaring H_i when the true hypothesis is H_j , for $i, j \in \{0, 1\}$. Here, U_{00} and U_{11} denote the utilities of correct decisions and their values are usually positive. On the other hand, U_{10} and U_{01} denote the utilities of wrong decisions and their values are usually negative. When the observation is r , the expected utility of a rational decision maker in declaring H_0 and H_1 are given by:

$$\begin{aligned} \text{EU}(\text{Declare } H_0) &= Pr(H_0|r)U_{00} + Pr(H_1|r)U_{01} \\ \text{EU}(\text{Declare } H_1) &= Pr(H_0|r)U_{10} + Pr(H_1|r)U_{11}, \end{aligned} \quad (11.28)$$

where $Pr(H_i|r)$ represents the probability that H_i is true if the observation is r ,

$$Pr(H_i|r) = \frac{f(r|H_i)\pi_i}{f(r)} = \frac{f_i(r)\pi_i}{f(r)} \quad (11.29)$$

for $i = 0, 1$, respectively, where $f(\cdot)$ and $f_i(\cdot)$ are the appropriate PDFs and π_i denotes the prior probability of H_i . When the observation is r , the decision maker decides hypothesis H_0 or H_1 whichever has a higher expected utility

$$\text{EU}(\text{Declare } H_1) \stackrel{H_1}{\geq} \text{EU}(\text{Declare } H_0). \quad (11.30)$$

Substitute the expression of $Pr(H_i|r)$ given in (11.29) into (11.28), and we obtain

$$\begin{aligned}\mathbf{EU}(\text{Declare } H_0) &= \frac{f_0(r)\pi_0}{f(r)}U_{00} + \frac{f_1(r)\pi_1}{f(r)}U_{01} \\ \mathbf{EU}(\text{Declare } H_1) &= \frac{f_0(r)\pi_0}{f(r)}U_{10} + \frac{f_1(r)\pi_1}{f(r)}U_{11}\end{aligned}$$

By substituting the expressions of $\mathbf{EU}(\text{Declare } H_0)$ and $\mathbf{EU}(\text{Declare } H_1)$ into (11.30), the utility based decision rule becomes the classical LRT:

$$\frac{f_1(r)}{f_0(r)} \underset{H_0}{\overset{H_1}{\geq}} \frac{\pi_0(U_{00} - U_{10})}{\pi_1(U_{11} - U_{01})} \triangleq \eta. \quad (11.31)$$

which is known to be optimal that minimizes the Bayesian cost.

In statistical signal detection literature, the decision making agent is always considered to be rational and the goal is to maximize some expected utility. Under expected utility theory, decision makers are rational in the sense that they are capable of calculating the expected utility of each outcome without biases. For instance, a typical property of rational decision makers is that they are indifferent between several actions if their expected utilities are the same. However, because of human cognitive biases in perceiving the utilities and the probabilities, a human decision maker usually prefers a deterministic gain over a probabilistic gain even if the two alternatives have the same expected utility. In many scenarios where the decisions are made by humans, cognitive biases may cause the results to deviate from the outcomes predicted under expected utility theory. In contrast to rational decision makers who select the hypothesis that maximizes the expected utilities, human decision makers act to maximize their subjective utilities, which is usually distorted because of cognitive biases. When computing the subjective utility of declaring H_0 and H_1 , we exploit PT by applying the value function $v(\cdot)$ given in (11.24) on the utilities and applying the probability weighting function $w(\cdot)$ given in (11.25) on the probabilities. In this case, when the observation is r , the subjective utilities of deciding H_0 and H_1 are:

$$\begin{aligned}\mathbf{SU}(\text{Declare } H_0) &= w(Pr(H_0|r))v(U_{00}) + w(Pr(H_1|r))v(U_{01}) \\ \mathbf{SU}(\text{Declare } H_1) &= w(Pr(H_0|r))v(U_{10}) + w(Pr(H_1|r))v(U_{11}).\end{aligned} \quad (11.32)$$

It is known that humans select the alternative which has a higher subjective utility given observation r :

$$\mathbf{SU}(\text{Declare } H_1) \underset{H_0}{\overset{H_1}{\geq}} \mathbf{SU}(\text{Declare } H_0). \quad (11.33)$$

Exploiting (11.32) and (11.33), the subjective utility based decision rule of human decision makers becomes:

$$\frac{w(Pr(H_1|r))}{w(Pr(H_0|r))} \underset{H_0}{\overset{H_1}{\geq}} \frac{v(U_{00}) - v(U_{10})}{v(U_{11}) - v(U_{01})} \triangleq \frac{V_{00} - V_{10}}{V_{11} - V_{01}}, \quad (11.34)$$

where $V_{00}, V_{01}, V_{10}, V_{11}$ are the subjective utilities by applying the value function (11.24) on $U_{00}, U_{01}, U_{10}, U_{11}$, respectively. We consider that the correct decisions' utilities V_{00} and V_{11} are positive, while wrong decision's utilities V_{01} and V_{10} are negative. Substituting the expression of the weighting function given in (11.25) and the expression of $Pr(H_i|r)$ given in (11.29), and using that $Pr(H_1|r) = 1 - Pr(H_0|r)$, we obtain $\frac{w(Pr(H_1|r))}{w(Pr(H_0|r))} = \frac{Pr(H_1|r)^\alpha}{Pr(H_0|r)^\alpha}$. Consequently, the decision rule given in (11.34) becomes

$$\frac{f_1(r)}{f_0(r)} \underset{H_0}{\overset{H_1}{\geq}} \left(\frac{V_{00} - V_{10}}{V_{11} - V_{01}} \right)^{\frac{1}{\alpha}} \frac{\pi_0}{\pi_1} \triangleq \eta_p. \quad (11.35)$$

Hence, the human's decision rule is in the form of a likelihood ratio test (LRT) with threshold η_p [18].

Theorem 1: *Under prospect theoretic framework, the optimal subjective utility based decision rule reduces to an LRT. The threshold of the LRT, η_p , is a monotonous function of parameters α and β .*

In many application scenarios, the likelihood ratio $\Lambda(r) = \frac{f_1(r)}{f_0(r)}$ is strictly increasing or decreasing with respect to r . For instance, this is true when $f_1(r)$ and $f_0(r)$ are Gaussian PDFs with different means and the same variance. Gaussian distributions are widely used as they represent the nature of a large number of problems in signal processing. In the rest of this section, we study human decision making for the binary hypothesis testing problem, and in particular, the observations under both hypotheses are assumed to follow Gaussian distributions given by:

$$H_0 : r \sim N(m_0, \sigma_s^2), \quad H_1 : r \sim N(m_1, \sigma_s^2) \quad (11.36)$$

where m_0 and m_1 represent the means of the signal under H_0 and H_1 , respectively, and σ_s^2 represents the variance of the signal under both hypotheses. We assume that $m_0 < m_1$ and the diminishing marginal utility parameter λ in (11.24) is set to be a fixed value 0.88. We focus on studying how behavioral parameters α and β in PT affect the human decision making performance. When the observations follow Gaussian distributions (11.36), the likelihood ratio test (11.35) becomes

$$\frac{f_1(r)}{f_0(r)} = e^{\frac{2(m_1 - m_0)r - (m_1^2 - m_0^2)}{2\sigma_s^2}} \underset{H_0}{\overset{H_1}{\geq}} \eta_p \quad (11.37)$$

which is equivalent to $r \underset{H_0}{\overset{H_1}{\geq}} t = F(\alpha, \beta) = \frac{2 \ln \eta_p \sigma_s^2 + (m_1^2 - m_0^2)}{2(m_1 - m_0)}$, where the cognitively biased threshold t is a monotone function F of prospect theory parameters α and β (because η_p is an inherent function of α and β).

In contrast to physical sensors whose decision thresholds can be set to be fixed values, humans have uncertainties in decision making due to complex factors such as time constraint, emotion, environment and so on. Individual level uncertainty is a prominent feature in human behavior. Variability exists in human perception and decision making even when the external conditions, such as the sensory signals and the task environment, are kept the same [34]. It is also known as trial-to-trial

variability in psychology literature, i.e., differences of responses are prominent when the same experiment is conducted multiple times using the same human subject. From the psychological perspective, the reasons that cause variability are: a) the initial state of the neural circuitry is unlikely to be the same at the beginning of each trial, and b) noises penetrate in each part of the nervous system, from the perception of outside observations to the process of decision making. These two reasons cause inevitable uncertainties in human decision making, where the uncertainties depend on factors such as time constraints, emotion, outside, and environment [35].

Inspired by the above discussion, we model the humans' decision thresholds as random variables [12, 25, 36]. In particular, the human's behaviorally biased decision threshold is modeled as $\tau = F(\alpha, \beta) + v$, where $v \sim N(0, \sigma_\tau^2)$. We use σ_τ^2 to denote the variance associated with a human while making a decision because of uncertainty. Note that τ is considered to be a Gaussian random variable, whose mean is determined by the average values of human behavioral parameters and the variance σ_τ^2 is impacted by the decision uncertainties. A larger value of σ_τ^2 represents higher uncertainty of a person in decision making. To quantify the individual uncertainty associated with the human decision threshold in real applications, one may perform the experiments as in [28] on the same human under different conditions, e.g., time constraints, emotions, and locations. In each trial of the experiment, the values of behavioral parameters α , β and λ of the human can be computed using regression. Since the variability of α , β and λ causes the human to change his/her decision threshold, the variance of the decision threshold σ_τ^2 can be derived by analyzing the statistics.

For the hypothesis testing problem (11.36), if a human uses a random decision threshold $\tau \sim N(m_\tau, \sigma_\tau^2)$, the probabilities of false alarm and detection can be computed as [18]

$$P_F = Q\left(\frac{m_\tau - m_0}{\sqrt{\sigma_s^2 + \sigma_\tau^2}}\right), \quad P_D = Q\left(\frac{m_\tau - m_1}{\sqrt{\sigma_s^2 + \sigma_\tau^2}}\right), \quad (11.38)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(-\frac{u^2}{2}) du$.

Next, we investigate the impact of decision uncertainty quantified in terms of σ_τ^2 on the quality of human decisions. For a human decision maker who employs a random decision threshold $\tau \sim N(m_\tau, \sigma_\tau^2)$ to make a decision in the binary hypothesis testing framework (11.36), the following theorem quantifies the relationship between the human decision making performance and the decision making uncertainty [18].

Theorem 2: *There is a pair of values $\{\underline{m}_\tau, \overline{m}_\tau\}$ where $\underline{m}_\tau < \overline{m}_\tau$ and both $\underline{m}_\tau$ and $\overline{m}_\tau$ can be obtained by solving m_τ in the following equation*

$$e^{\frac{2(m_1 - m_0)m_\tau - (m_1^2 - m_0^2)}{2\sigma_s^2}} \times \left(\frac{m_\tau - m_1}{m_\tau - m_0}\right) = \eta.$$

The pair $\{\underline{m}_\tau, \overline{m}_\tau\}$ has the following properties: a) For humans with $\underline{m}_\tau \leq m_\tau \leq \overline{m}_\tau$, the expected utility while making a decision monotonically decreases as σ_τ^2 becomes larger, i.e., the expected utility while making a decision is maximized for decision uncertainty $\sigma_\tau^{2*} = 0$. b) For humans with $m_\tau > \overline{m}_\tau$ and $m_\tau < \underline{m}_\tau$, the expected utility

is unimodal, i.e., first increases then decreases, as σ_τ^2 becomes larger. The optimal decision uncertainty σ_τ^{2*} is greater than 0 and satisfies:

$$e^{\frac{2(m_1 - m_0)m_\tau - (m_\tau^2 - m_0^2)}{2(\sigma_\tau^2 + \sigma_\tau^{2*})}} \times \left(\frac{m_\tau - m_1}{m_\tau - m_0} \right) = \eta.$$

Definition 1: In the hypothesis testing framework analyzed above, if a human's expected utility in decision making strictly decreases as σ_τ^2 becomes larger, i.e., $\underline{m}_\tau \leq m_\tau \leq \bar{m}_\tau$ and the best decision making performance is achieved for $\sigma_\tau^{2*} = 0$, the human is called **reasonable**. If the best decision making performance in terms of expected utility is achieved for decision uncertainty $\sigma_\tau^{2*} > 0$, i.e., $m_\tau > \bar{m}_\tau$ or $m_\tau < \underline{m}_\tau$, the person is called **extremely biased**.

We provide some simulation results to illustrate the performance when a human employs the random decision threshold that follows $N(m_\tau, \sigma_\tau^2)$ in the hypothesis testing problem (11.36) with the following parameters: $\pi_0 = 0.7, \pi_1 = 0.3, U_{11} = U_{00} = 20, U_{01} = -80, U_{10} = -20, m_0 = 0, m_1 = 5$, and $\sigma_s^2 = 2.25$. With this setup, it can be computed that $\underline{m}_\tau = -0.025$ and $\bar{m}_\tau = 5.015$. Hence, the left side extremely biased interval, the reasonable interval and the right side extremely biased interval of the human in terms of m_τ are $(-\infty, -0.025)$, $[-0.025, 5.015]$ and $(5.015, \infty)$, respectively. Figure 11.5 shows the expected utility of decision making as a function of the uncertainty of decision threshold σ_τ^2 for three different values of m_τ . We can see that the expected utility of a reasonable human is monotonically decreasing with respect to σ_τ^2 . For extremely biased human decision makers, the optimal value of decision uncertainty to achieve the maximum expected utility σ_τ^{2*} is greater than 0. Note that in this particular example, left side extremely biased humans whose decision threshold $m_\tau < \underline{m}_\tau$ have higher expected utilities than right side extremely biased human agents whose decision threshold $m_\tau > \bar{m}_\tau$. The reason for this phenomenon in this example is that the penalty of missed detection ($U_{01} = -80$) is more significant than the penalty of false alarm ($U_{10} = -20$). Right side extremely biased humans with larger values of decision thresholds are more likely to be penalized by missed detections causing their performance to be worse. Furthermore, it can be seen in Figure 11.5 that a left side extremely biased human performs better than a reasonable human when σ_τ^2 is greater than a certain value. It is because that as σ_τ^2 becomes larger, a reasonable human decision maker is more likely to employ larger values of decision thresholds than a left side extremely biased human, which causes the performance of the rational human to degrade due to the larger penalty associated with missed detections.

Remark 1: The decision making performance of extremely biased humans is improved due to the presence of decision uncertainty. Before the decision uncertainty reaches a certain value, the decision making performance increases as the decision uncertainty becomes larger, and after that point is reached the decision making performance starts to decrease as the decision uncertainty continues to increase. This phenomenon is analogous to noise-enhanced signal detection [37] where the quality of a suboptimal detector can be improved by adding noise under certain conditions. It is also known as stochastic resonance in the signal processing literature [37, 38].

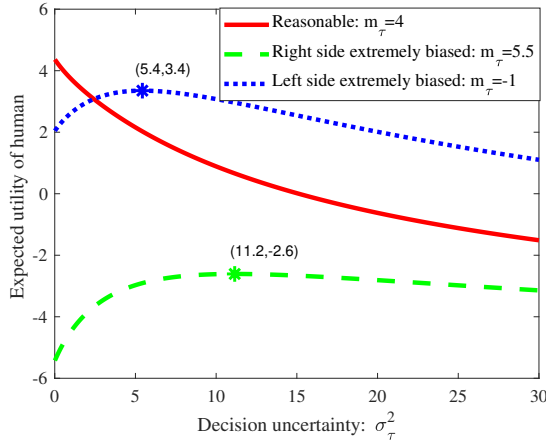


Figure 11.5 Expected utility of a human agent as decision uncertainty σ_τ^2 increases

11.2.2 Decision fusion involving human participation

In this subsection, we analyze the impact of an individual's behavioral biases (cognitive biases and uncertainties) on the performance of two decision making systems that involve human participation.

Human participates in decision making as an information source, FC is a rational machine

As shown in Figure 11.6, we first consider the scenario where a human agent acts as an information source to support the FC in making the final decision with the FC being rational (unbiased).

We consider that the FC observes r_0 and the human agent A observes r_a through independent observation channels. Identical and independently distributed additive Gaussian noises are assumed to exist in the observation channels of both the FC and the human agent A. The observations made by the FC and the agent A are denoted by r_0 and r_a to emphasize that the observations are received over two independent channels. Specifically, the human agent A makes a local decision on which hypothesis is present by comparing r_a to a threshold t_a :

$$d_a = \begin{cases} 1 & \text{if } r_a \geq t_a \\ 0 & \text{if } r_a < t_a \end{cases}$$

For ease of analysis, we first assume t_a to be a fixed decision threshold determined by the the human's behavioral parameters α_a and β_a , such that $t_a = F(\alpha_a, \beta_a)$. Decision making uncertainty of human agent A will be considered later in this subsection. When the FC receives the decision of agent A, $d_a = j \in \{0, 1\}$, it makes the final decision d_0 by fusing d_a and its own observation r_0 . Given d_a and r_0 , the FC's

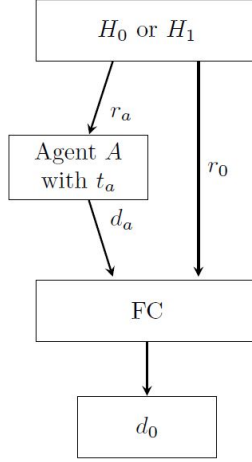


Figure 11.6 Human participating in decision making as an information source

expected utilities to declare H_0 and H_1 are given by:

$$\mathbf{EU}(\text{Declare } H_0) = Pr(H_0|r_0, d_a = j)U_{00} + Pr(H_1|r_0, d_a = j)U_{01}$$

$$\mathbf{EU}(\text{Declare } H_1) = Pr(H_0|r_0, d_a = j)U_{10} + Pr(H_1|r_0, d_a = j)U_{11},$$

respectively. Selecting the hypothesis that yields the larger expected utility gives the following decision rule:

$$\frac{Pr(H_1|r_0, d_a = j)}{Pr(H_0|r_0, d_a = j)} \underset{H_0}{\overset{H_1}{\geq}} \frac{U_{10} - U_{00}}{U_{01} - U_{11}}, \quad (11.39)$$

where $Pr(H_i|r_0, d_a = j)$ represents the probability that H_i is true given r_0 and $d_a = j$. Note that

$$Pr(H_i|r_0, d_a = j) = \frac{\pi_i Pr(d_a = j|H_i) f(r_0|H_i)}{f(r_0, d_a = j)}$$

for $i, j \in \{0, 1\}$. Denote the probabilities of false alarm and detection of agent A as $Pr(d_a = 1|H_0) = P_F^a$ and $Pr(d_a = 1|H_1) = P_D^a$, respectively. After substituting the expressions for $Pr(H_i|r_0, d_a = j)$, the decision rule (11.39) becomes:

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\geq}} \frac{1 - P_F^a}{1 - P_D^a} \frac{\pi_0(U_{10} - U_{00})}{\pi_1(U_{01} - U_{11})} = \frac{1 - P_F^a}{1 - P_D^a} \eta, \quad \text{if } d_a = 0, \quad (11.40)$$

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\geq}} \frac{P_F^a}{P_D^a} \frac{\pi_0(U_{10} - U_{00})}{\pi_1(U_{01} - U_{11})} = \frac{P_F^a}{P_D^a} \eta, \quad \text{if } d_a = 1. \quad (11.41)$$

By solving for r_0 in $\frac{f_1(r_0)}{f_0(r_0)} = \frac{1 - P_F^a}{1 - P_D^a} \eta$ for $d_a = 0$, and $\frac{f_1(r_0)}{f_0(r_0)} = \frac{P_F^a}{P_D^a} \eta$ for $d_a = 1$, the FC's decision thresholds applicable to observation r_0 for final decision making can be derived, and we denote them as t_0 and t_1 , respectively. When observations under

H_0 and H_1 follow Gaussian distributions (11.36), the probabilities of false alarm and detection are given by $P_F^a = Q(\frac{t_a - m_0}{\sigma_s})$ and $P_D^a = Q(\frac{t_a - m_1}{\sigma_s})$. The overall performance of the FC in terms of probabilities of false alarm and detection can be written as:

$$\begin{aligned} p_f &= \sum_{j=0}^1 Pr(d_0 = 1 | d_a = j, H_0) Pr(d_a = j | H_0) \\ &= P_F^a Q(\frac{t_1 - m_0}{\sigma_s}) + (1 - P_F^a) Q(\frac{t_0 - m_0}{\sigma_s}), \end{aligned}$$

and

$$\begin{aligned} p_d &= \sum_{j=0}^1 Pr(d_0 = 1 | d_a = j, H_1) Pr(d_a = j | H_1) \\ &= P_D^a Q(\frac{t_1 - m_1}{\sigma_s}) + (1 - P_D^a) Q(\frac{t_0 - m_1}{\sigma_s}), \end{aligned}$$

respectively. Hence, the FC's expected utility for decision making is:

$$U = \pi_0(1 - p_f)U_{00} + \pi_0 p_f U_{10} + \pi_1(1 - p_d)U_{01} + \pi_1 p_d U_{11}. \quad (11.42)$$

Some simulations are performed for the same hypothesis testing problem as discussed in Subsection 11.2.1. In Figure 11.7, when human agent A's decision threshold t_a changes, i.e., the cognitive bias of the human varies, we show the expected utilities in decision making of agent A and that of the FC. It can be seen that the threshold that yields the maximum decision making performance for agent A by itself is different from the threshold that yields the best decision making performance for the FC. In other words, a rationally behaving human who acts to maximize his/her expected utility (with decision threshold 2.28 indicated by the red dot) does not necessarily provide the maximum expected utility for the FC. In this particular example, a human who has some bias (with decision threshold equal to 2.41 indicated by the blue dot) results in a higher expected utility for the FC. The strategy of choosing the properly biased person differs when the specific setup of the hypothesis testing problem changes. By computing the optimal value of the decision threshold of agent A that helps the FC achieve the best decision making performance, we can determine the values of α and β corresponding to the most suitable cognitively biased person, to perform the task in different scenarios.

Next, we consider the uncertainties in human decision making and model the decision threshold employed by agent A as a Gaussian random variable $\tau_a \sim N(m_{\tau_a}, \sigma_{\tau_a}^2)$. In this scenario, P_F^a and P_D^a can be computed using (11.38), and the optimal decision rule at the FC can be derived analogous to the previous analysis. The FC's expected utility in decision making can also be computed. In the following, we illustrate the FC's decision making performance for different values of agent A's decision making uncertainty.

Continuing with the previous parameters for the hypothesis testing problem, Figure 11.8 plots the FC's expected utility in decision making as a function of the mean decision threshold of agent A. In the red, green and blue curves, agent A's decision making variances are $\sigma_{\tau_a}^2 = 0$, $\sigma_{\tau_a}^2 = 1$ and $\sigma_{\tau_a}^2 = 4$, respectively. In the

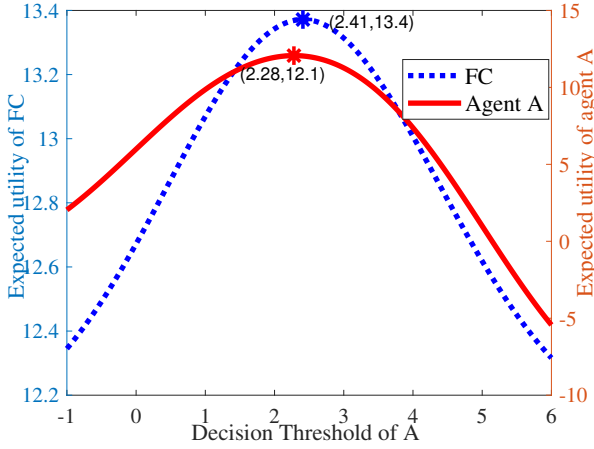


Figure 11.7 Expected utility as a function of threshold t_a used by agent A

middle range of m_{τ_a} where the human decision maker is reasonable, the red curve with smallest decision making variance performs better than the other two curves. In practical applications, it is preferable to have human agents who are reasonable in that their decision making is expected to be of higher quality compared to extremely biased humans and, in addition, their performance is more predictable in the presence of decision making uncertainty. On the extreme left or extreme right of the curve, i.e., when the decision threshold is significantly biased, a higher variance surprisingly yields better decision performance for the FC. Intuitively, for extremely biased humans whose decision thresholds significantly deviate from being rational, a higher variance is more probable to ‘rectify’ the biased thresholds to be close to be optimal. However, for reasonable humans whose behavioral thresholds are already close to the optimal, a large variance is more likely to push their behavioral thresholds away from the optimal values. As a result, a large value of variance helps improve the FC’s utility if the human is extremely biased, while it degrades the performance if the human is behaving rationally. This observation is consistent with our previous results about the impact of decision uncertainty on the a single human’s decision making performance as discussed in Figure 11.5.

Physical sensor acts as the information source and human is the decision maker at the FC

Looking at the system shown in Figure 11.6 from a different perspective, we study the scenario where A is a physical sensor that employs a fixed decision threshold t_a . On the other hand, a behaviorally biased human with PT parameters α , β and decision making uncertainty σ_{FC}^2 acts as the FC to make the final decision. Here, the physical sensor A sends its binary decisions $d_a = j \in \{0, 1\}$ to help the FC in making the decision d_0 . Since the FC is biased, we exploit $v(\cdot)$ and $w(\cdot)$ when computing the FC’s subjective utility of deciding either H_0 or H_1 being true. If agent A sends its

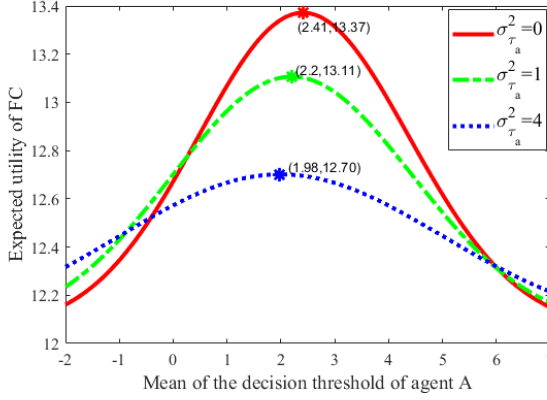


Figure 11.8 Expected utility of the FC as a function of the mean threshold of agent A

decision $d_a = j$, the subjective utilities of deciding H_0 and H_1 are given by

$$\begin{aligned} \text{SU}(\text{Declare } H_0) \\ = w(Pr(H_0|r_0, d_a = j))V_{00} + w(Pr(H_1|r_0, d_a = j))V_{01} \end{aligned} \quad (11.43)$$

and

$$\begin{aligned} \text{SU}(\text{Declare } H_1) \\ = w(Pr(H_0|r_0, d_a = j))V_{10} + w(Pr(H_1|r_0, d_a = j))V_{11}. \end{aligned} \quad (11.44)$$

The human decision maker at the FC determines d_0 by choosing the hypothesis that results in a larger value of subjective utility. By assuming that the FC's observation r_0 and agent A's decision d_a are independent, the likelihood ratio at the FC is increasing as a function of r_0 . In this case, the FC uses a threshold based decision rule and the mean of the decision threshold m_{FC}^j can be obtained by setting (11.43) equal to (11.44) for $j = 0, 1$, and the variance of the decision threshold is assumed to be σ_{FC}^2 . Upon receiving $d_a = j$, the FC compares r_0 to a decision threshold τ_j^f to make the final decision, where $\tau_j^f \sim N(m_{FC}^j, \sigma_{FC}^2)$ for $j = 0, 1$. In particular, the decision rule at the behaviorally biased FC is expressed as

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{1 - P_F^a}{1 - P_D^a} \left(\frac{V_{00} - V_{10}}{V_{11} - V_{01}} \right)^{\frac{1}{\alpha}} \frac{\pi_0}{\pi_1} = \frac{1 - P_F^a}{1 - P_D^a} \eta_p, \quad \text{if } d_a = 0, \quad (11.45)$$

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P_F^a}{P_D^a} \left(\frac{V_{00} - V_{10}}{V_{11} - V_{01}} \right)^{\frac{1}{\alpha}} \frac{\pi_0}{\pi_1} = \frac{P_F^a}{P_D^a} \eta_p, \quad \text{if } d_a = 1. \quad (11.46)$$

The probabilities of false alarm and detection of the human decision maker at the FC are given by:

$$p_f = \sum_{j=0}^1 Pr(d_0 = 1|d_a = j, H_0)Pr(d_a = j|H_0)$$

$$= Q\left(\frac{t_a - m_0}{\sigma_s}\right)Q\left(\frac{m_{FC}^1 - m_0}{\sqrt{\sigma_s^2 + \sigma_{FC}^2}}\right) + (1 - Q\left(\frac{t_a - m_0}{\sigma_s}\right))Q\left(\frac{m_{FC}^0 - m_0}{\sqrt{\sigma_s^2 + \sigma_{FC}^2}}\right)$$

and

$$p_d = \sum_{j=0}^1 Pr(d_0 = 1|d_a = j, H_1)Pr(d_a = j|H_1)$$

$$= Q\left(\frac{t_a - m_1}{\sigma_s}\right)Q\left(\frac{m_{FC}^1 - m_1}{\sqrt{\sigma_s^2 + \sigma_{FC}^2}}\right) + (1 - Q\left(\frac{t_a - m_1}{\sigma_s}\right))Q\left(\frac{m_{FC}^0 - m_1}{\sqrt{\sigma_s^2 + \sigma_{FC}^2}}\right),$$

where $Pr(d_0 = 1|d_a = j, H_i) = Q\left(\frac{m_{FC}^j - m_i}{\sqrt{\sigma_s^2 + \sigma_{FC}^2}}\right)$ for $i, j = \{0, 1\}$ can be computed using (11.38). Again, the expected utility of the FC in decision making can be obtained using (11.42).

In Figure 11.9, we plot the expected utility of the FC as a function of the decision threshold t_a of the physical sensor A. In Figure 11.9(a), the red curve denotes the baseline scenario where the FC is rational, and in the green and blue curves the FC is behaviorally biased with $\beta = 1.5$ and $\beta = 2$, respectively. When the FC is biased, we assume the probability distortion parameter to be $\alpha = 0.72$. It can be seen that the FC achieves higher expected utility when it acts rationally. On the other hand, the peak points on these curves (denoted by the red, green and blue dots) indicate that if the FC has different behavioral properties, the optimal decision threshold of A while assisting the FC to achieve the best performance is different. In the system considered here, we can adjust the threshold of the physical sensor A in order to help the FC/human achieve the best decision quality.

To find the optimal threshold of the physical sensor t_a^* , let us denote the thresholds of the LRT in (11.45) and (11.46) as $\eta_{p0} = \frac{1 - P_E^a}{1 - P_D^a} \eta_p$ and $\eta_{p1} = \frac{P_E^a}{P_D^a} \eta_p$, respectively. Let $g(x) = \frac{2\sigma_s^2 \log x + (m_1^2 - m_0^2)}{2(m_1 - m_0)}$, which is the inverse function of the LR $\frac{f_1(r)}{f_0(r)}$. In a manner analogous to that in [39], we can show that the decision threshold t_a^* employed by the physical sensor that minimizes the FC's expected cost satisfies the following condition:

$$G(t_a^*) = \frac{Q\left(\frac{g(\eta_{p1}) - m_0}{\sigma_s + \sigma_{FC}}\right) - Q\left(\frac{g(\eta_{p0}) - m_0}{\sigma_s + \sigma_{FC}}\right)}{Q\left(\frac{g(\eta_{p1}) - m_1}{\sigma_s + \sigma_{FC}}\right) - Q\left(\frac{g(\eta_{p0}) - m_1}{\sigma_s + \sigma_{FC}}\right)} \eta. \quad (11.47)$$

A brief sketch of the proof is shown in the following.

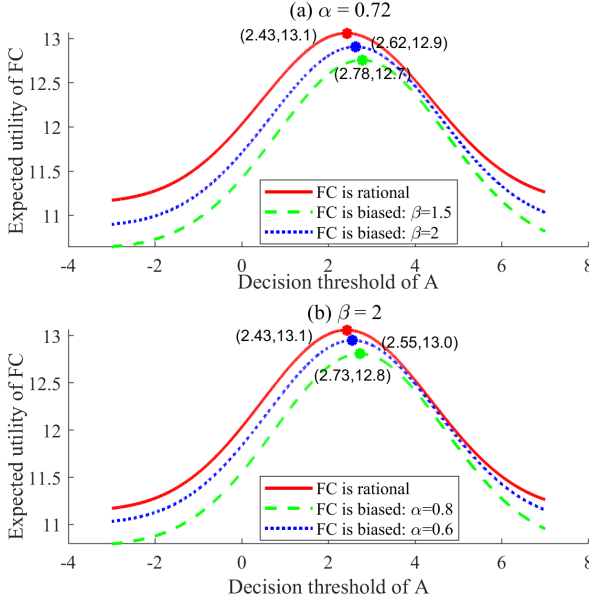


Figure 11.9 Expected utility of FC as a function of the decision threshold of agent A, when FC has behavioral biases

Proof. Exploiting the independence assumption, the Bayesian cost of human while making a decision is:

$$\sum_{d_0, d_a, H_k} \int \pi_k Pr(d_0|d_a, r_0) Pr(d_a|r_a) Pr(r_a|H_k) Pr(r_0|H_k) c_{d_0k} dr_0 dr_a$$

for $d_0, d_a, k \in \{0, 1\}$. By summing d_a over $\{0, 1\}$, ignoring the constant factors and using the fact $Pr(d_a = 1|r_a) = 1 - Pr(d_a = 0|r_a)$, we have

$$\begin{aligned} & \int_{r_a} Pr(d_a = 0|r_a) \sum_{d_0, H_k} \int_{r_0} \pi_k Pr(r_0|H_k) Pr(r_a|H_k) c_{d_0k} \\ & \times [Pr(d_0|d_a = 0, r_0) - Pr(d_0|d_a = 1, r_0)] dr_0 dr_a, \end{aligned} \quad (11.48)$$

which is minimized by setting $Pr(d_a = 0|r_a) = 0$ if

$$\begin{aligned} & \sum_{d_0, H_k} \int_{r_0} \pi_k Pr(r_0|H_k) Pr(r_a|H_k) c_{d_0k} \\ & \times [Pr(d_0|d_a = 0, r_0) - Pr(d_0|d_a = 1, r_0)] dr_0 \geq 0 \end{aligned} \quad (11.49)$$

and setting $Pr(d_a = 1|r_a) = 0$ if (11.49) does not hold.

Note that $\int Pr(r_0|H_k) Pr(d_0|d_a, r_0) dr_0 = Pr(d_0|d_a, H_k)$ and $Pr(d_0 = 0|d_a = 0, r_0) \geq Pr(d_0 = 0|d_a = 1, r_0)$. By setting (11.49) equal to 0 and summing over H_k for

$k = \{0, 1\}$, we obtain the condition that must be satisfied by the optimal decision threshold t_a^* of the physical sensor:

$$G(t_a^*) = \frac{\sum_{d_0=0}^1 \pi_0 c_{d_0 0} [Pr(d_0|d_a = 1, H_0) - Pr(d_0|d_a = 0, H_0)]}{\sum_{d_0=0}^1 \pi_1 c_{d_0 1} [Pr(d_0|d_a = 0, H_1) - Pr(d_0|d_a = 1, H_1)]},$$

Lastly, substituting $Pr(d_0 = 1|d_a = j, H_k) = Q(\frac{g(\eta_{pj}) - m_k}{\sigma_s + \sigma_{FC}})$ and $Pr(d_0 = 0|d_a = j, H_k) = 1 - Q(\frac{g(\eta_{pj}) - m_k}{\sigma_s + \sigma_{FC}})$ for $j, k = \{0, 1\}$ and after simplification, the condition in (11.47) follows. $\square$

Another interesting phenomenon in Figure 11.9(a) is that in this decision making system, a more loss averse FC (indicated by the blue curve that has $\beta = 2$) performs better than a less loss averse FC (indicated by the green curve that has $\beta = 1.5$) for the entire interval of t_a . It is because of the fact that behavioral parameters α, β and λ jointly impact the threshold used by a biased human. In our scenario, a larger value of β cancels out the effect of α and λ , making the threshold used by this human closer to that of a rational decision maker. In Figure 11.9(b), we set the human's loss aversion parameter to be $\beta = 2$ and show the expected utility in decision making with respect to t_a as α takes two values of 0.8, 0.6. Similar to the observations in Figure 11.9(a), a more biased probability distortion parameter $\alpha = 0.6$ helps the FC achieve better decision making performance than $\alpha = 0.8$ when $\beta = 2$. In general, decision making quality of a human does not depend on one single behavioral parameter, instead all the parameters should be considered together in a holistic manner.

11.3 Human Machine Collaboration for Binary Decision Making under Correlated Observations

In this section, we present a novel framework where the human and the machine collaboratively perform signal detection tasks [40]. In particular, we consider that the machine observes a continuous signal regarding the PoI, while the human possesses a categorical judgement through experience regarding the PoI through other information sources, inductive reasoning, experience, or other sources of information that are not available to the machine. The human decision and the machine observation are assumed to be statistically dependent. We attempt to use copulas to model the dependence between a continuous and a discrete random variable in the context of sensor fusion. Copulas have been used in the context of distributed detection for modeling the dependence between continuous data from different modalities [41, 42]. The use of copulas is very attractive for sensor fusion applications due to their ability to model dependent observations with arbitrary marginals and complex dependence structures. A comprehensive study of copulas is presented in [43].

We evaluate the performance of such a system and derive expressions for the probability of detection P_D and probability of false P_{FA} using Copula density functions. It is shown that when the machine's observation falls into a certain region,

there is no need to ask for human decisions as they do not improve the detection accuracy. Hence, we may save human's participation when the machine's observation falls into that region while maintaining the same system performance.

11.3.1 Human-machine collaboration model

Consider that a human and a machine work together to solve hypothesis testing problems where the two hypotheses are denoted as H_0 and H_1 . We consider that the machine acquires an objective measurement r regarding the PoI, where r is assumed to be a continuous random variable. The conditional PDFs of r under the two hypotheses are denoted by $f_0(r)$ and $f_1(r)$, respectively. On the other hand, we consider that the human does not observe r , but possesses an additional *side information* s regarding the PoI through his/her experience or other sources of information that are not available to the machine. For example: a) In weather forecasting, the machine may measure the objective temperature data and the human may observe the activities of animal migration, which are fused together to predict whether it is going to be a cold winter. b) In airplane/submarine navigation systems, the machine or physical sensors collect objective data such as velocity and altitude, which are combined with the human's judgement on the topography to determine the maneuver strategy. Beyond these two illustrative examples, this formulation is suitable to model numerous semi-autonomous systems for situational awareness and command and control, both in military and civilian domains, that involve human participation.

While the machine's observation r is a continuous random variable, we consider that the human has limited information processing ability and only makes categorical perceptions [44]. In this section, we assume that the side information s of the human is binary, and human's error behavior of s can be modeled via a binary symmetric channel (BSC) shown in Fig. 11.10. In particular, $Pr(s=i|H_i \text{ is true}) = \beta$ for $i=0,1$, where in this subsection we use β to represent the accuracy of the human and we assume that $\beta \geq 0.5$ (the smallest possible value of accuracy $1/2$ represents the response s is a random guess).

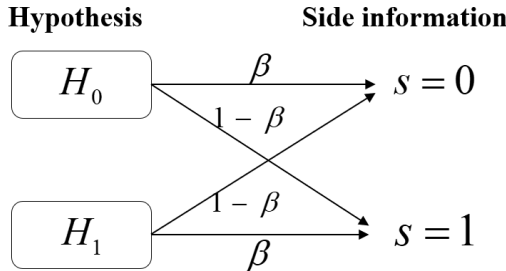


Figure 11.10 Human side information modeled as a BSC

When the machine's observation r and the human side information s are fused to make the final decision, we know that the FC's optimal decision rule that achieves

minimum Bayesian cost is the likelihood ratio test (LRT) [23]

$$L_f(r) = \frac{Pr(r, s|H_1)}{Pr(r, s|H_0)} \underset{H_0}{\overset{H_1}{\geq}} \frac{\pi_0(c_{10} - c_{00})}{\pi_1(c_{01} - c_{11})} \triangleq \eta, \quad (11.50)$$

where π_i represents the priors of H_i for $i = \{0, 1\}$. We denote c_{ij} as the *cost* of deciding H_i when the true hypothesis is H_j for $i, j = \{0, 1\}$. Under the assumption that r and s are independent of each other, the decision rule (11.50) becomes $L_f(r) = \frac{f_1(r)(1-\beta)}{f_0(r)\beta}$ if $s = 0$ and $L_f(r) = \frac{f_1(r)\beta}{f_0(r)(1-\beta)}$ if $s = 1$. However, the dependence of the machine observation and the human side information can not be ignored in practice. It is important to account for the dependencies in order to more accurately evaluate the system performance. Next, we consider that the human decision and the machine observation are dependent and use Copula theory to model these dependencies.

11.3.2 Copula Based decision fusion at the FC

In the following, we use copulas to characterize the dependence between the machine observation and the human decision. A copula is a joint distribution function on uniform marginals that can model the dependence between random variables with arbitrary marginal densities. A well studied result in the copula literature is Sklar's Theorem which lays the foundation of copula theory.

Sklar's Theorem: For random variables $X_1, \dots, X_d$, the joint cumulative distribution function can be modeled as:

$$F(x_1, \dots, x_d) = C(F_{X_1}(x_1), \dots, F_{X_d}(x_d)) \quad (11.51)$$

Further, the copula C uniquely models $F(x_1, \dots, x_d)$ if $X_1, \dots, X_d$ are continuous. When the random variables are not all continuous, the copula C is unique on $\text{ran } F_1(\cdot) \times \dots \times \text{ran } F_d(\cdot)$ where 'ran' refers to the range of the cumulative distribution function.

Sklar's Theorem allows for the use of copulas to model the joint distribution of a discrete random variable and a continuous random variable. However, there are infinite number of copulas that can describe the same joint distribution. While the non-uniqueness of the copula does not pose a problem for modeling dependent data, it does not allow for non-parametric inference of the copula from the data, in that the copula can not be learnt from the data.

We assume that the dependence between the machine observation r and the human decision s exists only under hypothesis H_1 ⁵. From the decision rule given in (11.50), we incorporate dependencies between r and s , and obtain the copula based LRT at the FC

$$L_c(r, s_i) \triangleq \frac{f_1(r) \left[\frac{\partial C(u, F_{h,1}(s_i))}{\partial u} - \frac{\partial C(u, F_{h,1}(s_{i-1}))}{\partial u} \right]}{f_0(r) p_{h,0}(s_i)} \underset{H_0}{\overset{H_1}{\geq}} \eta \quad (11.52)$$

⁵For example, we consider that under H_0 , the signal from the PoI is absent. Hence, r is sampled from the additive white Gaussian noise (AWGN) process, which is independent of the human side information s . The model can be easily generalized to the situations where r and s are dependent under both H_0 and H_1 .

where $p_{h,0}(s_i) = \beta$ if $s_i = 0$, $p_{h,0}(s_i) = 1 - \beta$ if $s_i = 1$, $u = F_1(r)$ with $F_1(\cdot)$ representing the cumulative distribution function (CDF) of the machine's observation under H_1 and $F_{h,1}(\cdot)$ representing the CDF of the human decision under H_1 . The procedures of deriving the joint density function in the numerator of (11.52), are described in the following.

$$Pr\{S \leq s, R \leq r\} = C(F_1(r), F_{h,1}(s)) \quad (11.53)$$

$$Pr\{S \leq s | R = r\} f_1(r) \stackrel{(a)}{=} \frac{\partial C(F_1(r), F_{h,1}(s))}{\partial r} \quad (11.54)$$

$$Pr\{S = s_i | R = r\} f_1(r) \stackrel{(b)}{=} \frac{\partial C(F_1(r), F_{h,1}(s_i))}{\partial r} - \frac{\partial C(F_1(r), F_{h,1}(s_{i-1}))}{\partial r} \quad (11.55)$$

$$Pr\{S = s_i, R = r\} f_1(r) \stackrel{(c)}{=} f_1(r) \left[\frac{\partial C(F_1(r), F_{h,1}(s_i))}{\partial r} - \frac{\partial C(F_1(r), F_{h,1}(s_{i-1}))}{\partial r} \right] \quad (11.56)$$

$$f_{R,S}(r, s) \stackrel{(d)}{=} f_1(r) \left[\frac{\partial C(u, F_{h,1}(s_i))}{\partial u} - \frac{\partial C(u, F_{h,1}(s_{i-1}))}{\partial u} \right] \quad (11.57)$$

where s_i and s_{i-1} are in the support $\tilde{S}$ of S and $s_{i-1} < s < s_i$. The support of S takes on discrete values s_k . Here, s_i is the value determined by the discrete variable and $s_{i-1} = \sup\{s : s < s_i, s \in \tilde{S}\}$, i.e the preceding point in the support $\tilde{S}$. Also, $u = F_1(r)$, which is the CDF of the machine observation under H_1 . We set $s_0 = -\infty$, where s_0 is a point in $\tilde{S}$ so that $F_{h,1}(s_0) = 0$. Since $Pr\{S \leq s, R \leq r\} = \int_{-\infty}^r \sum_{v: \{v \in \tilde{S}, v \leq s\}} f_{R,S}(u, v) du =$

$\int_{-\infty}^r \sum_{v: \{v \in \tilde{S}, v \leq s\}} f_{S|R}(v|u) f_R(u) du$, step (a) is derived by finding the partial derivative with respect to r using Leibniz's integral rule; step (b) comes from the definition of CDF for a discrete variable, step (c) is obtained from the definition of the conditional CDF and step (d) follows from the chain rule for derivatives.

Example: We compute the joint pdf for the machine observation $R \sim N(\alpha, \sigma^2)$ and $S \sim \text{Bernoulli}(\beta)$ using a bivariate Gaussian copula $C_G(u, v|\rho)$. The Gaussian copula has a correlation parameter ρ which represents the amount of dependency between the variables R and S . From (11.57), we have:

$$f_{R,S}(r, s) = f_1(r) \left[\frac{\partial C_G(u, F_{h,1}(s_i)|\rho)}{\partial u} - \frac{\partial C_G(u, F_{h,1}(s_{i-1})|\rho)}{\partial u} \right] \quad (11.58)$$

For a Gaussian copula, $\frac{\partial C_G(u, v|\rho)}{\partial u} = \Phi \left[\frac{\Phi^{-1}(v) - \rho \Phi^{-1}(u)}{\sqrt{1-\rho^2}} \right]$ where $\Phi(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$ and $u = F_R(r)$. The expression for the derivative is given in [45]. Then, the joint pdf

of r and s is expressed as:

$$f_{R,S}(r,s) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(r-\alpha)^2}{2\sigma^2}} \left\{ \Phi \left[\frac{\Phi^{-1}(F_S(s_i)) - \rho\Phi^{-1}(u)}{\sqrt{(1-\rho^2)}} \right] - \Phi \left[\frac{\Phi^{-1}(F_S(s_{i-1})) - \rho\Phi^{-1}(u)}{\sqrt{(1-\rho^2)}} \right] \right\} \quad (11.59)$$

We use the LRT to determine when it is necessary to request side information from the human. More specifically, we determine when the human's decision can augment the machine's observation to yield improved performance, so that the overall probability of error decreases. It can be seen from (11.52) that the LRT when the human decisions are $s_i = 1$ and $s_i = 0$ simplifies to

$$\frac{f_1(r)}{f_0(r)} \left[1 - \frac{\partial C(u, 1-\beta)}{\partial u} \right] \stackrel{H_1}{\underset{H_0}{\geq}} \eta(1-\beta) \quad (11.60)$$

$$\frac{f_1(r)}{f_0(r)} \left[\frac{\partial C(u, 1-\beta)}{\partial u} \right] \stackrel{H_1}{\underset{H_0}{\geq}} \eta(\beta) \quad (11.61)$$

respectively. Given a fixed value of β , the terms on the left side of (11.60) and (11.61) are functions of r . If the value of r is such that either,

$$\left\{ \frac{f_1(r)}{f_0(r)} \left[\frac{\partial C(u, 1-\beta)}{\partial u} \right], \frac{f_1(r)}{f_0(r)} \left[1 - \frac{\partial C(u, 1-\beta)}{\partial u} \right] \right\} > \eta\beta \quad \text{or} \quad (11.62)$$

$$\left\{ \frac{f_1(r)}{f_0(r)} \left[\frac{\partial C(u, 1-\beta)}{\partial u} \right], \frac{f_1(r)}{f_0(r)} \left[1 - \frac{\partial C(u, 1-\beta)}{\partial u} \right] \right\} < \eta(1-\beta) \quad (11.63)$$

the FC decides H_1 and H_0 respectively to be true, regardless of the value of s . Hence, in these two regions indicated by (11.62) and (11.63), the side information of the human does not improve the global decision solely based on the machine's observation.

Next, we show that when the marginal densities under the two hypotheses H_1 and H_0 have Gaussian distributions with shifted-means, i.e., $f_1(r|\alpha_1) \sim N(\alpha_1, \sigma^2)$, $f_0(r|\alpha_0) \sim N(\alpha_0, \sigma^2)$, and the Signal-to-Noise ratio (SNR) $\frac{\alpha_1 - \alpha_0}{\sigma^2}$ is large enough, the human decision is not required when the machine observation r is outside a region $A = [d', d'']$ for any value of η . We derive the SNR conditions in the following paragraph.

The likelihood ratio $L_m(r) = \frac{f_1(r)}{f_0(r)}$ of the machine's observation is a strictly increasing function of r given that the distributions $f_1(\cdot|\alpha_1)$ and $f_0(\cdot|\alpha_0)$ are from the same family and $\alpha_1 > \alpha_0$. Let $\phi(r|\beta) = \frac{\partial C(u, 1-\beta)}{\partial u}$, then it is easy to see that the functions $\phi_0(r|\beta) = L_m(r)\phi(r|\beta)$ and $\phi_1(r|\beta) = L_m(r)(1 - \phi(r|\beta))$ are strictly increasing if

$$\frac{d}{dr}(L_m(r)\phi(r|\beta)) > 0 \quad (11.64)$$

and

$$\frac{d}{dr}(L_m(r)(1 - \phi(r|\beta))) > 0 \quad (11.65)$$

After simplifying the derivatives in the two equations, we have the conditions

$$\frac{\alpha_1 - \alpha_0}{\sigma^2} > \max \left\{ \sup_{r \in \mathbb{R}} \left(\frac{-\phi'(r|\beta)}{\phi(r|\beta)} \right), \sup_{r \in \mathbb{R}} \left(\frac{\phi'(r|\beta)}{1 - \phi(r|\beta)} \right) \right\} \quad (11.66)$$

If the SNR satisfies (11.66), $\phi_1(r|\beta)$ and $\phi_0(r|\beta)$ are injective functions and invertible. Then, the region $A = [d', d'']$ that requires the human's decision to improve the system performance is given by:

$$d' = \max\{\phi_1^{-1}(\eta\beta), \phi_0^{-1}(\eta\beta)\} \quad (11.67)$$

and

$$d'' = \min\{\phi_1^{-1}(\eta(1-\beta)), \phi_0^{-1}(\eta(1-\beta))\} \quad (11.68)$$

The derivatives of the Gaussian copula and the Student's-t copula with respect to the variable u are needed in order to compute the likelihood ratio. The procedures of deriving these derivatives can be found in [45] and are summarized in Table 11.1.

Table 11.1 Derivatives of the Gaussian and Student's-t copulas

Copula Derivatives	
Copula Family	Partial Derivative $\frac{\partial C(u,v)}{\partial u}$
Gaussian	$\Phi \left\{ \frac{\Phi^{-1}(F_S(s_i)) - \rho \Phi^{-1}(u)}{\sqrt{1-\rho^2}} \right\}$
Student's t	$t_{v+1} \left\{ \frac{t_v^{-1}(F_S(s_i)) - \rho t_v^{-1}(u)}{\sqrt{\frac{(v+(t_v^{-1}(u))^2)(1-\rho^2)}{(v+1)}}} \right\}$

It can be shown that for a Gaussian copula, the derivative of $\phi(r|\beta)$, $\phi'(r|\beta) = \frac{-\rho}{\sqrt{1-\rho^2}} f_1(r) \frac{f\left(\frac{\phi^{-1}(v) - \rho \phi^{-1}(u)}{\sqrt{1-\rho^2}}\right)}{f\left(\frac{\phi^{-1}(u)}{2}\right)}$, where $f_1(\cdot)$ is the marginal PDF under H_1 and $f(\cdot)$ is the PDF of a standard normal distribution. Also, $\phi(r|\beta) \in [0, 1]$ and when either $\phi(r|\beta) = 0$ or $1 - \phi(r|\beta) = 0$, it is required that the SNR $\frac{\alpha_1 - \alpha_0}{\sigma^2}$ must be infinitely large for both $\rho > 0$ and $\rho < 0$ so that $\phi_1(r|\beta)$ and $\phi_0(r|\beta)$ are strictly increasing for all values of r and for the region A to be of the form $[d', d'']$. When $\rho = 0$, we have the product copula Π which corresponds to the scenario where the human decision and machine observation are independent and in this case, any SNR > 0 is sufficient.

11.3.3 Performance evaluation

Next, we derive the expression for the probability of error P_e of the system under the Bayesian criterion. We first compute the expressions for the probability of detection P_D and the probability of false alarm P_{FA} . With the definition of copulas, we get:

$$Pr\{R > r | S = s_i, H_1\} = 1 - C(F_1(r), F_{h,1}(s_i)) + C(F_1(r), F_{h,1}(s_{i-1})) \quad (11.69)$$

where $F_1(r)$ is the CDF of the machine observation r . It should be noted that the likelihood ratio simplifies to $\frac{\phi_1(r|\beta)}{1-\beta}$ when $s_i = 1$ and $\frac{\phi_0(r|\beta)}{\beta}$ when $s_i = 0$. The functions $\phi_1(r|\beta)$ and $\phi_0(r|\beta)$ are monotonically increasing if the SNR satisfies the conditions in (11.66) and hence, are injective and invertible. The inverse functions of $\phi_1(\cdot|\beta)$ and $\phi_0(\cdot|\beta)$ are denoted as $\phi_1^{-1}(\cdot)$ and $\phi_0^{-1}(\cdot)$ respectively. We denote $c_1 = \phi_1^{-1}(\eta(1-\beta))$ and $c_0 = \phi_0^{-1}(\eta\beta)$. The LRT conditioned on the values of s_i are expressed as:

$$r \underset{H_0}{\overset{H_1}{>}} c_1 \quad \text{when } s_i = 1 \quad (11.70)$$

$$r \underset{H_0}{\overset{H_1}{>}} c_0 \quad \text{when } s_i = 0 \quad (11.71)$$

The probability of detection P_D is then expressed as:

$$P_D = Pr\{R > c_1 | S = 1, H_1\} Pr\{S = 1 | H_1\} \\ + Pr\{R > c_0 | S = 0, H_1\} Pr\{S = 0 | H_1\} \quad (11.72)$$

Using equations (11.69), (11.70) and (11.71), P_D can be given by:

$$P_D = 1 - \beta F_1(c_1) - C(F_1(c_1), 1 - \beta) \\ + \beta \left[C(F_1(c_1), 1 - \beta) - C(F_1(c_0), 1 - \beta) \right] \quad (11.73)$$

where $Pr(R > c_1 | S = 1, H_1) = 1 - C(F_1(c_1), 1) + C(F_1(c_1), F_{h,1}(0)) = 1 - F_1(c_1) + C(F_1(c_1), 1 - \beta)$, due to the fact that $C(u, 1) = u$ for any copula C [43]. Moreover, we obtain $Pr(R > c_0 | S = 1, H_1) = 1 - C(F_1(c_1), F_{h,1}(0)) + C(F_1(c_1), \text{and } F_{h,1}(-\infty)) = 1 - C(F_1(c_1), 1 - \beta)$ due to the fact that $C(u, 0) = 0$ [43].

We further derive the expression for the probability of false alarm P_{FA}

$$P_{FA} = Pr\{R > c_1 | S = 1, H_0\} Pr\{S = 1 | H_0\} \\ + Pr\{R > c_0 | S = 0, H_0\} Pr\{S = 0 | H_0\} \quad (11.74)$$

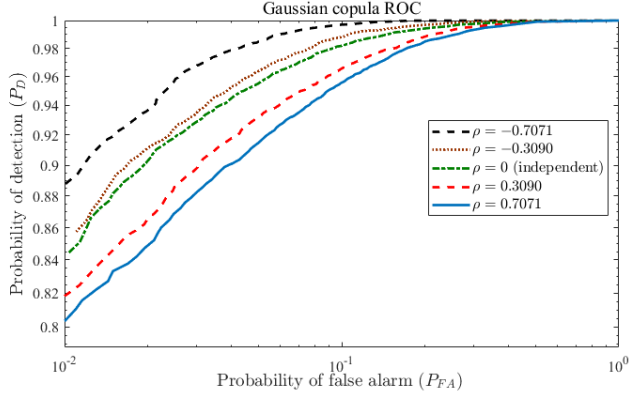
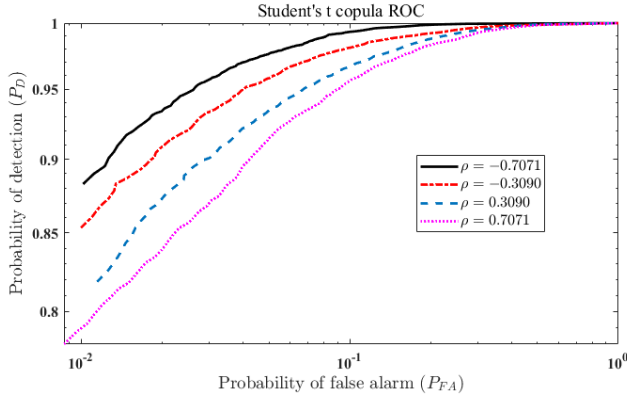
which can be written as

$$P_{FA} = \beta(1 - F_0(c_1)) + (1 - \beta)(1 - F_0(c_0)) \\ = \beta(F_0(c_0) - F_1(c_1)) + 1 - F_0(c_0) \quad (11.75)$$

In the Bayesian setting, the probability of error P_e is in form of

$$P_e = \pi_1(1 - P_D) + \pi_0(P_{FA}) \quad (11.76)$$

Some experiments are conducted for illustration of the performance. First, we show the Receiver Operator Characteristics (ROC) for the Gaussian copula and the Student's t copula families. We set SNR of the machine's observation to be $\frac{\alpha_1 - \alpha_0}{\sigma^2} = 3$ and the human's accuracy to be $\beta = 0.8$. The ROC is plotted for different values of the copula parameter ρ (common to both families). In Figure 11.11


 Figure 11.11 ROC for a Gaussian Copula for different ρ

 Figure 11.12 ROC for a Student's t Copula for different ρ and $\nu = 3$

and Figure 11.12, we plot the ROC for a Gaussian copula and a Student's t copula for different values of the dependence parameter ρ . The degree of freedom in the Student's t copula is set equal to 3 in all the curves. It can be seen that for both the Gaussian copula and the Student's t copula, when the human decision and machine observation are positively correlated, there is an overlap of information that will reduce the overall information that can be used for decision making. On the other hand, when the data is negatively correlated, the human decision and machine observation could act as critics to each other and prevent false alarms or missed detection, thus enhancing the overall performance of the system.

In Figure 11.13, we set $\eta = 0.4$, $\beta = 0.8$. For a Gaussian copula with $\rho = 0.3090$, we show the range of the region where the human's decision is not required. We plot the functions $\phi_1(r)$ and $\phi_0(r)$ for two different values of SNR: 0.75 and 0.8. For the conditions given in equations (11.62) and (11.63), the region that does not require human assistance is larger when the machine's observation has higher

value of SNR. It should be noted that in such a case, the regions that require human decisions are not continuous.

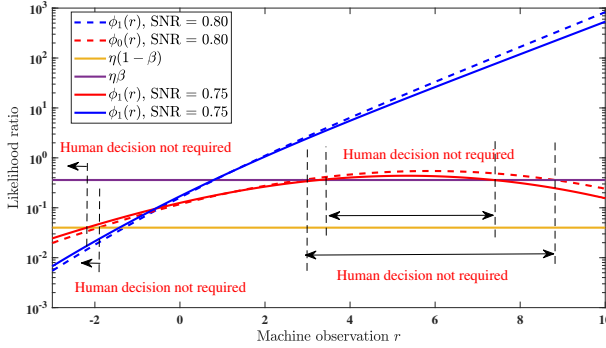


Figure 11.13 Effect of low SNRs on the decision region

In Figure 11.14, we illustrate how the performance of the detection system degrades if we neglect the dependence between the human decision and the machine observations. The SNR of the marginals is set to 3 and the parameter $\beta = 0.8$. It can be seen that for both $\rho = 0.7071$ and $\rho = -0.7071$ with a Gaussian copula, if dependencies are ignored, the probability of detection P_D for different values of probability of false alarm P_{FA} is considerably smaller.

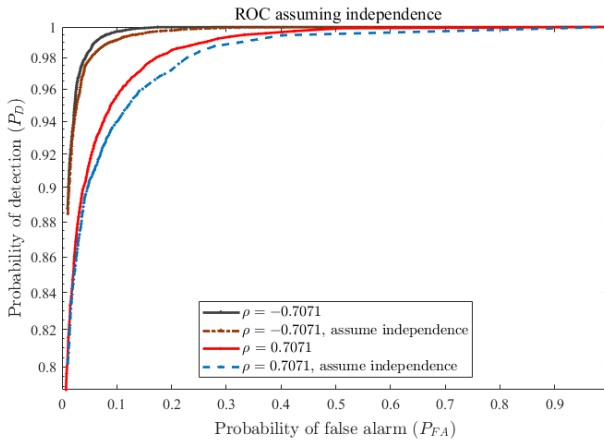


Figure 11.14 Loss in performance on ignoring dependence between human decision and machine observation

11.4 Current Challenges in Human-Machine Teaming

Human behavior and decision making are complex processes that represent the intricate interplay between the psychological activity within humans and the influence of outside environment. A fully cognitive human-machine collaboration architecture requires the machine to be able to understand, anticipate, and augment the performance of the human; and the human to have the ability to support, supervise, and enhance the automation conducted by the machine [22]. To advance the objective of designing an interactive symbiosis where humans and machines are tightly coupled together, several research directions include, but not limited to the following.

1. **Behavioral informatics:** For the machine to better understand human behavior in different applications, it is necessary to explore psychology findings and characterize how human behavior is impacted by time constraints, memory limitations, emotion state as well as stimulus from the outside environment. To achieve ‘order of magnitude increases in available, net thinking power resulting from linked human-machine dyads’ [46], it becomes imperative to perform human cognitive state sensing for designing efficient communication interfaces between the human and the machine. Another interesting topic is the real time prediction of human cognitive workload based on sensor-based brain signals such as electroencephalogram (EEG), as well as the design of system augmentations such as offloading tasks or assisting users with modality-specific support.
2. **Trust in autonomous systems:** In human-machine collaboration, the authors in [47] have described trust as ‘the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party’. In particular, many autonomous systems employed in high stake applications are black boxes that do not explain how the decision are made. The challenge is to develop a quantitative definition of trust and establish clear guidelines to construct human-machine transparency and enhance calibrated trust between the human and the machine.
3. **Situational awareness:** Situational awareness (SA) refers to the user’s familiarity of the task environment, the perception of the task status, and the anticipation of future states. If humans are not appropriately incorporated in the loop, it is very likely that the human is not aware of or not familiar with the machine’s task execution. In such a situation where there is over-reliance on machine automation, the human’s understanding of the work environment, i.e., SA, is jeopardized. The loss of SA (also referred to as complacency or automation induced decision biases in different works) compromises the human’s level of expertise and ability to perform the automated tasks manually in case of unpredictable automation failure and it may cause severe breakdown in critical applications like autopilot and submarine navigation systems. Hence, the concerns of SA must be addressed in the design of human-machine symbiosis to prevent irreparable damage.
4. **Herding, nudging and incentives:** Humans are also known to be subject to herding and nudging phenomena. To elicit desirable outputs from humans, fu-

ture research work can proceed with some explorations along these lines. a) The optimum design and task allocation of collaborative human-machine networks. This will include change in strategies of individual nodes, e.g., adapting the threshold of some or all the nodes or shaping the input to selected nodes during the inference process. b) The suitable distribution of the tasks and workload to be performed by humans and machines leading to semi-autonomous systems. c) Another important consideration will be the incentivization measures of humans to actively engage in the inference process, which can be posed in a reinforcement learning based framework.

11.5 Summary

In almost all cognitive radar systems developed so far, the objective function is based solely on objective performance measures and is devoid of any human perception considerations. The incorporation of human in the loop will generalize cognitive systems by allowing humans and machines being tightly coupled in the same working environment for advanced interaction. In this chapter, we reviewed the state of the art in how human behavior and decision making can be modeled in the statistical signal processing framework, with emphasis on three topics. First, the decision making problem in human-machine networks was considered where the humans employ random thresholds and the machines employ fixed thresholds to make binary local decisions. The asymptotic performance of the integrated system was derived by considering humans might possess side information regarding the PoI. Next, the behavioral economics concept prospect theory was exploited to study the behavior of human binary decision making under cognitive biases, where the thresholds employed by humans were modeled as a Gaussian random variable. Two decision making systems involving humans' participation were discussed, and we showed the impact of human cognitive biases on the decision making performance. Finally, we discussed a collaborative environment to solve binary hypothesis testing problems where Copula theory was used to model the dependency of the machine's observation and the human's side information. The conditions under which the human's side information will yield improved detection performance were derived.

While the topics and research directions discussed in this chapter might serve as starting points to advance the next generation cognitive radar systems that involve human participations, novel theoretical frameworks for collaborative human-machine decision making in complex environments require inputs from different disciplines such as statistical signal processing, artificial intelligence, machine learning, economics, experimental psychology, and neuroscience. The ultimate goal is to merge the best of humans with the best of machines in task environments so that humans and machines can interact and complement each other. Application scenarios may include: decisions are made autonomously by machines or the decisions are made by a human or a semi-autonomous system where humans and machines collaborate in making the final decision. Developments in this area are envisaged to result in significant revolutions on the design of many autonomous and semi-autonomous systems

for situational awareness and command and control, both in military and civilian application, that involve human-machine collaboration.

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