A Sufficient Condition for Optimality of Digital versus Analog Relaying in a Sensor Network

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***Abstract*—This paper compares the efficacy of digital versus analog relaying in a sensor network when the ultimate goal is detection. A simplified scenario is considered in which a binary decision is to be made at a fusion center based on data it receives from a single sensor. The sensor computes a statistic corresponding to its observations and forwards it over a noisy channel to the fusion center. Two relay schemes: "estimate-and-forward" (analog relaying) and "detect-and-forward" (digital relaying) are compared, in terms of the ultimate detection performance they support at the fusion center. With this performance criterion, the relative merit of the two schemes is shown to depend on the observation SNR at the sensor and the SNR of the communication link connecting the sensor and the fusion center. A sufficient condition, in terms of these SNRs, for the superiority of digital relaying over analog relaying is derived for this simple network model.**

***Index Terms*—Hypothesis-testing, signal-to-noise ratio, sensor networks, analog/digital relays.**

I. Introduction

Recently, wireless sensor networks (WSNs) have attracted much attention of the research community. Due to their high flexibility, enhanced surveillance coverage, robustness, mobility, and cost effectiveness, WSNs have wide applications and high potential in military surveillance, security, monitoring of traffic, and environment. Usually, a WSN consists of a large number of lowcost and low-power sensors, which are deployed in the environment to collect observations and preprocess the observations. Each sensor node has limited communication capability that allows it to communicate with other sensor nodes via a wireless channel. Normally, there is a fusion center that processes data from sensors and forms a global situational assessment.

The ability to detect events of interest is a key capability of the sensor network technology. Detection is the "kick-start" procedure for the operation of any sensor network. Indeed, the physical attributes of a target, like its position and velocity, can be ascertained only after having detected its presence. Furthermore, in some applications such as surveillance, industrial monitoring etc., the detection of an intruder or a hazard is the prime goal.

The decision-making problem, where sensors preprocess their observations before transmitting data to the fusion center, is termed decentralized detection. Decentralized detection scenarios for sensor networks typically entail geographically dispersed sensors that collect observations about an "event" of interest and transmit information about these individual observations to a fusion center. The fusion center produces an estimate about the event, based on the data it receives from the sensors. If the event is binary with a known prior probability distribution, the problem falls into the Bayesian detection framework, and the probability of error at the fusion center is a typical metric of performance. When no prior distribution on the event is available, Neyman-Pearson detection seeks to minimize the probability of false alarm subject to a constraint on the probability of missed detection [5]. A key challenge in decentralized detection is to come up with decision rules at the sensors, and fusion rules at the fusion center so as to optimize the detection performance at the fusion center.

Wireless sensor nodes are typically tiny devices powered by batteries, and hence are subject to stringent constraints on the resources such as, bandwidth and power. To design an efficient system for detection in sensor networks, it is imperative to understand the interplay between data processing at the sensor nodes, resource allocation, and overall performance in distributed sensor systems. A clear understanding of this interplay can be leveraged to gain insight into the efficient design of sensor networks. Decentralized detection has received much attention in the literature due to its importance in the event driven sensor networks. In-depth treatments of this field can be found in the work of Tsitsiklis [7], Viswanathan *et al.* [8] and Blum *et al.* [1], and the references therein. A recent survey on channel-aware distributed detection, where sensors communicate to the fusion center over noisy (and fading) links, can be found in [3].

Early treatments of distributed detection adopted various simplifying assumptions, particularly about independence of observations at the sensors, and about communication between the sensor nodes and the fusion center, which was often assumed to be perfect. When these assumptions hold, the performance of a decentralized system is optimized by each sensor transmitting its likelihood ratio to the fusion center. The fusion center forms a global likelihood ratio from the product of these and achieves performance equivalent to what would be possible if all the raw sensor data were available at the fusion center. If the communication links between the sensors and the fusion center are imperfect, performance may actually be improved by quantizing the individual sensor likelihood ratios prior to transmission to the fusion center. Observations along this line have been made by other authors in various contexts. In [2], for example, it is observed that analog sensors perform better than their digital counterpart below a certain threshold SNR in large sensor networks where the metric of performance is the Chernoff exponent. In [6], a distributed detection method based on the method of types is considered. Again in this setting, it is observed that hard-decision fusion (digital relaying) can outperform soft-decision fusion (analog relaying) in the single sensor case.

In this paper, comparison of analog and digital relay schemes is undertaken from a classical decision theoretic perspective for a simple network model consisting of a single sensor communicating with the fusion center over an additive gaussian noise channel. A Bayesian situation is assumed and probability of error at the fusion center is the performance metric. In this setting, a sufficient condition for superiority of digital relaying, given a fixed average transmit power, is derived analytically in terms of the observation signal-to-noise ratio (SNR) at the sensor and the SNR of the communication channel between the sensor node and the fusion center. Although the network model used here is highly simplified, it is hoped that this work will contribute to a foundation for analysis of more realistic scenarios, leading to advances in sensor placement strategies and inference algorithms in sensor networks as well as the design of wireless relay networks [4] in which a relay assists communication between a source-destination pair.

The rest of this paper is organized is as follows. Section II presents the system model and assumptions. Section III introduces the relaying methods and presents the mathematical framework. Section IV compares the performance of relaying schemes. Section V discusses simulation results, and some concluding remarks are given in Section VI.

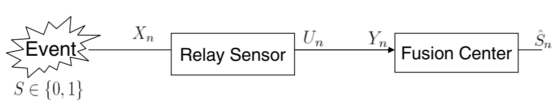

Fig. 1. Block diagram of a typical sensor relay network.

II. System Model

We consider a single sensory relay network, consisting of a relay-sensor and fusion center, with a power constraint at the relay. The system is as shown in the Fig. 1. The prime objective of the network is to make a decision on a binary event at the fusion center with minimum detection error. The job of relay sensor is to assist the fusion center in making a decision on the event. We assume that the underlying phenomenon is an equally-likely binary event, $S \in \{0, 1\}$. In terms of null-hypothesis (H_0) and target-hypothesis (H_1), we write

$$H_0 : S = 0, \quad P(H_0) = 0.5$$
$$H_1 : S = 1, \quad P(H_1) = 0.5.$$

The sensor observes a noisy stochastic process X_n associated with the event. We represent the observation process at the sensor as

$$X_n = hS_n + Z_n, \; n = 1, \ldots, \tag{1}$$

where h represents the scaling factor accounting for the uncertainties in the amplitude of the event sensed by the sensor, and Z_n is an i.i.d additive Gaussian process with $Z_n \sim \mathcal{N}(0, \sigma_z^2)$. We assume that the sensor has knowledge of h, and hence, the sensor observations are independent conditioned on the hypothesis (S_n) and h. Upon observing, sensor processes X_n to obtain a statistic U_n, which is relayed to the fusion center, adhering to an average transmit power constraint of P. The local processing rule for the observations at the sensor node, denoted by γ, is defined as

$$\gamma : \mathcal{X} \to \mathcal{U}, \tag{2}$$

where $\mathcal{X}$ is the observation space and $\mathcal{U}$ denotes the output space of the sensor. Due to the transmit power constraint P at the sensor, it is clear that $E[|U|^2] \leq P$, for all $U \in \mathcal{U}$. Observe that the processing rule at the sensor node, γ, depends on the relaying scheme.

Relay sensor, after having computed a statistic U_n from its observations, transmits U_n to the fusion center over a wireless link for decision making. We assume that fusion center has no access to the observations of the event, and has to make a decision solely based on the information sent from the relay. We represent the signal received by the fusion center as

$$Y_n = gU_n + W_n, \; n = 1, \ldots, \tag{3}$$

where g represents channel attenuation, and W_n is an i.i.d additive Gaussian process with $W_n \sim \mathcal{N}(0, \sigma_w^2)$. We assume that the fusion center is cognizant of its channel state g, and hence the observations are conditionally independent given g and the hypothesis. Fusion center has to make a decision $\hat{S}_n$ based on the information relayed by the sensor. The objective is to minimize the detection error under the transmit power constraint at the relay. In what follows, we formulate and analyze the problem in hand under classical binary hypothesis testing framework, and develop a fair idea about the relaying schemes. We assume that the detection is performed on a sample-by-sample basis. In what follows, for presentational convenience, we omit the use of temporal subscript n.

III. Relaying Schemes

Upon obtaining the noisy observations of the event, the sensor is posed with the problem of computing a statistic (that is, to design γ) so as to aid fusion center in decision making. The senors can be "digital" or "analog" depending on the processing schemes. A digital sensor may quantize its observations and communicate its decisions in the form of bits, while an analog sensor may compute the sufficient statistics of

$$H_0: \quad f_Y(y|H_0,g) = \frac{1}{\sqrt{2\pi\sigma_w^2}}\left((1-p)\exp-\frac{(y+g\sqrt{P})^2}{2\sigma_w^2} + p\exp-\frac{(y-g\sqrt{P})^2}{2\sigma_w^2}\right)$$
$$H_1: \quad f_Y(y|H_1,g) = \frac{1}{\sqrt{2\pi\sigma_w^2}}\left((1-p)\exp-\frac{(y-g\sqrt{P})^2}{2\sigma_w^2} + p\exp-\frac{(y+g\sqrt{P})^2}{2\sigma_w^2}\right). \quad (4)$$

its observations, which is a real number, and may transmit it as an analog signal. Assessing the performances of these schemes in different regimes of network parameters is key to the design of sensor and relay networks. One wishes to deploy analog or digital sensors depending on which scheme is superior in a given regime.

A. Digital Relaying (Detect and Forward)

The relay sensor performs a binary hypothesis testing on the observations and the decision is conveyed in the form of bits. Thus, the decision variable U is binary. That is, with the power constraint, $U \in \{-\sqrt{P}, \sqrt{P}\}$. We express the likelihood function at the sensor as

$$\begin{aligned} H_0: X &\sim f_X(z_i|H_0,h), \\ H_1: X &\sim f_X(z_i|H_1,h). \end{aligned}$$

where

$$f_X(x|H_0,h) = \frac{1}{\sqrt{2\pi\sigma_z^2}}\exp-\frac{x^2}{2\sigma_z^2};$$

$$f_X(x|H_1,h) = \frac{1}{\sqrt{2\pi\sigma_z^2}}\exp-\frac{(x-h)^2}{2\sigma_z^2}.$$

From the fundamentals of detection theory [5], it is clear that the optimal processing rule is given by

$$U = \gamma(X) = \begin{cases} +\sqrt{P} & \text{if} \quad f_X(x|H_1,h) \geq f_X(x|H_0,h) \\ -\sqrt{P} & \text{if} \quad f_X(x|H_1,h) < f_X(x|H_0,h). \end{cases} \quad (5)$$

More succinctly, we have the sensor's processing rule as

$$\gamma(X) = \sqrt{P}\left[2\mathbf{I}(X \geq h/2) - 1\right], \quad (6)$$

where $\mathbf{I}(\cdot)$ is the indicator function.

Next, consider the fusion rule at the fusion center. Fusion center receives Y, the noisy version of the statistic U communicated by sensor over the noisy link. Fusion center is faced with the task of making decision $\hat{S}$, on S, based on the received signal Y. Observe that the distribution of Y, and therefore the fusion rule, depend on the decision rule γ, of the sensor. Therefore, to derive the decision rule at the fusion center, it is essential first to evaluate the detection error probabilities at the sensor. To this end, we define $\texttt{SNR}_o \triangleq \frac{1}{4}\frac{h^2}{\sigma_z^2}$, as the observation SNR, which is the "signal-to-noise ratio" of the observations at the sensor. Then, for a given $\texttt{SNR}_o$, we note that the probability of error at the sensor, p, is given by:

$$p = P(X \geq h/2|S=0, \texttt{SNR}_o) = Q\left(\sqrt{\texttt{SNR}_o}\right). \quad (7)$$

We note that the received signal Y obeys:

$$\begin{aligned} H_0: \quad & Y = -\sqrt{P}g + W \ \ w.p. \ 1-p \\ & Y = \sqrt{P}g + W \ \ w.p. \ p \\ H_1: \quad & Y = \sqrt{P}g + W \ \ w.p. \ 1-p \\ & Y = -\sqrt{P}g + W \ \ w.p. \ p. \end{aligned}$$

Particularly, Y is conditionally distributed as a mixture-Gaussian distribution given by (4).

We point out that, in reality, the optimal detection strategy involves coupling between the decision procedures at the sensor and the fusion center. However, the evaluation of thresholds and the analysis of the optimal scheme is intractable in general. Therefore, in the developments of this section, we adapt the so-called "person-by-person optimization" approach (PBPO) [7], where the decision at the fusion center is optimized assuming fixed decision rules at the sensor.

Therefore, following PBPO approach, the decision making at the fusion center boils down to a classical hypothesis testing with

$$\text{Choose } \hat{S} = 1, \text{ if } L(Y) \geq 1,$$

where $L(y)$ is the likelihood ratio, given by

$$L(y) = \frac{p\exp-(\frac{2g\sqrt{P}y}{\sigma_w^2}) + 1 - p}{(1-p)\exp-(\frac{2g\sqrt{P}y}{\sigma_w^2}) + p}. \quad (8)$$

After some steps, the decision rule simplifies to

$$\text{Choose } \hat{S} = 1 \text{ if } gY \geq 0.$$

Next, we evaluate the detection error due to "digital relaying" scheme. We let $\texttt{SNR}_l \triangleq g^2P/\sigma_w^2$ denote the link SNR, i.e., signal-to-noise ratio of the link between sensor and the fusion center. For convenience, define $\texttt{SNR} = [\texttt{SNR}_o, \texttt{SNR}_l]$. The detection error at the fusion center, when aided by a digital sensor, is given by

$$P_{ED}(\texttt{SNR}) \quad = \quad p + (1-2p)Q\left(\sqrt{\texttt{SNR}_l}\right), \quad (9)$$

where p is given by the equation (7), and $Q(\cdot)$ is the $Q-$function given by $Q(x) = \frac{1}{\sqrt{2\pi}}\int_0^x e^{-\frac{u^2}{2}}du$.

B. Analog Relaying (Estimate and Forward)

This case employs analog sensor to aid fusion center. Relay sensor constructs the sufficient statistic of the phenomenon, scales the message for the given power constraint and transmits it to the sink. Essentially, the sensor node acts as an analog relay amplifier with the output space, $\mathcal{U} = \Re$ with $E[|U|^2] \leq$

P for all $U \in \mathcal{U}$. It is clear that the sufficient statistic T is given by the log likelihood ratio,

$$T(x) = \log \frac{f_X(x|H_1, h)}{f_X(x|H_0, h)} = \frac{h}{2\sigma_z^2}(2x - h). \qquad (10)$$

It follows that T is a Gaussian RV with variance $Var(T) = 4\texttt{SNR}_o$, and $E[T|H_0] = -2\texttt{SNR}_o$ and $E[T_i|H_1] = 2\texttt{SNR}_o$.

Accounting for the average power constraint, the message sent from the relay is given by

$$U(X) = \sqrt{\frac{P}{4\texttt{SNR}_o(1+\texttt{SNR}_o)}}T(X) \qquad (11)$$

so that

$$H_0 : U \sim \mathcal{N}\left(-\sqrt{\frac{P\texttt{SNR}_o}{1+\texttt{SNR}_o}}, \frac{P}{1+\texttt{SNR}_o}\right)$$

$$H_1 : U \sim \mathcal{N}\left(\sqrt{\frac{P\texttt{SNR}_o}{1+\texttt{SNR}_o}}, \frac{P}{1+\texttt{SNR}_o}\right).$$

Fusion center receives Y, a noisy version of U, and performs decision on the event based on Y, so as to minimize the detection error. The decision rule at the fusion center is the likelihood ratio test, given as:

$$\text{Choose } \hat{S} = 1, \text{ if } \frac{f_Y(y|H_1, g)}{f_Y(y|H_0, g)} \geq 1.$$

We note that

$$H_0 : Y \sim \mathcal{N}\left(-\sqrt{\frac{g^2P\texttt{SNR}_o}{1+\texttt{SNR}_o}}, g^2\frac{P}{1+\texttt{SNR}_o} + \sigma_w^2\right)$$

$$H_1 : Y \sim \mathcal{N}\left(\sqrt{\frac{g^2P\texttt{SNR}_o}{1+\texttt{SNR}_o}}, g^2\frac{P}{1+\texttt{SNR}_o} + \sigma_w^2\right).$$

It follows that the optimal rule simplifies to

$$\text{Choose } \hat{S} = 1 \text{ if } gY \geq 0.$$

Consequently, for a given set of SNR parameters, $\texttt{SNR}$, the detection error at the fusion center when aided by an analog sensor can be shown to be

$$P_{EA}(\texttt{SNR}) = Q\left(\sqrt{\frac{\texttt{SNR}_l\texttt{SNR}_o}{\texttt{SNR}_l + \texttt{SNR}_o + 1}}\right). \qquad (12)$$

IV. Comparison of Analog and Digital Relaying

In this section, we do the performance comparison of analog and digital relaying schemes, in terms of observation and link SNRs. It is unclear, a priori, about the regimes in which one scheme outperforms the other. We partly answer the above question by providing a sufficient condition for the optimality of digital scheme over the analog scheme. Before presenting our main result, we state the following lemma.

Lemma 1: Let $a, b \geq 0$ such that $a + b \leq \frac{1}{2}$, then

$$Q\left(\frac{1}{\sqrt{a+b}}\right) \geq Q\left(\frac{1}{\sqrt{a}}\right) + Q\left(\frac{1}{\sqrt{b}}\right).$$

Proof: Relegated to Appendix.

The following result establishes that for the values of SNRs beyond certain threshold, digital relaying is superior over analog relaying.

Proposition *1:* **[Optimality of Digital Relaying]:** *For all observation and link SNRs, $\texttt{SNR} = [\texttt{SNR}_o, \texttt{SNR}_l]$ such that $1/\texttt{SNR}_o + 1/\texttt{SNR}_l \leq 1/2$, it is optimal to use digital relaying over analog relaying, i.e., $P_{ED}(\texttt{SNR}) \leq P_{EA}(\texttt{SNR})$.*

Proof: From (9) and (12), and using the fact that $Q(\cdot)$ is a decreasing function of its argument, it is clear that

$$P_{ED}(\texttt{SNR}) \leq Q\left(\sqrt{\texttt{SNR}_o}\right) + Q\left(\sqrt{\texttt{SNR}_l}\right) \qquad (13)$$

and

$$P_{EA}(\texttt{SNR}) \geq Q\left(\sqrt{\frac{\texttt{SNR}_l\texttt{SNR}_o}{\texttt{SNR}_l + \texttt{SNR}_o}}\right). \qquad (14)$$

Setting $a = \frac{1}{\texttt{SNR}_o}$ and $b = \frac{1}{\texttt{SNR}_l}$, and applying Lemma 1, we obtain

$$\begin{aligned} P_{EA}(\texttt{SNR}) - P_{ED}(\texttt{SNR}) \\ \geq\ & Q\left(\frac{1}{\sqrt{a+b}}\right) - \left[Q\left(\frac{1}{\sqrt{a}}\right) + Q\left(\frac{1}{\sqrt{b}}\right)\right] \\ \geq\ & 0. \end{aligned}$$

■

Proposition 1 asserts that for the single sensor case, under the regime of moderately high observation and link SNRs, digital scheme performs better than analog scheme. The reason for this behavior can be explained as follows. Under digital scheme, since only the decision bits are communicated, sensor just acts as a amplifier-repeater on the event and hence the power spent per symbol is more, which, in turn, manifests the distortions suffered by the signal over the forward link. In case of analog scheme, the sufficient statistic, which is a real number, is communicated and the power spent on the symbol is insufficient to overcome the deleterious effects of the channel. Thus, when the SNR either at the backward link or at the forward link grows large, analog and digital schemes become equivalent.

V. Simulation Results

In this section, we evaluate the performance of digital and analog schemes. The performance metric is the decision error as a function of link SNR, for a fixed observation SNR. Fig. 2 shows the performance curves as a function of $\texttt{SNR}_l$, for an observation SNR of 3dB. It can be seen that the digital scheme clearly outperforms analog scheme. As $\texttt{SNR}_l$ increases, the difference in the performance diminishes due to the fact that

$$\lim_{\texttt{SNR}_l \to \infty} P_{ED}(\texttt{SNR}) = \lim_{\texttt{SNR}_l \to \infty} P_{EA}(\texttt{SNR}) = Q(\sqrt{\texttt{SNR}_o}). \qquad (15)$$

VI. Conclusions

In this work, we studied the problem binary hypothesis testing in a single sensory relay network. In particular, we studied and compared two schemes, namely: detect-and-forward (digital relaying) and estimate-and-forward (analog relaying).

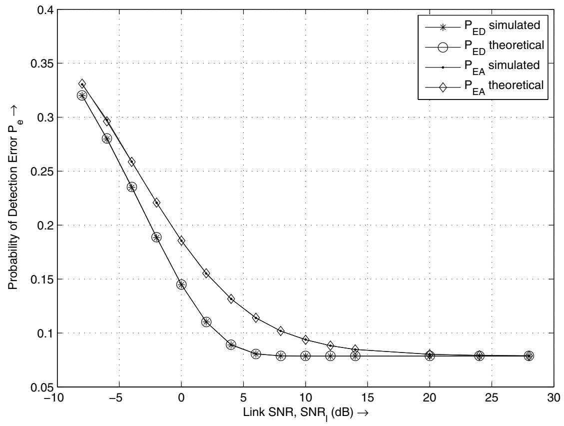

Fig. 2. Performance comparison for $\texttt{SNR}_o = 3dB$.

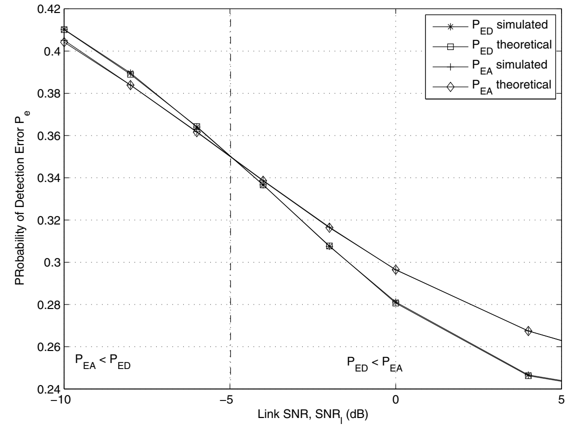

Fig. 3. Performance comparison for $\texttt{SNR}_o = -3dB$.

We observed that the performance of relaying scheme depends on observation as well as link SNRs. We established a sufficient condition for the optimality digital relaying over analog relaying. This can have important implications on the design of sensor and communication relay networks. As a part of the future work, we wish to address the necessary condition for the optimality of digital sensors. Furthermore, the developments in the paper are carried under a classical hypothesis testing framework. It will be interesting to carry out a similar analysis and comparison with respect to different classes detectors like NP-detector, min-max detector etc.

APPENDIX

PROOF OF LEMMA 1

Let $a \geq b$, so that $\frac{1}{\sqrt{a+b}} \leq \frac{1}{\sqrt{a}} \leq \frac{1}{\sqrt{b}}$. We have

$$\begin{aligned}
&Q\left(\frac{1}{\sqrt{a+b}}\right) - \left[Q\left(\frac{1}{\sqrt{a}}\right) + Q\left(\frac{1}{\sqrt{b}}\right)\right] \\
&= \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{a+b}}}^{\frac{1}{\sqrt{a}}} e^{-\frac{x^2}{2}} dx - \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{b}}}^{\infty} e^{-\frac{y^2}{2}} dy \\
&\geq \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{a+b}}}^{\frac{1}{\sqrt{a}}} \sqrt{a} x e^{-\frac{x^2}{2}} dx - \frac{1}{\sqrt{2\pi}} \int_{\frac{1}{\sqrt{b}}}^{\infty} \sqrt{b} y e^{-\frac{y^2}{2}} dy \\
&= \frac{e^{-\frac{1}{2(a+b)}}}{\sqrt{2\pi}} \left[\sqrt{a} - \left(\sqrt{a}\, e^{-\frac{b}{2a(a+b)}} + \sqrt{b}\, e^{-\frac{a}{2b(a+b)}}\right)\right] \\
&\geq \frac{e^{-\frac{1}{2(a+b)}}}{\sqrt{2\pi}} \left[\sqrt{a} - \left(\sqrt{a}\, e^{-\frac{b}{a}} + \sqrt{b}\, e^{-\frac{a}{b}}\right)\right] \\
&\geq \frac{e^{-\frac{1}{2(a+b)}}}{\sqrt{2\pi}} \sqrt{a} \left[1 - \left(e^{-\frac{b}{a}} + e^{-\frac{a}{b}}\right)\right] \\
&\geq 0,
\end{aligned}$$

where the first inequality follows from the fact that $x \leq \frac{1}{\sqrt{a}}$ for the first integral and $y \geq \frac{1}{\sqrt{b}}$ for the second integral. Second inequality follows from the assumption that $a + b \leq \frac{1}{2}$, third inequality is by $a \geq b$, and the last inequality is due to fact that $\left(e^{-x} + e^{-\frac{1}{x}}\right) \leq 1$ for $x \geq 0$.

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