Distributed Inference and Information Fusion in Human-Sensor Networks

Pramod K. Varshney

Sensor Fusion Lab
Department of EECS, Syracuse University

Collaborator: Baocheng Geng
Department of CS, University of Alabama at Birmingham

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Outline

- **The Distributed Detection Problem**
- Decision Making by Human-Machine Teams
- Prospect Theoretic Human Decision Making
  - Subjective utility based decision rule
  - Amelioration of cognitive biases
  - Human team selection
- Conclusion

Distributed Detection and Information Fusion

- Binary hypothesis testing: determination of the presence or absence of a target (H_1 or H_0)

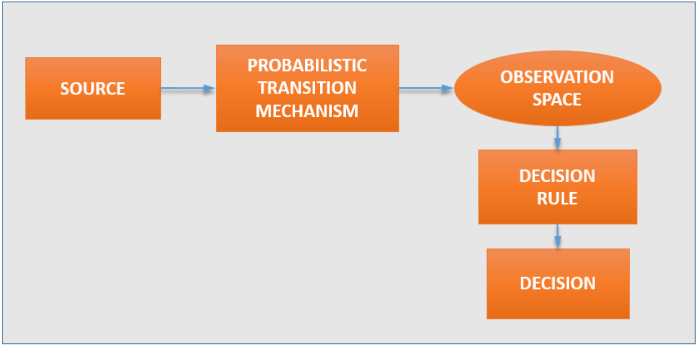

Figure 1: Components of a hypothesis testing problem

Distributed Detection and Information Fusion

- Solution of a detection problem by a team of interconnected detectors/agents

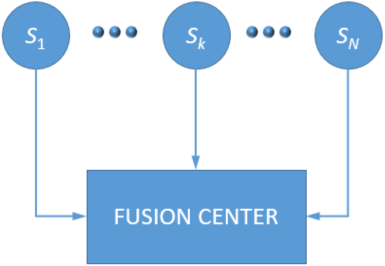

Figure 2: Parallel topology

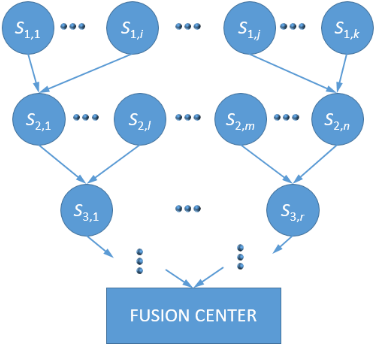

Figure 3: Tree topology

Detection Theory for Distributed Settings

Distributed Detection

- Different criteria
  - Bayesian, Neyman-Pearson, CFAR, Information theory, Nonparametric methods
- Different topologies
  - Parallel, Serial, Feedback, Unified model
- Sequential detection

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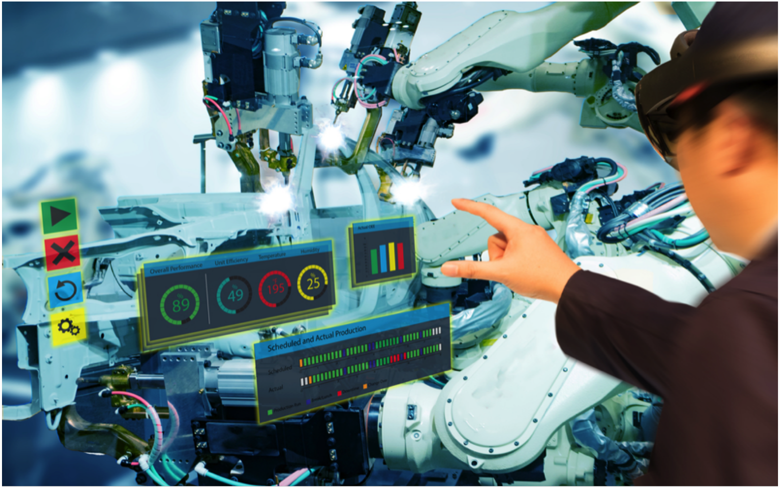
Autonomous Cars

Decision Making by Human-Machine Teams[1]



[1] https://geospatialmedia.s3.amazonaws.com/

Some Application Areas

To improve decision quality and to enhance situational awareness, human-sensor inference networks are important in many applications such as

- Autonomous driving, smart manufacturing
- Internet of things (IoT)
- Natural disasters early warning, alert and response system (EWARS)
- Healthcare and remote surgery
- Robotics
- National security and surveillance systems

Human-Sensor Networks

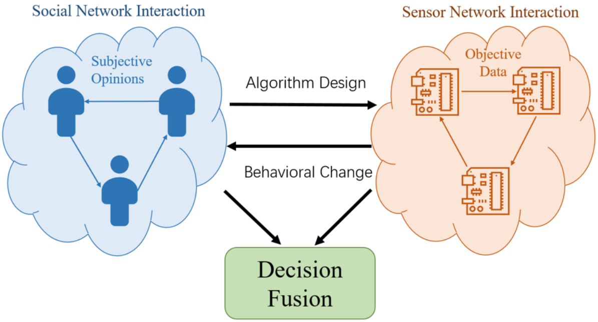


Figure 4: Human-sensor collaboration network

- The measurements from the physical sensors affect the behavior, actions and decisions of the humans
- The behavior of humans in turn determines the optimal algorithm design in the sensor network.

Decision Making in Human-Machine Teams

There are fundamental differences between the *perfect* rationality of machines/physical sensors and *bounded* rationality of humans.

- Limited information processing capacity of humans
- Cognitive limitations and biases of humans
- Perception noise of humans
- Behavioral uncertainty of humans

Literature Review: From the perspective of signal processing and information fusion

- Decision making with quantized priors leads to discrimination[2]
- Bayesian hierarchical structure to characterize the behavior of human decision fusion[3]
- Selection, ordering and presentation of data to a human[4]
- Cognitive biases in group decision making and crowdsourcing[5]

[2] Lav R. Varshney and Kush R. Varshney, Proceedings of the IEEE, 2017
[3] Vempaty et al., IEEE TSP, 2018
[4] Mourad and Tewfik, IEEE ICASSP, 2018
[5] Hube et al., Proceedings of the CHI Conference on Human Factors in Computing Systems, 2019

Collaborative Decision Fusion that Includes Human Participants (Our Work)

- Psychology experiments suggest individuals often use threshold-based schemes for decision making.
- It is unlikely that everyone uses the same threshold when the same phenomenon is observed: model thresholds as random variables [6][7].
- Integration of human and sensor inputs for situational awareness[8].
  - When and how integrating human sensors can enhance the overall fusion performance
  - How side information of humans affect the system performance

[6] Wimalajeewa and Varshney, “Collaborative human decision making with random local thresholds”, IEEE Transactions on Signal Processing, 2013

[7] Wimalajeewa and Varshney, “Asymptotic performance of categorical decision making with random thresholds”, IEEE Signal Processing Letters, 2014

[8] Wimalajeewa, Varshney and Rangaswamy, “On integrating human decisions with physical sensors for binary decision making,”, IEEE FUSION, 2018

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Utility based Human Decision Making

- Psychology studies suggest expected utility theory (EUT) as an accurate way of describing human decision making
  - Among the alternative actions $i \in \mathcal{I}$ producing utility u_i (cost c_i), the decision maker always chooses the alternative that has the maximal utility (minimal cost)

$$i^* = \arg\max_{i \in \mathcal{I}} u_i$$

  - Under the hypothesis testing framework, humans first calculate the expected utility of deciding each alternative hypothesis, and second, select the one with the largest expected utility

EUT Based Human Decision Making

- Given observation r, a rational decision maker's expected utility of declaring both hypotheses are

$$\mathbf{EU}(\text{Declare } H_0) = \Pr(H_0|r)u_{00} + \Pr(H_1|r)u_{01}$$
$$\mathbf{EU}(\text{Declare } H_1) = \Pr(H_0|r)u_{10} + \Pr(H_1|r)u_{11},$$

  where

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

- The decision rule is

$$\mathbf{EU}(\text{Declare } H_1) \underset{H_0}{\overset{H_1}{\gtrless}} \mathbf{EU}(\text{Declare } H_0)$$

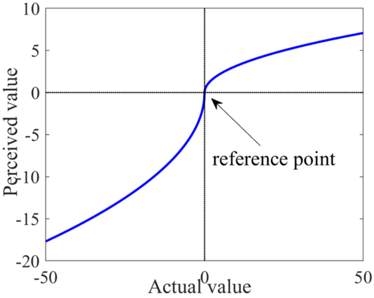
  which is

$$\frac{f_1(r)}{f_0(r)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{\pi_0(u_{00} - u_{10})}{\pi_1(u_{11} - u_{01})} \triangleq \eta$$

Prospect Theoretic Human Decision Making

The Nobel prize winning prospect theory[9] provides a framework to describe the way people choose between probabilistic alternatives that involve risk.

- The value function characterizes humans' asymmetric valuation towards gains and losses



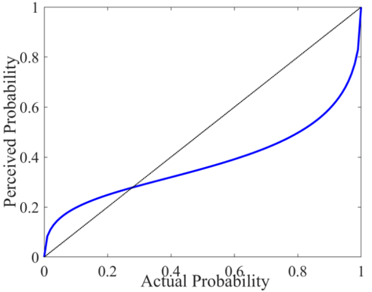
$$v(x) = \begin{cases} x^{\lambda} & x \geq 0 \\ -\beta(-x)^{\lambda} & x < 0 \end{cases}$$

where the average value of loss aversion parameter β and the diminishing marginal utility parameter λ are 2.25 and 0.88, respectively

[9] D. Kahneman and A. Tversky, "Prospect theory: an analysis of decision under risk", Handbook of the fundamentals of financial decision making, 1979.

Prospect Theory

- The weight function characterizes the humans' distorted perception of probabilities
- Risk seeking in small probability events and risk aversion in large probability events



$$w(p) = \frac{p^\alpha}{(p^\alpha + (1-p)^\alpha)^{1/\alpha}}$$

where the average value of the probability distortion parameter α is 0.72.

Utility Based Human Decision Making Under PT

- With human cognitive biases modeled by PT, the subjective utilities of declaring both hypotheses given r are

$$\textbf{SU}(\text{Declare } H_0) = w\big(\Pr(H_0|r)\big)v(u_{00}) + w\big(\Pr(H_1|r)\big)v(u_{01})$$
$$\textbf{SU}(\text{Declare } H_1) = w\big(\Pr(H_0|r)\big)v(u_{10}) + w\big(\Pr(H_1|r)\big)v(u_{11})$$

- The decision rule is

$$\textbf{SU}(\text{Declare } H_1) \underset{H_0}{\overset{H_1}{\gtrless}} \textbf{SU}(\text{Declare } H_0)$$

which is

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

Results[10]

- The threshold of the LRT η_p, is a monotone function of behavioral parameters α and β.
- In applications where $L(r) = \frac{f_1(r)}{f_0(r)}$ is an increasing function with respect to r, e.g., Gaussian pdfs.

$$\begin{aligned} H_0 &: r \sim \mathcal{N}(m_0, \sigma_s^2) \\ H_1 &: r \sim \mathcal{N}(m_1, \sigma_s^2) \end{aligned} \tag{1}$$

  - The human decision rule reduces to a threshold based decision rule based on observation r
  - The decision threshold t is monotonic with respect to α and β

[10] Geng et al., "Prospect theoretic human decision making in multi-agent systems", IEEE Transactions on Signal Processing, 2020

Numerical Results

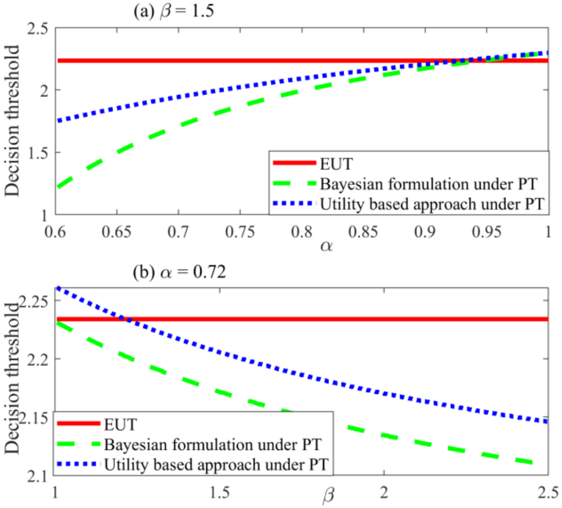


Figure 5: Decision thresholds with respect to behavioral parameters.

Amelioration Of Human Cognitive Biases

The LRT threshold employed by a cognitively biased decision maker, η_p, is different from the optimal threshold. Hence, we want to ameliorate the effect of cognitive biases and help humans make higher quality decisions.

- **Modification of the observation (pre-processing):** To help a human achieve the best decision making performance, we provide a modified version of the measurement r' to the human

  $$r' = r + g(\eta_p) - g(\eta)$$

  where $g(\cdot)$ is the inverse function of $L(r)$, so that the human's decision rule becomes the optimal rule $r \underset{H_0}{\overset{H_1}{\gtrless}} g(\eta)$.

Amelioration Of Human Cognitive Biases

- **Adaptation of physical sensor's threshold:** FC is a human that fuses the physical sensor's decision d_p and its own observation r_0.

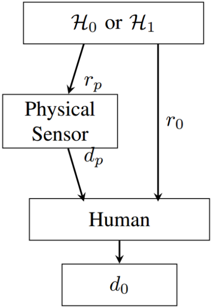


Figure 6: Decision making involving human and a physical sensor.

- The physical sensor employs threshold t to make a decision: $d_p = \begin{cases} 1, & r_p \geq t \\ 0, & r_p < t \end{cases}$
- The human makes the final decision by fusing d_p, r_0: $L(r_0, d_p) \underset{H_0}{\overset{H_1}{\gtrless}} \eta_p$

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{1-P_F^p}{1-P_D^p}\eta_p \triangleq \eta_0, \text{ if } d_p = 0$$

$$\frac{f_1(r_0)}{f_0(r_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P_F^p}{P_D^p}\eta_p \triangleq \eta_1, \text{ if } d_p = 1$$

Numerical Results

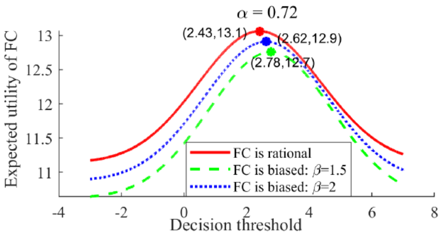


Figure 7: Decision making performance w.r.t the threshold of the sensor.

- Rational human has the best decision making performance.
- For the human with different loss aversion attitudes, the optimal threshold of the physical sensor is different.

Fusion of Decisions Made by Two Human Agents

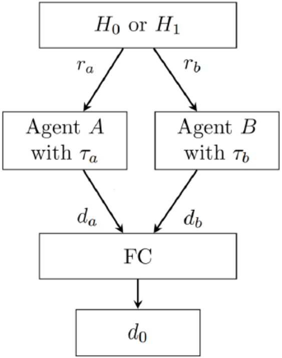


Figure 8: Decision fusion of two human agents.

- The two humans observe the signal independently, they employ thresholds $\tau_a \sim \mathcal{N}(m_{t_a}, \sigma_{t_a}^2)$ and $\tau_b \sim \mathcal{N}(m_{t_b}, \sigma_{t_b}^2)$ to make binary decisions.
- The FC makes the final decision based on $\frac{\Pr(d_a=i, d_b=j|H_1)}{\Pr(d_a=i, d_b=j|H_0)} \gtrless_{H_0}^{H_1} \eta$
- Decision making performance of the FC depends on the human's thresholds τ_a and τ_b.

Numerical Results

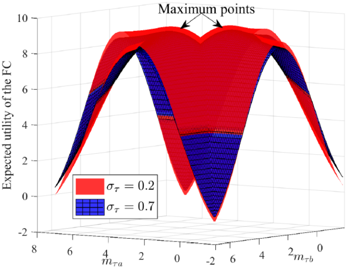


Figure 9: Decision making involving two humans.

- For certain decision making variances $\sigma^2_{t_a} = \sigma^2_{t_b} = \sigma^2_\tau$, there are a pair of optimal values of m_{τ_a} and m_{τ_b} so that the FC has the best performance.
- When m_{τ_a} and m_{τ_b} are "rational"[a], small decision variance (red plot) has higher utility.
- When m_{τ_a} and m_{τ_b} are "extremely biased"[b], large decision variance (blue plot) has higher utility.

[a] Within the means of signal amplitudes under H_0 and H_1
[b] Outside of the means of signal amplitudes under H_0 and H_1

Portfolio Theory based Human Team Selection[11]

- In most crowdsourcing contexts, responses of the humans have typically been assumed to be independent. However, human decisions in real applications are likely to be correlated.
- There are restrictions on the number of humans that can be selected because of budget constraints.
- In this work, we
  - Model the perceptual similarity via the correlations among local agents' observations.
  - Model the behavioral similarity via the correlations among local agents' prospect theoretic parameters.
  - Obtain the mean vector $\mu_{\boldsymbol{\delta}} = [\mu_{\delta_1}, \ldots, \mu_{\delta_n}]$ that represents the humans' average probabilities of error, and obtain the covariance matrix $\Sigma_{\boldsymbol{\delta}}$ shows the dependency structure of $\mu_{\boldsymbol{\delta}}$.

[11] Geng et al., "Collaborative Human Decision Making with Heterogeneous Agents", IEEE Transactions on on Computational Social Systems, 2021

Portfolio Theory based Human Team Selection

- Markowitz's portfolio theory (MPT) solves the problem of asset allocation and diversification by maximizing the expected return while constraining the level of risk, i.e., the total variance of the selected assets returns.
- Let $\boldsymbol{s} = [s_1, \ldots, s_i, \ldots, s_n]$ denote the human selection vector, we aim to minimize the sum of the error probabilities of the selected humans while keeping the variance of C_N[12] below a target value σ_t^2:

$$\min_{\mathbf{s}} \quad \mu_s = \boldsymbol{s}\mu'_{\boldsymbol{\delta}} \tag{2}$$

$$\text{s.t.} \quad \sigma_{\boldsymbol{s}}^2 = \boldsymbol{s}\Sigma_{\boldsymbol{\delta}}\boldsymbol{s}' \leq \sigma_t^2, \tag{3}$$

$$\boldsymbol{s}\mathbb{1}' = m \text{ and } s_i \in \{0, 1\} \text{ for } i = 1, \ldots, n \tag{4}$$

where m is the number of humans to be selected.

[12] C_N denotes the number of selected humans who make incorrect decisions.

Numerical Results

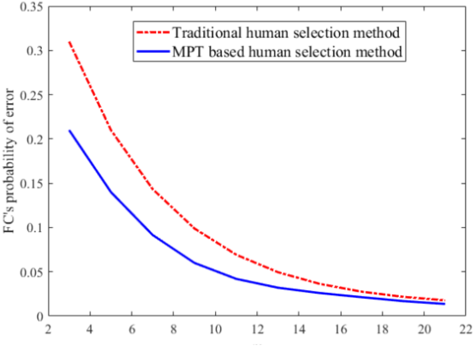


Figure 10: FC's probability of error as the number of selected human increases[13]

[13] Traditional human selection method refers to selecting the humans who have the lowest error probabilities.

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Conclusion

- Human behavior and decision making involve intricate interplay between human psychological activity and operating environment, which are heterogeneous across
  - Age, gender, cultural background, time and location
  - Nature of the task, job environment, etc.
- Future directions
  - Behavioral informatics: go deeper into psychology and characterize how human behavior is affected by time pressure, emotion state and stimulus from the outside environment.
  - Human behavior driven resource usage policies for signal detection.
  - Herding, nudging and incentives: elicit desirable outcomes from humans.