

# How efficient are we at fusing decisions?

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## I. RESEARCH QUESTION

Decision fusion is the process of integrating decisions made by multiple entities about the same phenomenon into a single final decision. In this work, we address the problem of decision fusion by humans and develop experiments to understand this human behavior. Consider the following framework (Fig. 1), where a set of local decision makers (LDMs) observe a phenomenon and make decisions regarding its presence or absence (Yes/No binary decisions). These local decisions are received by a global decision maker (GDM) who fuses the received data to make the final decision. In the signal processing literature, such problems have been extensively studied when the decision makers (local and global) are machines/sensors [1]. The problem of fusing multiple human decisions has been investigated in different contexts in the literature (see [2], [3] and references therein). In this work, we address the case when all the decision makers are humans. When the global decision maker is also a human, it is of interest to understand the act of decision fusion by the human. It is of special interest to compare the behavior of humans and sensors/machines while performing this task. To summarize, the research focus of this work is to answer the question: “how different are humans, in comparison with sensors/machines, at fusing data from multiple sources?”.

## II. EXPERIMENTAL DESIGN

In order to understand this behavior, we designed experiments which replicate the process of Fig. 1. The experiment consisted of data collection in two stages: the first stage models the local decision making and the second stage models the data fusion aspect. For the first stage, human subjects were asked to take part in a recognition task where a database  $\mathcal{D}$  consisting of 100 words were shown to the subjects. Then a set  $\mathcal{S}$  of 200 words was created, consisting of 100 words of the database  $\mathcal{D}$  and 100 new words denoted by set  $\mathcal{N}$ , to perform the local decision making task. These subjects of the first stage, also called sources in the sequel, performed 200 recognition tasks, one per word in set  $\mathcal{S}$ . They were supposed to recognize if the word is an old one belonging to the set  $\mathcal{D}$  or a new one from set  $\mathcal{N}$ ; this replicates the local decision making process of Fig. 1. In the second stage, a new set of human subjects had to decide whether the word was present in the original database  $\mathcal{D}$  by using decisions from the sources (subjects of first stage of experiment). These human subjects of second stage replicate

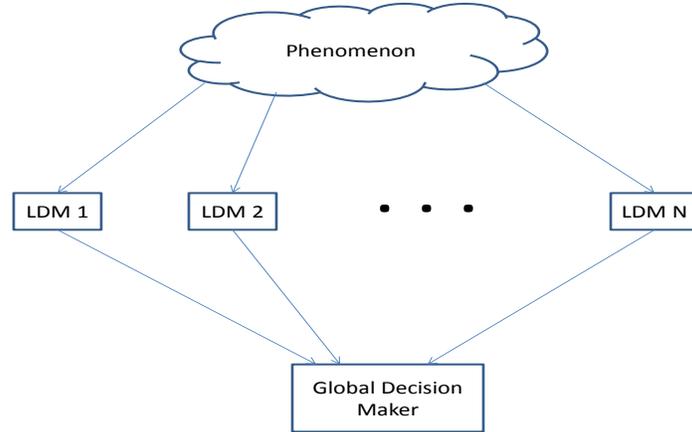


Fig. 1. System model consisting of local decision makers (LDMs) and a global decision maker.

the role of a fusion center/global decision maker (Fig. 1). Note that these decision makers of second stage have no direct access to the database; their only source of information is from the sources. Data from variable number of sources ( $N$ ) was presented to these subjects. This value  $N$  was either 2, 5, 10, or 20. The subjects were also presented with the sources' reliabilities and bias values (false positive rate and false negative rate or sensitivity and specificity).

### III. DATA ANALYSIS

In order to compare the decisions of humans and machines, we need to evaluate the decision which a machine would output when provided with the same set of local decisions as input. For this purpose, we first present the optimal decision fusion rule for a machine.

#### A. Optimal fusion rule for a machine

When the sources' reliabilities are available, the optimal decision fusion is given by the Chair-Varshney (CV) rule [4]. Represent the "Yes/No" decisions of the  $i$ th local decision maker as follows

$$u_i = \begin{cases} +1, & \text{if the decision is "Yes",} \\ -1, & \text{if the decision is "No".} \end{cases} \quad (1)$$

After receiving the  $N$  decisions  $\mathbf{u} = [u_1, \dots, u_N]$ , the global decision  $u_0 \in \{-1, +1\}$  is made as follows:

$$u_0 = \begin{cases} +1, & \text{if } a_0 + \sum_{i=1}^N a_i u_i > 0, \\ -1, & \text{otherwise,} \end{cases} \quad (2)$$

where

$$a_0 = \log \frac{P_1}{1 - P_1}, \quad (3)$$

$$a_i = \begin{cases} \log \frac{1-P_{M,i}}{P_{F,i}}, & \text{if } u_i = +1, \\ \log \frac{1-P_{F,i}}{P_{M,i}}, & \text{if } u_i = -1, \end{cases} \quad (4)$$

and  $P_1$  is the prior probability that the underlying hypothesis is “Yes” (+1),  $P_{M,i}$ ,  $P_{F,i}$  represent the false negative (miss-detection) and false positive (false alarm) rates respectively, of the  $i$ th decision maker.

### B. Comparison with machine-based rules

We compared the final decisions by 21 human subjects with the decision from the Chair-Varshney rule.<sup>1</sup> Each human subject of second stage typically performed 100 tasks, 25 each with  $N = 2, 5, 10, 20$ . We have found that the final decisions made by the humans match those of the machine around 80–90% of the times. The closeness with the optimal fusion rule (of machines) increases with an increase in  $N$  from 2–20. By defining the “match value” of a subject as the fraction of times his/her decision matches the decision made by the machine with the same input data, we compare individual participant’s performance. Although there is 80–90% match overall, further analysis shows that the individual “match value” has a lot of variation across subjects. For example, when  $N = 5$ , while participant #46 has a low match value of 0.54, participant #29 has a high “match value” of 0.98. Fig. 2 shows the distribution of the “match value” between the human’s decision and the optimal rule’s decision.

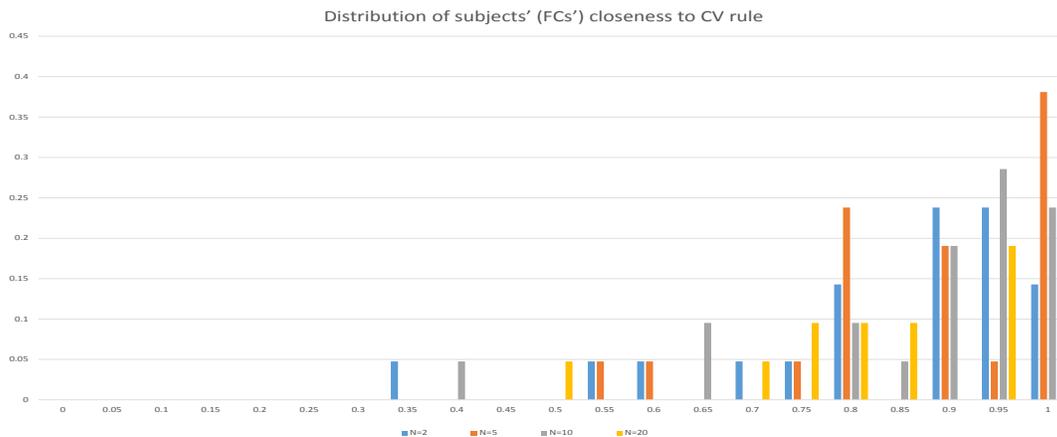


Fig. 2. Distribution of subjects’ “match value” between the human decision and the optimal rule’s decision.

### C. Modeling Approaches

To model the observed behavior, we can use a 2-step decision model as follows (Fig. 3):

- In the first step, a deterministic decision  $v$  is determined using optimal fusion rule (Chair-Varshney rule).

<sup>1</sup>Note that in our setup,  $P_1 = 0.5$ , implying  $a_0 = 0$ .

- The second step is the randomization step, where a “match value”  $p$  is sampled from a distribution  $f_p(\cdot; N)$  which is dependent on the number of sources  $N$ . Note that this distribution is determined by model fitting on data in Fig. 2. The final decision is now given by:

$$d = \begin{cases} v, & \text{with probability } p \\ 1 - v, & \text{with probability } 1 - p \end{cases} \quad (5)$$

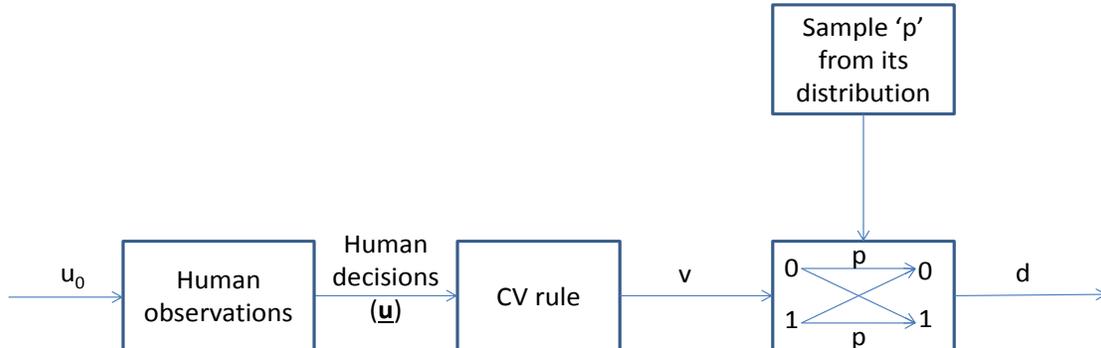


Fig. 3. 2-step model where the first step determines a deterministic decision using Chair-Varshney (CV) rule and the second step models the randomness of the decision making.

Due to the limited number of data points, a bootstrap model is used for data fitting, where  $n = 15$  data points among the total  $T = 21$  data points are randomly selected for which a Beta distribution with parameters  $\alpha(N)$  and  $\beta(N)$  are fit. This process is repeated for  $N_{mc} = 1000$  times. If  $\alpha_j$  and  $\beta_j$  represent the parameters from the  $j^{th}$  trial, the final parameters are decided by taking an average of these parameters. Also, note that the values of  $\alpha(N)$  and  $\beta(N)$  depend on the number of sources  $N$ . The results are shown in Table I.

TABLE I  
PARAMETERS FOR DIFFERENT VALUES OF  $N$

$N$	$\alpha(N)$	$\beta(N)$
2	5.2066	1.1620
5	3.1265	0.4742
10	1.8265	0.2533
20	3.3097	0.4349

#### IV. DISCUSSION

From this preliminary study, we observe that a deterministic rule used by machines, such as the Chair-Varshney rule, does not characterize the human behavior, which is not deterministic in nature. For a given set of data, all machines use the same optimal deterministic rule and, therefore, give the same output at any time instant. On the

other hand, the output changes for different humans and in some cases, for the same human at different time instant, as pointed by Payne and Bettman in [5]. This suggests the use of a randomized decision rule, which is the focus of ongoing research, as discussed above. We are currently going over the data with a fine-tooth comb to identify the individual cases when the decisions of humans and machines do not match. A psychological understanding of these particular cases can help us in comprehending this complex phenomenon.

It is important to repeat the experiment with online participants, such as Turkers from Amazon Mechanical Turk<sup>2</sup>. Hidden variables like demographics, motivation, etc, can affect the parameters of the randomized decision rule model discussed above. From the experiments, we can determine an ensemble of parameters, which help us in getting population-level insight into individual differences regarding how people fuse decisions. Further, one might get different results from online participants as compared to the typical subjects who are college students.

We are also collecting data with increased number of sources ( $N$ ) in order to verify some asymptotic approximations. In other words, we would like to verify the hypothesis that humans use heuristic decision rules when the amount of data is large. On similar lines, we are also considering time-constrained tasks, to verify if heuristic rules such as ‘pick-the-best’ work well under such time-constrained situations.

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<sup>2</sup><https://www.mturk.com/>