Combining Two Visual Cognition Systems Using Confidence Radius and Combinatorial Fusion

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Abstract. When combining decisions made by two separate visual cognition systems, simple average and weighted average using statistical means are used. In this paper, we extend the visual cognition system to become a scoring system using Combinatorial Fusion Analysis (CFA) based on each of the statistical means M_1, M_2, and M_3 respectively. Eight experiments are conducted, structured CFA framework. Our main results are: (a) If the two individual systems are relatively good, the combined systems perform better, and (b) rank combination is often better than score combination. A unique way of making better joint decisions in visual cognition using Combinatorial Fusion is demonstrated.

Keywords: Combinatorial Fusion Analysis (CFA), decision-making, visual cognition, rank-score characteristics (RSC) function.

1 Introduction

In the past few decades, decision-making has been of growing interest for many researchers. Whether it be the combination of some aspects of vision alone [8, 21], or visual information joined with other senses [6-8, 15], the role of visual sensory perception is vital to such varied topics as environmental interpretation, decision-making, and determinations of human beings.

Research previously conducted by groups including Bahrami et al [1], Kepecs et al [12], and Ernst and Banks [3], have focused on the interactive decision-making of people, specifically dealing with visual perception. The data gathered by Bahrami was plotted against four predictive models: Coin-Flip (CF), Behavioral Feedback (BF), Weighted Confidence Sharing (WCS), and Direct Signal Sharing (DSS). Bahrami concludes that of the four models, only the WCS model can be fit over empirical data. His findings indicate that the accuracy of the decision-making is aided by communication between the pairs and can greatly improve the overall performance of the pair.

Ernst elaborates on the concept of weighted confidence sharing [5]. In his paper, he presents a hypothetical scenario in which two referees in a soccer match determine whether the ball falls behind a goal line. Both Ernst and Bahrami agree that using the

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predictive models of Coin-Flip or Behavioral Feedback omit information which could lead to the pair's optimal joint decision. Though Ernst indicates that a beneficial joint determination can be found by the WCS model, he concludes that this approach can be improved. Bahrami's WCS model can be applied within Ernst's scenario as the distance of the individual's decision (d_i) divided by the spread of the confidence distribution (σ), or d_i / σ_i. A more heavily weighted estimate through joint opinion, represented as d_i / σ_{i2}, can be produced through a modified version of WCS (which closely resembles DSS) using σ^2. It is also noted by Bahrami, and validated by Ernst's study, that joint decision-making is often less accurate when individuals with dissimilar judgments attempt to come to a consensus. Although Bahrami and Ernst utilized different experimental methods, their aim is still the same: to devise an algorithm for optimal decision-making between two individuals based on their visual sensory input.

In this work, we use Combinatorial Fusion Analysis (CFA) to expand upon Ernst and Bahrami's studies and to further optimize joint decision-making. The fusion of multiple scoring systems (MSS) ([10, 11, 22]) using Combinatorial Fusion Analysis has been used successfully in many different research areas ([10, 11], [14, 16, 17, 18, 20, 22]). Each visual cognition system is treated as a scoring system in our work, and then reaches an optimized consensus by implementing CFA framework. Section 2 reviews the concept of multiple scoring systems via Combinatorial Fusion Analysis. A modified version of the soccer goal line decision proposed by Ernst [4, 5] is used as the data collection method. In this method, two subjects observe a small target being thrown into the field. The subjects are separately asked of their decision on their perceived landing point of the target and their respective confidence measurements in their decisions. The experiments, which consist of 8 pairs of human observers, and the results after applying Combinatorial Fusion Analysis, are discussed in Section 3. A summary of the results and a discussion of future work are found in Section 4.

2 Combining Visual Cognition Systems

2.1 Statistical Mean

When an individual needs to make a decision based on visual input, he or she often considers a variety of multiple choices. The consideration of these various choices, or candidates, can be viewed as the individual's scoring system for his decision. Several methods have been presented to combine these scoring systems ([1], [3], [5], [12], [15]). The method of combination used in this paper is the CFA framework [10-11].
To determine a joint decision, either an average or a weighted average approach can be used to determine a mean. Average mean is defined as:

$$M_1 = \frac{d_1 + d_2}{2} \quad , \tag{1}$$

σ mean is defined as:

$$M_2 = \frac{\frac{d_1}{\sigma_1} + \frac{d_2}{\sigma_2}}{\frac{1}{\sigma_1} + \frac{1}{\sigma_2}} \quad , \tag{2}$$

and σ^2 mean is defined as:

$$M_3 = \frac{\frac{d_1}{\sigma_1^2} + \frac{d_2}{\sigma_2^2}}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}} \quad , \tag{3}$$

where d_1 and d_2 are the two decisions and σ_1 and σ_2 are the confidence measurement of the respective systems.

2.2 Treating Each Visual Cognition System as a Scoring System

In our experiment, two human subjects provide two separate decisions on where they individually perceived a target has landed in a field. The two participants serve as the scoring systems, p and q. Each coordinate on the plane can be considered as a candidate to be scored by scoring systems p and q. Each participant is asked a radius measurement of confidence about his or her decision, which allows for a weighted evaluation of the visual space. This radius r is used to calculate the spread of the distribution around the perceived landing point of the target, calling it σ. In this paper, we use:

$$\sigma = 0.5r \; . \tag{4}$$

Set Visual Common Space. The σ values are used to determine the positions of the combined means and denoted as M_i, such that m_i=d(M_i,A), where A is the actual site. P, Q, and A exist in a two dimensional space as x- and y- coordinates. Three formulas are used to calculate the mean of P and Q. These three different combined means fall somewhere in between points P and Q and M_i is determined as a coordinate.

The range of confidence σ extends beyond the scope of line PQ, so the scope of the observation area to either side of P and Q is widened. The upper and lower bounds of the extension (P' and Q') are appended to P and Q respectively using 30% of the longer of the two distances, PM_i or M_iQ. Hence this is the middle point of P'Q', and d(P,Q) is the distance between P and Q (Fig. 1).

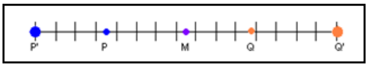


Fig. 1. Diagram of the layout of intervals used to organize the data in each experiment

The length of the line segment P'Q' is then partitioned into 127 intervals d_i, i = 1, 2, …, 127, with each interval length d(P',Q')/127. The center interval contains the M_i being used. This extended space with P'Q', and A accounts for points that may fall outside of the scope of line PQ. The line P'Q' that is divided into 127 intervals is referred to as the common visual space.

Treat P and Q as Two Scoring Systems. The confidence radii values, σ_P and σ_Q , are the variances of P and Q and are used to create normal distribution probability curves for each participant. The following formula is used to determine normal distribution:

$$Y = (1/(\sigma * \surd (2 \pi))) * e(-(x - \mu)**2)/(2* \sigma **2) \; , \tag{5}$$

where x is a normal random variable, μ is the mean, and σ is the standard deviation. Theoretically, a normal distribution curve infinitely spans, therefore our two scoring systems p and q create overlapping distributions that span the entire visual plane. Each of the 127 intervals d_1, ..., d_{127} has a score by p and a score by q. For each respective curve P and Q, each interval d_i is given a score between 0 and 1. This is the score function s. Score function s is ranked from highest to lowest to obtain the rank function r. The d_i with the lowest integer as its rank has the highest score (Fig 2).

2.3 Combining Two Visual Scoring Systems Using Combinatorial Fusion Analysis (CFA)

In Combinatorial Fusion Analysis, we do another iteration of processing on the score and rank functions. In CFA, two methods of combination are used for a set of p scoring systems A_1, A_2, …, A_P on the set D of locations. One is score combination (SC):

$$s_{sc}(d) = (\sum_{i=1}^{p} s_{Ai}(d)) / p \quad , \tag{6}$$

The other is rank combination (RC):

$$s_{rc}(d) = (\sum_{i=1}^{p} r_{Ai}(d)) / p \quad , \tag{7}$$

where d is in D, and s_A and r_A are score function and rank function of the scoring system A, from D to R and N respectively. For each of the 127 intervals d_1, ..., d_{127}, the score values and rank values of p and q are combined, respectively. Score combination of p and q is labeled C, and rank combination of p and q is labeled D. The score function s_C of the combination by score in our experiment is defined as:

$$s_C(d_i) = [s_p(d_i)+s_q(d_i)] / 2 \ . \tag{8}$$

The score function s_D of the combination by rank in our experiment is defined as:

$$s_D(d_i) = [r_p(d_i)+r_q(d_i)] / 2 \ . \tag{9}$$

Each of the score functions, $s_C(d_i)$ and $s_D(d_i)$, are sorted in descending order to obtain the rank function of the score combination, $r_C(d_i)$, and the rank function of the rank combination, $r_D(d_i)$. Each interval d_i is ranked. CFA considers the top ranked intervals in C and D as the optimal points and these are used for evaluation (Fig 2). The performance of the points (P, Q, M_i, C, and D) is determined by each points' distance from target A, the shortest distance being the highest performance (Fig 3).

3 Experiments

3.1 Data Sets

As in our previous paper [2], pairs of participants were chosen from a random selection of patrons at a public park. The pair was situated 40 feet from a marked plane of 250 by 250 inches and stood 10 feet apart from each other. The 1.5 by 1.5 inch target that the participants observed was constructed of metal washers and was designed to be heavy enough to be thrown far distances, small enough to be hidden once on the ground, and of irregular shape to limit travel once in the grass. A measuring tool with x- and y- axes of 36 by 36 inches was used to measure participants' confidences. Five experiment coordinators were on site—two coordinators stood with the participants, one coordinator stood to the side of the participants, and the fourth and fifth coordinators stood in the field beside the marked plane.

From next to where the participants stood, the third coordinator threw the target into the plane. The participants independently and simultaneously directed the two predesignated coordinators to where they believed the target landed and a small marker was placed on the ground at each spot. Independent and simultaneous determination of landing site works to minimize the effect of one participant's decision on the other's decision as well as the time taken to mark the participants' initial decisions. It may be intuitive to think that a person who sees a target land knows exactly where the target lands—in practice, this is not the case. Although the two participants observe the same target, the two participants have different perceptions of where they independently think it landed. The confidence tool was then taken to the plane and each participant was asked his or her radius of confidence around the spot he or she perceived the target landed. Each participant expressed his or her confidence radius by directing the field coordinators to expand or contract the circle about the confidence measuring tool. The x- and y- coordinates for the three points (P, Q, and A) were recorded. 8 numerical values were obtained for each pair of test subjects: the 2 x-coordinates of P and Q, the 2 y-coordinates of P and Q, the 2 confidence values for P and Q, and the x- and y- coordinates for actual A. The participants were also interviewed for information including gender, height, eyesight, and other factors that may influence visual perception. This process was repeated for 8 experiments (Table 1).

Table 1. Coordinates of P, Q, and A and confidence radius (CR) of P and Q for the 8 experiments

		(X, Y)	CR		(X, Y)	CR		(X, Y)	CR		(X, Y)	CR
P	Exp. 1	(169, 85)	24	Exp. 2	(158.25, 180)	23	Exp. 3	(92, 92.75)	12	Exp. 4	(18.75, 49.5)	13
Q		(194.5, 142.5)	13.5		(151, 194.5)	12		(84, 138)	11		(29.5, 35.5)	10.5
A		(187.25, 110.75)			(158.75, 207)			(81, 119.5)			(39.25, 21.25)	
P	Exp. 5	(231, 17.5)	8.5	Exp. 6	(157.5, 64)	13.5	Exp. 7	(13, 17)	10.5	Exp. 8	(144.5, -51)	13
Q		(215, 69)	16.5		(174.75, 132.75)	20		(24.25, 84.25)	3.5		(144.5, 0)	11
A		(229.5, 52.75)			(162.25, 78.5)			(19.5, 74.5)			(152, 9)	

3.2 Example of Combining Visual Cognition Systems Using Statistical Mean

For each experiment, the confidence radius r is used to calculate the spread of the distribution around the perceived landing point of the target, σ. The σ values for P and Q, σ_P and σ_Q respectively, are used to determine M_i. In the following example, we will use M_i on Experiment 1 and 6 (Table 2).

The scope of P and Q is widened by 30% on both sides of P and Q. The extended line segment P'Q' is referred to as the common visual space. This is divided into 127

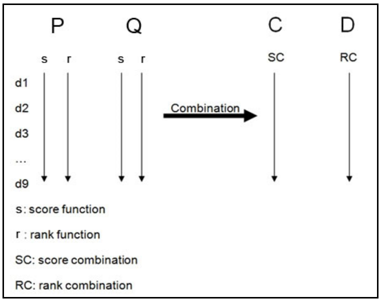


Fig. 2. Score and rank function for respective scoring systems P and Q undergo CFA to produce Score Combination C and Rank Combination D

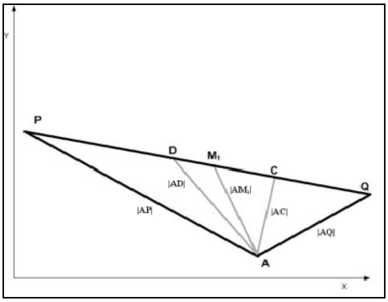


Fig. 3. Layout of M_1, C, and D in relation to P, Q, and their distance to A. The distances between the 5 estimated points and A are noted on each line

intervals d_i, i = 1, 2, …, 127 with each interval length d(P',Q')/127. The normal distribution curves for participant P and participant Q are determined, resulting in a score for each d_i (Fig 4). This is score function s. Score function s is ranked from highest with rank 1, to lowest with rank 127, to obtain the rank function R.

Using the CFA framework, score combination C and rank combination D are obtained. CFA considers the top ranked intervals in C and D as the optimal points and these points are used for evaluation. The performance of the five points (P, Q, M_i, C, and D), for i = 1, 2, and 3 respectively, is determined by each points' numerical distance from the target A, the shortest distance being the highest performing point.

Table 2. Raw data of experiments 1 and 6

	X	Y	r		X	Y	r
	Exp. 1				Exp. 6		
P	169	85	24	P	157.5	64	13.5
Q	194.5	142.5	13.5	Q	174.75	132.75	20
A	187.25	110.75		A	162.25	78.5	

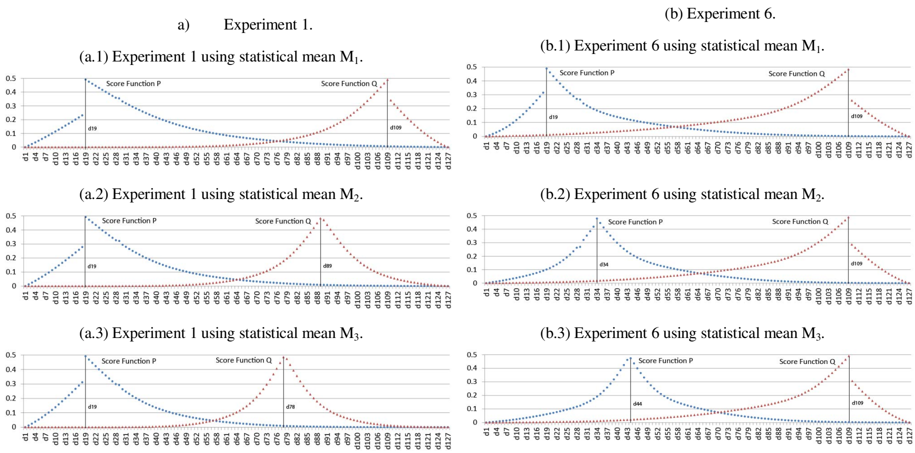


Fig. 4. Score functions of scoring systems P and Q using statistical mean M_1, M_2, and M_3 and for (a) Experiment 1, and (b) Experiment 6, respectively

3.3 Results and Analysis

The decision of Participant p, marked as P, and the decision of Participant q, marked as Q, are used to obtain line segment PQ. The radii of confidence are used to calculate the two σ values to locate the coordinates of points M_1, M_2, and M_3 along the extended P'Q'. To combine and compare the two visual decision systems of p and q, a common plane must be implemented to be evaluated by the different systems. The 127 intervals along the P'Q' line serve as the common visual space to be scored.

When P'Q' has been partitioned into the 127 intervals mapped according to M_i, the intervals are scored according to the normal distribution curves of P and Q using the standard deviation σ_P and σ_Q, respectively. Both systems assume the set of common interval midpoints $d_1, d_2, d_3, \ldots, d_{127}$. Each scoring system, p and q, consists of a score function. We define score functions $s_P(d_i)$ and $s_Q(d_i)$ that map each interval, d_i, to a score in systems P and Q, respectively. The rank function of each system maps each element d_i to a positive integer in N, where $N = \{x \mid 1 \leq x \leq 127\}$. We obtained the rank functions $r_P(d_i)$ and $r_Q(d_i)$ by sorting $s_P(d_i)$ and $s_Q(d_i)$ in descending order and assigning a rank value from 1 to 127 to each interval.

P, Q, M_i, C, and D, for i = 1, 2, and 3, are calculated and the distances to target A are computed. The points are ranked by performance from 1 to 7 (Table 3). The point with the shortest distance from the target is considered the best.

Table 3. Performance of (P, Q), confidence radius of (P, Q), performance of M_i, performance ranking of P, Q, M_i, C, and D when using M_i, and improvement (impr.) of (C or D)

Experiment #	Performance P, Q	Confidence radius P, Q	Best M_i	M_1						M_2						M_3					
				P	Q	M_1	C	D	Impr. % (C or D)	P	Q	M_2	C	D	Impr. % (C or D)	P	Q	M_3	C	D	Impr. % (C or D)
1	**31.2**, 32.57	24, **13.5**	M_1	3	5	1	4	2	2.94	3	5	1	2	4	0.99	2	5	1	3	3	-2.97
2	27.0, **14.71**	23, **12**	M_3	5	1	4	2	3	-0.23	5	1	4	2	2	-0.56	5	1	4	2	2	-0.35
3	28.9,**18.74**	12, **11**	M_3	5	4	1	3	2	25.85	5	4	1	3	2	17.23	5	4	1	3	2	11.32
4	35.0, **17.27**	3, **10.5**	M_3	5	1	4	2	3	-0.41	5	1	4	2	3	-0.80	5	1	4	2	3	-0.81
5	35.2, **21.78**	**8.5**, 16.5	M_1	5	3	1	4	2	3.36	5	2	1	3	4	-60.73	5	1	2	3	3	-61.85
6	**15.2**, 55.67	**13.5**, 20	M_3	3	5	4	2	1	6.93	4	5	1	3	2	9.85	4	5	1	2	2	4.67
7	**6.96**, 10.85	10.5, **3.5**	M_1	2	5	1	4	3	-40.89	1	4	2	3	3	-55.41	1	5	2	3	3	-55.60
8	60.4,**11.72**	13, **11**	M_3	3	1	2	4	4	-1155.23	3	1	2	4	4	-1155.23	3	1	2	4	4	-1155.23

M_1 performed the best of the three midpoints M_1, M_2, and M_3 in 3 trials. M_3 was best in 5 trials, and M_2 performed the best in none of the trials (Table 1). For all 8 experiments, if the better performing individual was more confident, M_3 was the highest performing M_i (Exp. 2, 3, 4, 6, and 8), while if the worse performing individual was more confident, M_1 was the highest performing M_i (1, 5, and 7). In all of the trials, rank combination D performed either equally as well or better when the better midpoint was used to map intervals than when the alternate midpoint was used.

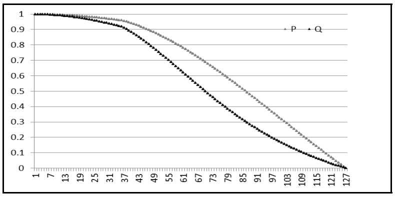
Out of the 8 cases, when mapping the intervals by using M_1, D performs better than both P and Q in 4 cases (1, 3, 5, 6). When mapping intervals using M_2, D performs better than both P and Q in 2 cases (3 and 6). When using M_3, D is better than both P and Q in 2 cases (3 and 6). When using the described M_1, M_2, or M_3, D is better than both P and Q in 4 cases (1, 3, 5, 6). In 18 out of 24 cases of experiments ran on M_1, M_2, and M_3, C performed worse than D.

When examining individual systems P, Q, and systems of combination C, D, and M_i, Rank combination D gives relatively good results. Additionally, as opposed to intervals that are always mapped according to one M_i, mapping intervals around the best performing midpoint increases D's average performance.

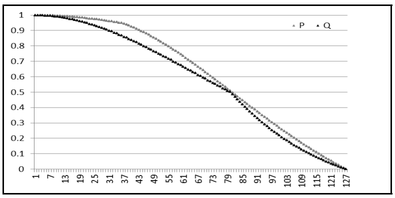
Our recent study takes into consideration the confidence of the individuals when analyzing mapping schema. In scenarios where the record of an individual's performance is known, this scheme can possibly serve well. When making visual cognitive decisions, if it is known that an individual generally performs well and is confident about his decision, mapping intervals utilizing M_3 may be the best scheme. However, if an individual is confident but is known to perform poorly or if his performance is

(a) Experiment 1.

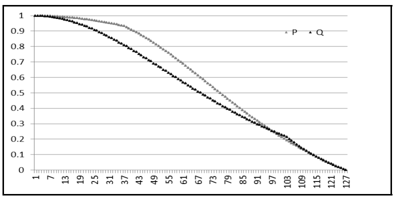
(a.1) Experiment 1 using statistical mean M_1.



(a.2) Experiment 1 using statistical mean M_2.

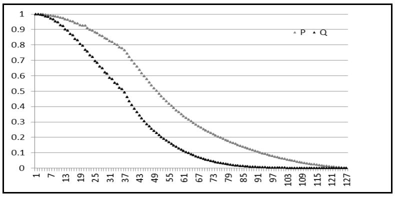


(a.3) Experiment 1 using statistical mean M_3.

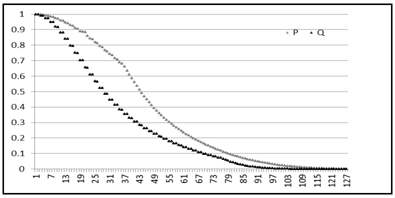


(b) Experiment 6.

(b.1) Experiment 6 using statistical mean M_1



(b.2) Experiment 6 using statistical mean M_2



(b.3) Experiment 6 using statistical mean M_3.

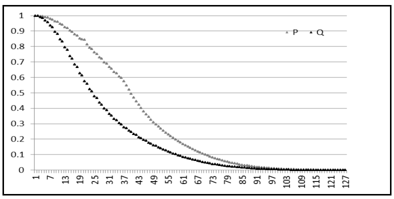


Fig. 5. Rank Score Characteristics (RSC) Graphs for (a) Experiment 1 and (b) Experiment 6 using statistical mean M_1, M_2, and M_3

unknown, mapping around M_1 may be the best scheme. The dissimilarity and inaccuracy of individual decisions is the main factor in determining when two people should or should not combine their decisions. Our current research signifies that D has the potential to perform best only if P and Q are relatively good and cognitively diverse.

According to this data and data from previous experiments, rank combination D mapped on M_1 appears to be the most consistent. This may indicate that combination by rank is particularly sensitive to extraction of the meaningful characteristics of a best-performing individual decision. Furthermore, our analysis demonstrates that combinatorial fusion is a useful vehicle for driving weighted combination.

Out of the 8 experiments, five satisfy Koriat's criterion [13] (Exp. 2, 3, 4, 6, and 8), four have positive rank combinations (Exp. 1, 3, 5, and 6), and five have improved M_i (Exp. 1, 3, 5, 6, and 7). This demonstrates that combinatorial fusion can be used to complement other combination methods.

4 Conclusion and Future Work

Though there have been other proposed methods for combining visual cognitive decision-making, we use Combinatorial Fusion Analysis to refine the process. Our analysis has produced more optimal decisions at a successful rate. This work provides previously established cognition models with new observations and considerations. As with other domains, when the scoring systems both perform well and are diverse, rank and score combination of multiple scoring systems are useful ([9], [19], [22]).

We compute the cognitive diversity [11] between two systems p and q, $d(f_P, f_Q)$, where f_p is the rank-score characteristic function with $f_P(i) = (s \circ r^{-1})(i) = s(r^{-1}(i))$. For example, in Experiment 6, the relatively higher cognitive diversity leads to a better rank combination D. This is an important component to the CFA framework. The rank-score combination (RSC) graphs (Fig 5) are integral to the computation of the cognitive diversity of the two systems, and may help to better predict which cases are best suited for CFA. We will also use the CFA framework to analyze how aspects like gender or occupation affect decision-making. We continue to add more trials to the data pool and look to conduct trials with more people added to each experiment. Our research has demonstrated that CFA can serve as a useful tool in understanding how to derive the best decision from a pair of individually made decisions. CFA demonstrates much flexibility in combining multiple visual cognition systems.

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References

1. Bahrami, B., Olsen, K., Latham, P., Roepstroff, A., Rees, G., Frith, C.: Optimally interacting minds. Science 329(5995), 1081–1085 (2010)
2. Batallones, A., McMunn-Coffran, C., Mott, B., Sanchez, K., Hsu, D.F.: Comparative study of joint decision-making on two visual cognition systems using combinatorial fusion. Active Media Technology, 215–225 (December 2012)

3. Ernst, M.O., Banks, M.S.: Humans integrate visual and haptic information in a statistically optimal fashion. Nature 415, 429–433 (2002)
4. Ernst, M.O.: Learning to integrate arbitrary signals from vision and touch. Journal of Vision 7(5), 1–14 (2007)
5. Ernst, M.O.: Decisions made better. Science 329(5995), 1022–1023 (2010)
6. Gepshtein, S., Burge, J., Ernst, O., Banks, S.: The combination of vision and touch depends on spatial proximity. J. Vis. 5(11), 1013–1023 (2009)
7. Gold, J.I., Shadlen, N.: The neural basis of decision making. Annual Review of Neuroscience 30, 535–574 (2007)
8. Hillis, J.M., Ernst, M.O., Banks, M.S., Landy, M.S.: Combining sensory information: mandatory fusion within, but not between, senses. Science 298(5598), 1627–1630 (2002)
9. Hsu, D.F., Taksa, I.: Comparing rank and score combination methods for data fusion in information retrieval. Information Retrieval 8(3), 449–480 (2005)
10. Hsu, D.F., Chung, Y.S., Kristal, B.S.: Combinatorial Fusion Analysis: methods and practice of com dd ddbining multiple scoring systems. In: Hsu, H.H. (ed.) Advanced Data Mining Technologies in Bioinformatics, pp. 1157–1181. Idea Group Inc. (2006)
11. Hsu, D.F., Kristal, B.S., Schweikert, C.: Rank-Score Characteristics (RSC) function and cognitive diversity. Brain Informatics, 42–54 (2010)
12. Kepecs, A., Uchida, N., Zariwala, H., Mainen, Z.: Neural correlates, computation and behavioural impact of decision confidence. Nature 455, 227–231 (2008)
13. Koriat, A.: When are two heads better than one. Science, 360–362 (April 20, 2012)
14. Lin, K.-L., Lin, C.-Y., Huang, C.-D., Chang, H.-M., Yang, C.-Y., Lin, C.-T., Tang, C.Y., Hsu, D.F.: Feature selection and combination criteria for improving accuracy in protein structure prediction. IEEE Transactions on NanoBioscience 6(2), 186–196 (2007)
15. Lunghi, C., Binda, P., Morrone, C.: Touch disambiguates rivalrous perception at early stages of visual analysis. Current Biology 20(4), R143–R144 (2010)
16. Lyons, D.M., Hsu, D.F.: Combining multiple scoring systems for target tracking using rank–score characteristics. Information Fusion 10(2), 124–136 (2009)
17. McMunn-Coffran, C., Paolercio, E., Liu, H., Tsai, R., Hsu, D.F.: Joint decision making in visual cognition using Combinatorial Fusion Analysis. In: Proceedings of the IEEE International Conference on Cognitive Informatics and Cognitive Computing, pp. 254–261 (2011)
18. McMunn-Coffran, C., Paolercio, E., Fei, Y., Hsu, D.F.: Combining visual cognition systems for joint decision making using Combinatorial Fusion. In: Proceedings of the 11th IEEE International Conference on Cognition Informatics and Cognition Computing, pp. 313–322 (2012)
19. Ng, K.B., Kantor, P.B.: Predicting the effectiveness of naive data fusion on the basis of system characteristics. J. Am. Soc. Inform. Sci. 51(12), 1177–1189 (2000)
20. Paolercio, E., McMunn-Coffran, C., Mott, B., Hsu, D.F., Schweikert, C.: Fusion of two visual perception systems utilizing cognitive diversity. In: Proceedings of the 12th IEEE International Conference on Cognitive Informatics and Cognitive Computing (2013)
21. Tong, F., Meng, M., Blake, R.: Neural basis of binocular rivalry. Trends in Cognitive Sciences 10(11), 502–511 (2006)
22. Yang, J.M., Chen, Y.F., Shen, T.W., Kristal, B.S., Hsu, D.F.: Consensus scoring for improving enrichment in virtual screening. Journal of Chemical Information and Modeling 45, 1134–1146 (2005)