Combinatorial Fusion Analysis in Brain Informatics: Gender variation in facial attractiveness judgment

D. Frank Hsu[1], Takehito Ito[2], Christina Schweikert[1], Tetsuya Matsuda[2], and Shinsuke Shimojo[3]

[1] Department of Computer and Information Science, Fordham University
New York, NY 10023, USA
[2]Tamagawa University Brain Science Institute
6-1-1, Tamagawa Gakuen, Machida, Tokyo 194-8610, Japan
[3]Division of Biology/Computation and Neural Systems,
California Institute of Technology, Pasadena, CA 91125, USA

Abstract: Information processing in the brain or other decision making systems, such as in multimedia, involves fusion of information from multiple sensors, sources, and systems at the data, feature or decision level. Combinatorial Fusion Analysis (CFA), a recently developed information fusion paradigm, uses a combinatorial method to model the decision space and the Rank-Score Characteristic (RSC) function to measure cognitive diversity. In this paper, we first introduce CFA and its practice in a variety of application domains such as computer vision and target tracking, information retrieval and Internet search, and virtual screening and drug discovery. We then apply CFA to investigate gender variation in facial attractiveness judgment on three tasks: liking, beauty and mentalization using RSC function. It is demonstrated that the RSC function is useful in the differentiation of gender variation and task judgment, and hence can be used to complement the notion of correlation which is widely used in statistical decision making. In addition, it is shown that CFA is a viable approach to deal with various issues and problems in brain informatics.

1 Introduction

Using genomic profiles and biomarkers to diagnose and treat diseases and disorders, advances in biomedicine have made personalized medicine a possibility. Recent developments in molecular biology have made molecular networks a major focus for translational science [37]. Molecular networks, which connect molecular biology to clinical medicine, encompass metabolic pathways, gene regulatory networks, and protein-protein interaction networks. On the other hand, the Human Connectome Project aims to map all the brain connections in one thousand human subjects. Consequently, we will be able to understand more about the function of the brain at the systems and network levels

[35]. So, the brain system and its connectivity are sure to translate research discoveries from the laboratory to the clinic. It will also contribute to the development of novel diagnosis and therapeutic treatment of neurodegenerative and psychiatric diseases and disorders.

1.1 Brain System

The human brain is a complex system consisting of billions of neurons and tens or hundreds of billions of connections. Dowling [8] studies the brain system in terms of three levels: cellular and molecular, computational and systems, and cognitive and behavior. Each level represents each of the three layers of the brain's structure, function, and application, respectively. At the "Structure" layer, the brain consists of neurons and nerves, synapses and action potentials, anatomical areas and their connections. At the "Application" layer, the brain's activity controls real world cognition and behavior, including neurodegenerative diseases and disorders. The middle "Function" layer consists of perception, memory, neural circuits and networks and their connectivity. This layer serves as the glue between the cellular and molecular layer and the real world cognition and behavior layer. It is also the clue to the function of the brain including human information processing for learning, stimuli, reward, choice, and decision making, and functional mechanisms for sensing, motoring, and multi-perception (visual, auditory, tactile, and olfactory) (see Figure 1).

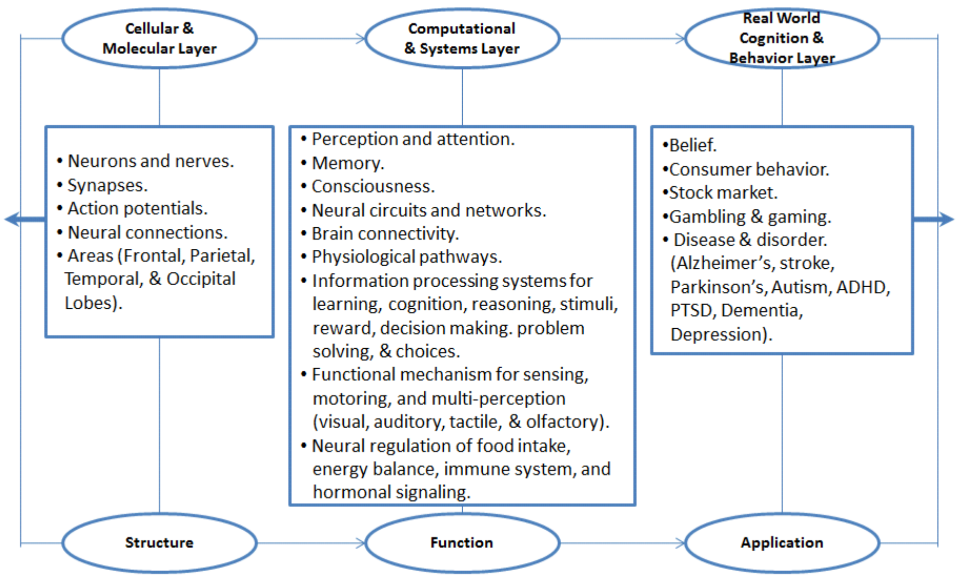

Figure 1: Scope and Scale of the Brain System.

1.2 Informatics

Over the last decade, since the debut of the World Wide Web in the 1990's, the number of information users and providers has increased exponentially. According to Norvig [32], the nature of information content has changed drastically from simple text to a mix of text, speech, still and video images and to histories of interactions with friends and colleagues, information sources and their automated proxies. Raw data sources now include sensor readings from GPS devices and GIS locations, medical devices such as EEG/MEG/fMRI, and other embedded sensors and robots in organizations and in the environment. Communication conduits include twisted pair, coaxial cables and optical fibers, wireline, wireless, satellite, the Internet, and more recently, information appliances such as smart phones and intelligent computing systems.

The word "Informatics" has been used in a variety of different contexts and disciplines. Webster's Dictionary (10th Edition) describes it as "Information science", and is stated as "the collection, classification, storage, retrieval, and dissemination of recorded knowledge treated both as a pure and as an applied science." Hsu et al [19] suggest the following:

"Informatics is the science that studies and investigates the acquisition, representation, processing, interpretation, and transformation of information in, for, and by living organisms, neuronal systems, interconnection networks, and other complex systems."

As an emerging scientific discipline consisting of methods, processes, practices, and applications, informatics serves as the crucial link between the domain data it acquires and the domain knowledge it will transform it to (see Figure 2).

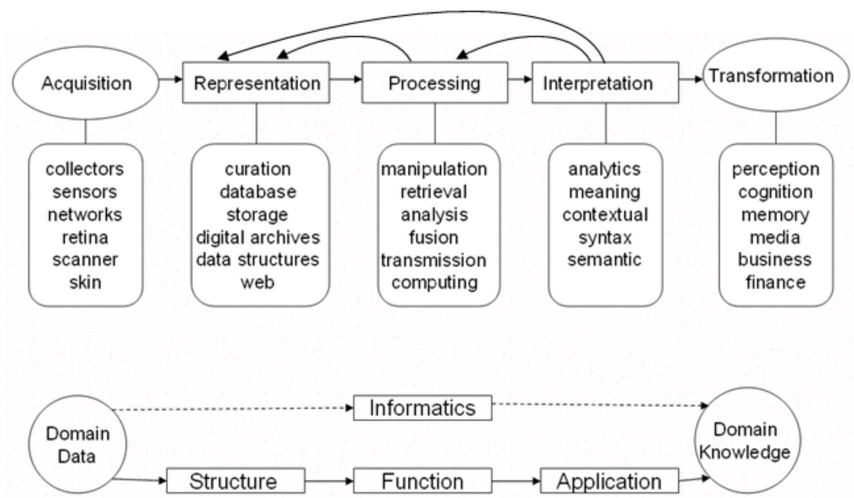

Figure 2: Scope and Scale of Informatics (Hsu et al [19]).

From Figure 2, we see that converting data into knowledge in an application domain is a complicated process of a serious information processing endeavor. As such, a pipeline of three layers has emerged where the "Information" layer serves as the connection and glue between the "Data" layer and the "Knowledge" layer.

Data ---> Information ---> Knowledge.

1.3 Brain Informatics

The brain system is a complex system with a complicated structure, dynamic function and a variety of diverse applications in cognition, behavior, diseases and disorders. To study the brain and to utilize the data obtained from such study or experiments requires a new kind of scientific discovery called the Fourth Paradigm by Jim Gray [14]. This emerging branch of contemporary scientific inquiry utilizes "data exploration" to coherently probe and/or unify experiment, theory, and simulation. In a similar fashion, experiments today increasingly involve very large datasets captured by instruments or generated by simulators and processed by software. Information and knowledge are stored in computers or data centers as databases. These databases are analyzed using mathematical, statistical and computational tools, reasoning, and techniques.

A point raised by Jim Gray is 'how to codify and represent knowledge in a given discipline X?'. Several generic problems include: data ingest and managing large datasets, identifying and enforcing common schema, how to organize and reorganize these data and their associated analyses, building and executing models, documenting experiments, curation and long-term preservation, interpretation of information, and transformation of information to knowledge. All these issues are complicated and hence require powerful computational and informatics methods, tools, and techniques. Hence the concept of "CompXinfor" is born which means computational-X and X-informatics for a given discipline X. One example is computational biology and bioinformatics. Another is computational brain and brain informatics. So, brain informatics is a data-driven science using a combination of experiment, theory, and modeling to analyze large structured (and unstructured) and normal (and peculiar) data sets. Simulation, modeling, and visualization techniques are also added to the process. This kind of e-science inquiry does need modern mathematical, computational and statistical techniques. It also requires a variety of methods and systems embedded in such fields as artificial intelligence, machine learning, data mining, information fusion, and knowledge discovery. Figure 3 gives the three levels of knowledge domain for informatics in general and for brain informatics in particular.

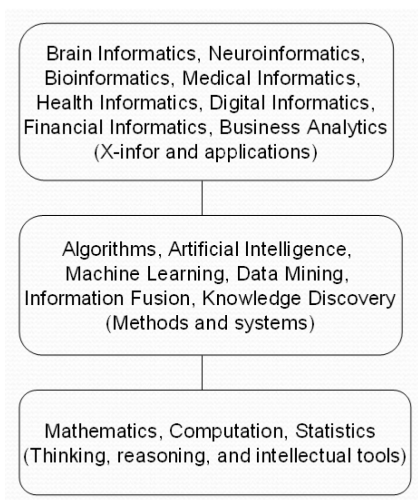

Figure 3: The three levels of (Brain) Informatics knowledge domain (Hsu et al [19]).

As illustrated in Figure 1, the field of “Brain Science” is evolving at the “Function” layer with neural circuits and brain connectivity as its main focus. These are complemented by other findings in genome-wide gene expression and epigenetic study. There have been many sources of databases resulting from multifaceted experiments and projects. The neuroscience information framework [1] is an example of efforts to integrate existing knowledge and databases in neuroscience. Combining the scope and scale of the brain system and informatics (see Figures 1 and 2), a brain information system framework (BISF) is needed to give a coherent approach in the integration of diverse knowledge and a variety of databases in studies and experiments related to the brain (see Figure 4).

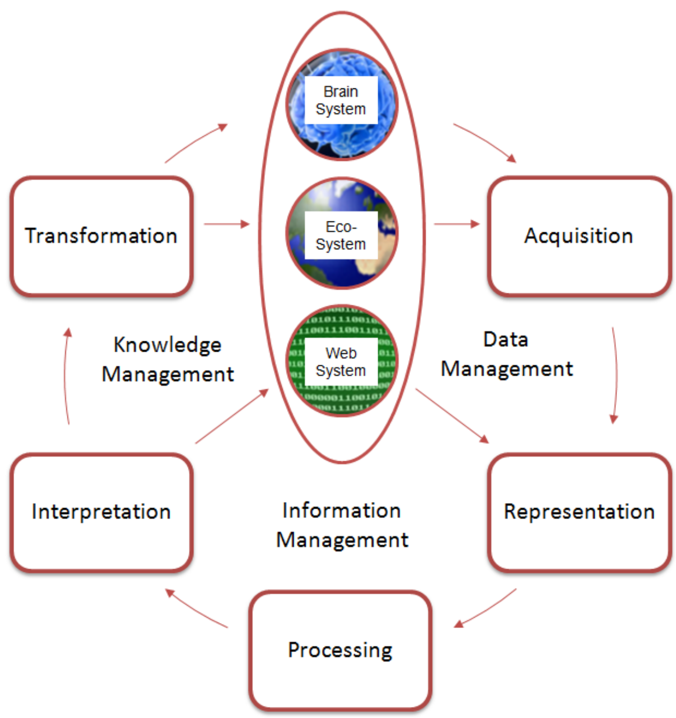

Figure 4: Brain Information System Framework (BISF).

Other than the brain itself, data can be collected from the ecosystem in the environment and the various web systems on the Internet [11]. At the “data management” level, various data types from different sensors or imaging devices (e.g. fMRI/EEG) and sources are acquired, curated and represented as databases and data structures. Information extracted and patterns recognized from these data can be processed (retrieved, computed, transmitted, mined, fused, or analyzed) at the “information management” level. Further analysis and interpretation can be performed at the knowledge management level. Useful knowledge is extracted from the insightful interpretation of information and actionable data. This valuable knowledge is then transformed (in a feedback loop) to benefit the understanding of the brain system, the function of the ecosystem and the operation of various web systems.

1.4 Information Fusion

In each of the three levels of brain information system management – data, information, and knowledge, fusion is needed at the data, feature, and decision levels due to the following characteristics [2, 7, 18]:

- A variety of different sets of structured or unstructured data are collected from diverse devices or sources originated from different experiments and projects.
- A large group of different sets of features, attributes, indicators, or cues are used as parameters for different kinds of measurements.
- Different methods or decisions may be appropriate for different feature sets, data sets or temporal traces.
- Different methods or systems for decision and action may be combined to obtain innovative solutions for the same problem with diverse data and/or feature sets.

Information fusion is the combination or integration of information (at the data, feature, and decision level) from multiple sources or sensors, features or cues, classifiers or decisions so that efficiency and accuracy of situation analysis, evidence-based decision making, and actionable outcomes can be greatly enhanced [2, 18, 22, 39]. As shown in Figure 2, information fusion plays a central role in the informatics processing pipeline.

Combinatorial fusion analysis (CFA), a recently developed information fusion method and an informatics paradigm, consists of multiple scoring systems and uses a rank-score characteristic (RSC) function to measure the cognitive diversity between a pair of two scoring systems. The architecture and workflow of CFA is illustrated in Figure 5.

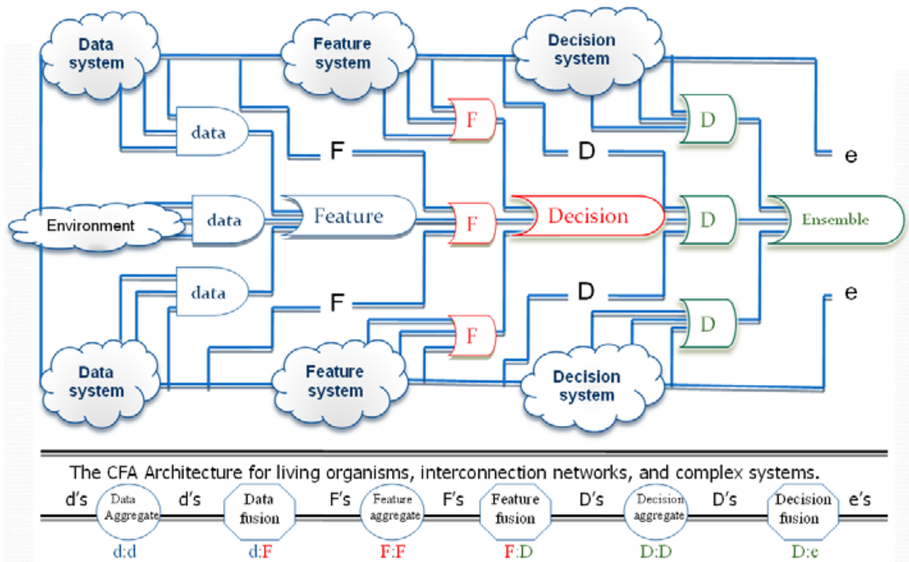

Figure 5: The CFA Architecture and Workflow [19].

2 Combinatorial Fusion Analysis

2.1 Multiple Scoring Systems (MSS)

Let D be a set of documents, genes, molecules, tracks, hypotheses, or classes with $|D| = n$. Let $N = [1, n]$ be the set of integers from 1 to n and R be the set of real numbers. A set of p scoring systems $A_1, A_2, \ldots, A_p$ on D has each scoring system A consisting of a score function s_A, a rank function r_A derived by sorting the score function s_A, and a Rank-Score Characteristic (RSC) function f_A defined as f_A: $N \rightarrow R$ in Figure 6.

$$\begin{tikzcd} \mathbf{D} \arrow[r, "r_A"] \arrow[dr, "s_A"'] & \mathbf{N} \arrow[d, "f_A"] \\ & \mathbf{R} \end{tikzcd}$$

$$f_A(i) = (s_A \circ r_A^{-1})(i) = s_A(r_A^{-1}(i))$$

Figure 6: Rank-Score Characteristic (RSC) Function.

Given a set of p scoring systems $A_1, A_2, \ldots, A_p$, there are many different ways to combine these scoring systems into a single system A^* (e.g. see [15, 16, 18, 21, 25, 31, 40, 43]). Let $C_s(\sum A_i) = E$ and $C_r(\sum A_i) = F$ be the score combination and rank combination defined by $s_E(d) = (1/p)\sum s_{Ai}(d)$ and $s_F(d) = (1/p)\sum r_{Ai}(d)$, respectively, and let r_E and r_F be derived by sorting s_E and s_F in decreasing order and increasing order, respectively. Hsu and Taksa studied comparisons between score combination and rank combination [17] and showed that rank combination does perform better under certain conditions.

Performances can be evaluated in terms of true/false positives and true/false negatives, precision and recall, goodness of hit, specificity and sensitivity, etc. Once performance measurement P is agreed upon for the score combination $E = C_s(A,B)$ and rank combination $F = C_r(A,B)$ of two scoring systems A and B, the following two most fundamental problems in information fusion can be asked.
(a) When is $P(E)$ or $P(F)$ greater than or equal to $max\{P(A), P(B)\}$?
(b) When is $P(F)$ greater than or equal to $P(E)$?

2.2 Rank-Score Characteristic (RSC) Function and Cognitive Diversity

For a scoring system A with score function s_A, as stated before and shown in Figure 6, its rank function r_A can be derived by sorting the score values in decreasing order and assigning a rank value to replace the score value. The diagram in Figure 6 shows mathematically, for i in $N=[1,n]$: $f_A(i) = (s_A \circ r_A^{-1})(i) = s_A(r_A^{-1}(i))$. Computationally, f_A can be derived simply by sorting the score values by using the rank values as the keys. The example in Figure 7 illustrates a RSC function on $D = \{d_1, d_2, \ldots, d_{12}\}$ using the computational approach of sorting, reordering, and composition.

D	**Score function s:D→R**	**Rank function r:D→N**		**RSC function f:N→R**	
d_1	3	10		1	10
d_2	8.2	3		2	9.8
d_3	7	4		3	8.2
d_4	4.6	7		4	7
d_5	4	8		5	5.4
d_6	10	1		6	5
d_7	9.8	2		7	4.6
d_8	3.3	9		8	4
d_9	1	12		9	3.3
d_{10}	2.5	11		10	3
d_{11}	5	6		11	2.5
d_{12}	5.4	5		12	1

Figure 7: Computational Derivation of RSC Function.

Let D be a set of twenty figure skaters in an international figure skating competition, and consider the example of three judges A, B, C assigning scores to each of the skaters at the end of a contest. Figure 8 illustrates three potential RSC functions f_A, f_B, and f_C, respectively. In this case, each RSC function illustrates the scoring (or ranking) behavior of the scoring system, which is each of the three judges. The example shows that Judge A has a very evenly distributed scoring practice while Judge B gives less number of skaters high scores and Judge C gives more skaters high scores.

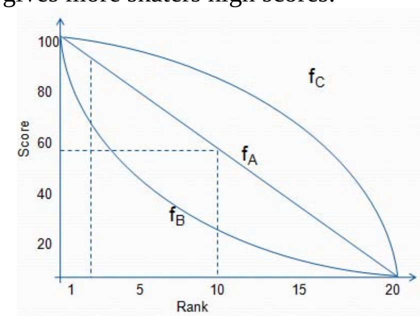

Figure 8: Three RSC functions f_A, f_B, and f_C.

This example highlights a use of multiple scoring systems, where each of the three scoring systems (judges) makes a judgment as to how good a given skater is.

In the case of two systems A and B, the concept of diversity $d(A,B)$ is defined (see [18]). For scoring systems A and B, the diversity $d(A,B)$ between A and B has the following three possibilities:

(a) $d(A,B)= 1-d(s_A,s_B)$, where $d(s_A,s_B)$ is the correlation (e.g. Pearson's z correlation) between score functions s_A and s_B,

(b) $d(A,B)=1-d(r_A,r_B)$, where $d(r_A,r_B)$ is the rank correlation (e.g. Kendall's tau τ or Spearman's rho ρ) between rank functions r_A and r_B, and

(c) $d(A,B)=d(f_A, f_B)$, the diversity between RSC functions f_A and f_B.

Correlation is one of the central concepts in statistics. It has been shown that correlation is very useful in many application domains which use statistical methods and tools. However, it remains a challenge to interpret correlations in a complex system or dynamic environment. For example, in the financial domain, Engle discussed the challenge of forecasting dynamic correlations which play an essential role in risk forecasting, portfolio management, and other financial activities [9]. Diversity, on the other hand, is a crucial concept in informatics. In computational approaches such as machine learning, data mining, and information fusion, it has been shown that when combining multiple classifier systems, multiple neural nets, and multiple scoring systems, higher diversity is a necessary condition for improvement [3, 18, 22, 39, 41]. Figure 9 shows some comparison on a variety of characteristics between correlation and diversity.

	Likely Target	Domain Rules	Reasoning / Method	Opposite Concept	Measurement / Judgment	Fusion Level
Correlation / Similarity	Object	Syntactic	Statistics	Difference	Data	Data
Diversity / Heterogeneity	Subject	Semantic	Informatics	Homogeneity	Decision	Feature / Decision

Figure 9: Correlation/Similarity vs. Diversity/Heterogeneity (Hsu et al [19]).

2.3 Examples of CFA Domain Applications

We exhibit six examples of domain applications using Combinatorial Fusion Analysis in information retrieval, virtual screening, target tracking, protein structure prediction, combining multiple text mining methods in biomedicine, and on-line learning where RSC function is used to define cognitive diversity [17, 25, 26, 27, 30, 42]. Other domains of application include bioinformatics, text mining and portfolio management [24, 29, 38, 40].

(a) Comparing Rank and Score Combination Methods

Using the symmetric group S_{500} as the sample space for rank functions with respect to five hundred documents, Hsu and Taksa [17] showed that under certain conditions, such as higher values of the diversity $d(f_A, f_B)$, the performance of rank combination is better than that of score combination, $P(F) \geq P(E)$, under both performance evaluation of precision and average precision.

(b) Improving Enrichment in Virtual Screening

Using five scoring systems with two genetic docking algorithms on four target proteins: thymidine kinase (TK), human dihydrofolate reductase (DHFR), and estrogen receptors of antagonists and agonists (ER antagonist and ER agonist), Yang et al [42] demonstrated that high performance ratio and high diversity are two conditions necessary for the fusion to be positive, i.e. combination performs better than each of the individual systems.

(c) Target Tracking Under Occlusion

Lyons and Hsu [27] applied a multisensory fusion approach, based on the CFA and the RSC function to study the problem of multisensory video tracking with occlusion. In particular, Lyons and Hsu [27] demonstrated that using RSC function as a diversity measure is an effective method to study target tracking video with occlusions.

(d) Combining Multiple Information Retrieval Models in Biomedical Literature

Li, Shi, and Hsu [25] compare seven systems of biomedical literature retrieval algorithms. They then use CFA to combine those systems and demonstrated that combination is better only when the performance of the original systems are good and they are different in terms of RSC diversity.

(e) Protein Structure Prediction

Lin et al [26] use CFA to select and combine multiple features in the process of protein structure prediction and showed that it improved accuracy.

(f) On-line Learning

Mesterharm and Hsu [30] showed that combining multiple sub-experts could improve the on-line learning process.

3 Facial Attractiveness Judgment

3.1 Neural Decision Making

Facial attractiveness judgment is a kind of neural decision making process related to perception. It consists of collection and representation of all sources of priors, evidence, and value into a single quantity which is then processed and interpreted by the decision rule to make a choice or commitment so that the decision can be transformed and used to take action [12]. Unlike information theory and a host of other biostatistical, econometric, and psychometric tools used for data analysis, we use the method and practice of combinatorial fusion analysis, which is related to the signal detection theory (SDT) defined by Green and Swets [13] (1966). SDT provides a conceptual framework for the process to convert single or multiple observations of noisy evidence into a categorical choice [10, 12, 13, 20, 23, 28, 34, 36]. As described in Section 2, CFA is a data-driven, evidence-based information fusion paradigm which uses multiple scoring systems and the RSC function to measure cognitive diversity between each pair of scoring systems [17, 24, 26, 27, 29, 30, 38, 40, 42].

3.2 Gender Variation in Facial Attractiveness Judgment

In the facial attractiveness judgment domain, people are asked to rate the beauty of a face image. We want to explore the factors which influence a person's decision. How much will personal perception or preference affect one's rating? Will the opinions of others influence the judgment? We are interested in examining these questions and, in particular, analyzing how the results vary for female and male subjects rating either female or male faces. In order to gain insight into the variations in attractiveness judgment for females and males, two face rating experiments were conducted. The experiments and their analysis are described below.

The subjects in the first and second experiments were divided into two and three groups, respectively, each with a mix of male and female subjects as follows:

Experiment 1	**Experiment 2**
Group 1: 60 subjects (12 males, 48 females)	Group 1: 61 subjects (32 males, 29 females)
Group 2: 68 subjects (29 males, 39 females)	Group 2: 101 subjects (58 males, 43 females)
	Group 3: 82 subjects (27 males, 55 females)

In the first experiment, the faces to be rated include two sets of images: 100 male faces and 100 female faces and in the second experiment there are two sets of faces, each with 50 male or 50 female faces. The subjects in the first experiment were asked to rate each face on a scale of 1 to 7 according to: (1) personal evaluation: How much do you like it? and (2) general evaluation: If 100 people are asked how much they like the face, how do you think they would evaluate it? We call these two tasks (1) “liking” and (2) “mentalization”, respectively.

The subjects in the second experiment are asked to rate the faces on a scale of 1 to 7 according to the following three tasks:

(1) Judge the attractiveness: How much do you like it?
(2) Judge the beauty: How do you rate the face in terms of its beauty?
(3) Mentalization: If 100 people are asked how much they like the face, how do you think they would evaluate it?

We name these three tasks: (1) “liking”, (2) “beauty”, and (3) “mentalization”. The task of beauty evaluation is added to this second experiment in order to see how judgments according to personal liking, beauty, and mentalization evaluation are related and how they may influence each other.

Experiment 1: Data Set Description:

Face	**Task**	**Group**	**Subject**
2(M/F)	2(L/M)	2(G1/G2)	2(M/F)
1:male	1:liking	1:group 1	1:male
2:female	2:mentalization	2:group 2	2:female

Since we are interested in comparing face genders, tasks, and subject genders, we integrate the two groups into one data set and categorize the data by Face (male / female), Task (liking / mentalization), and Subject (male / female) as outlined in the following table. We use "+" to denote integration of two groups. There are a total of 41 male subjects and 87 female subjects in this experiment.

Face	Task	Subject	Group 1 + Group2
male	liking	Male	A(1, 1, +, 1)
male	liking	female	A(1, 1, +, 2)
male	mentalization	male	A(1, 2, +, 1)
male	mentalization	female	A(1, 2, +, 2)
female	liking	male	A(2, 1, +, 1)
female	liking	female	A(2, 1, +, 2)
female	mentalization	male	A(2, 2, +, 1)
female	mentalization	female	A(2, 2, +, 2)

Experiment 2 - Data Set Description:

Face	**Task**	**Group**	**Subject**
2(M/F)	3(L/B/M)	3(G1/G2/G3)	2(M/F)
1:male	1:liking	1:group 1	1:male
2:female	2:beauty	2:group 2	2:female
	3:mentalization	3:group 3	

As in the first experiment, we then integrate all three groups into one larger data set. Here, we categorize the data according to: Face (male / female), Task (liking / beauty / mentalization), and Subject (male / female) and all combinations as shown in the following table. There are a total of 117 male subjects and 127 female subjects.

Face	Task	Subject	Groups 1, 2, and 3
male	liking	Male	A(1, 1, +, 1)
male	liking	female	A(1, 1, +, 2)
male	beauty	male	A(1, 2, +, 1)
male	beauty	female	A(1, 2, +, 2)
male	mentalization	male	A(1, 3, +, 1)
male	mentalization	female	A(1, 3, +, 2)
female	liking	male	A(2, 1, +, 1)
female	liking	female	A(2, 1, +, 2)
female	beauty	male	A(2, 2, +, 1)
female	beauty	female	A(2, 2, +, 2)
female	mentalization	male	A(2, 3, +, 1)
female	mentalization	female	A(2, 3, +, 2)

3.3 Experimental Results

There are many interesting observations that can be made on this data set; here we describe a few observations to demonstrate the potential of CFA analysis in this area. We observe that female subjects are more critical (more stringent) than male subjects, for the mentalization task when evaluating either female or male faces. The RSC graph in Figure 9 compares male and female subjects when judging male faces for the mentalization task, where the female RSC function is consistently lower than the male RSC function.

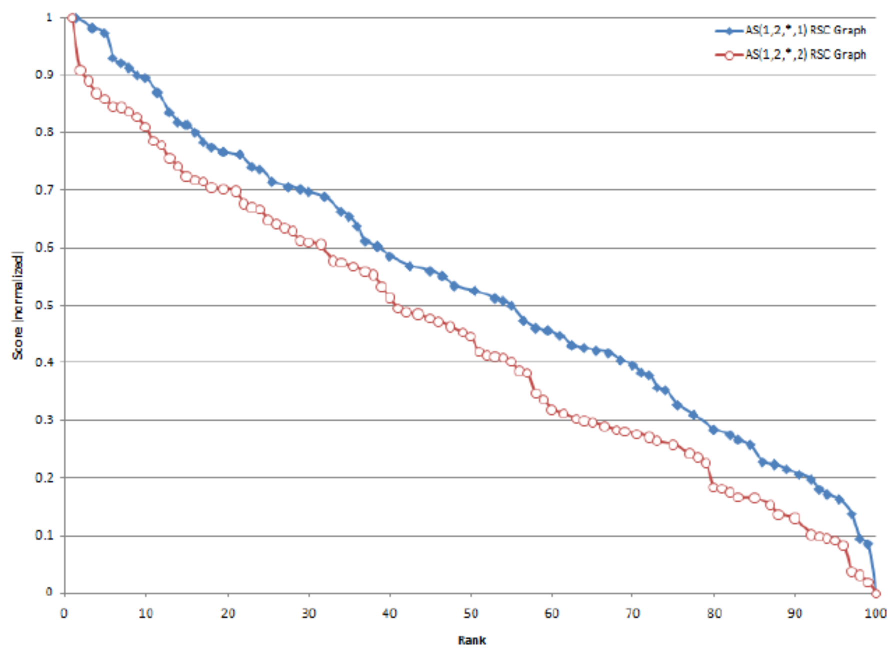

Figure 9 – RSC Graphs for male (blue) and female (red) subjects when evaluating male faces for the mentalization task (Experiment 1).

We observe that, in both data sets, there is little diversity between male and female subjects when judging female faces for the liking task. Figure 10 shows the RSC graph for male and female subjects evaluating male faces for the liking task. Comparing the RSC graphs in Figures 9 and 10, it is observed that male and female subjects demonstrated greater diversity in their scoring behavior for the mentalization task, compared to the liking task in this case; similar is true when evaluating female faces in the first experiment.

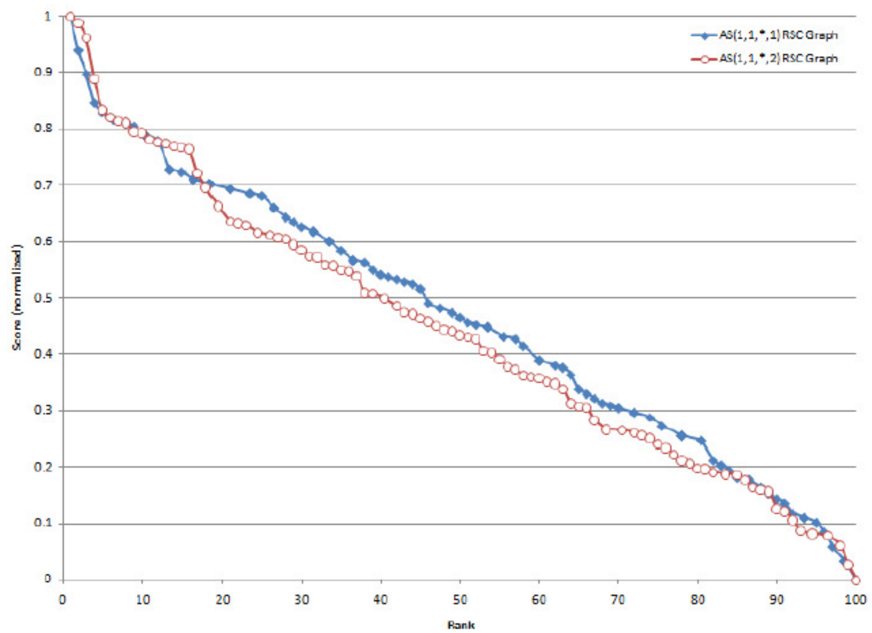

Figure 10 – RSC Graphs for male (blue) and female (red) subjects evaluating male faces under the liking task (Experiment 1).

When comparing face genders, it is observed in both experiments that there is very little diversity between male and female faces, in terms of how they are scored under the mentalization task; this is true for both male and female subjects. This is demonstrated in the following four figures (Figures 11, 12, 13, and 14).

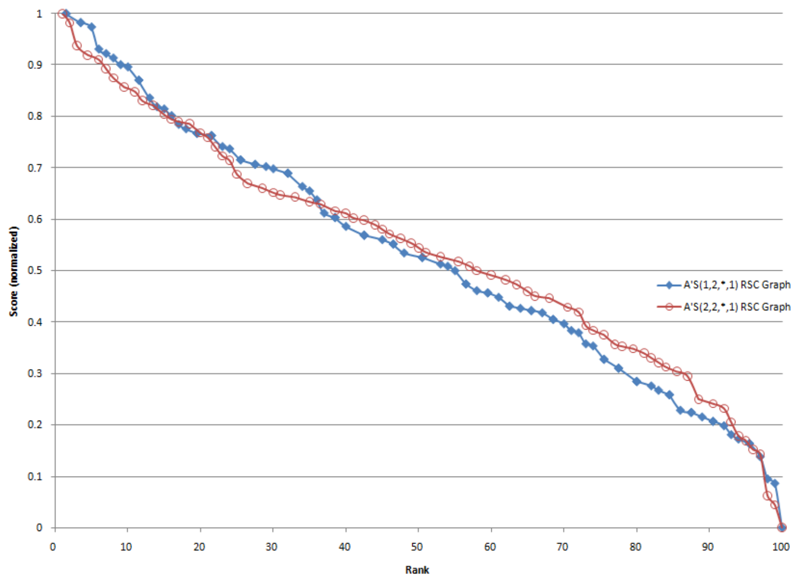

Figure 11 - RSC Graphs for male (blue) and female (red) faces when evaluated by male subjects under the mentalization task (Experiment 1).

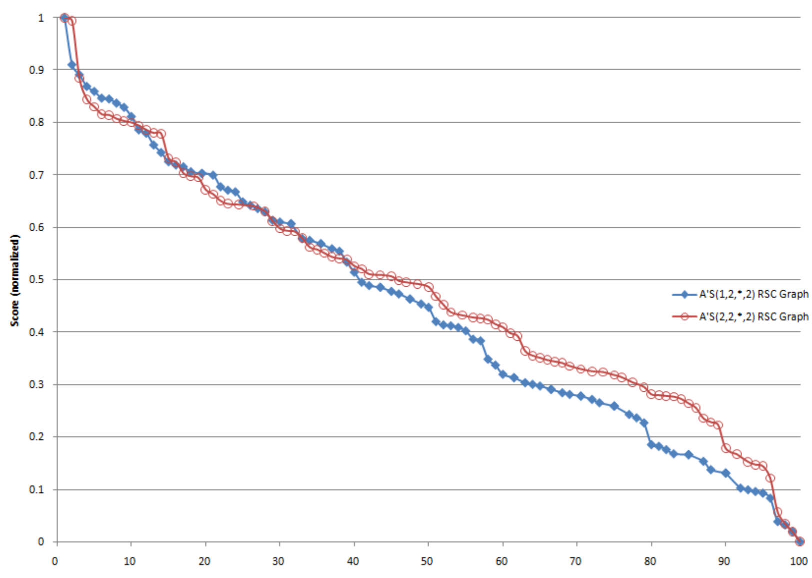

Figure 12 - RSC Graphs for male (blue) and female (red) faces when evaluated by female subjects under the mentalization task (Experiment 1).

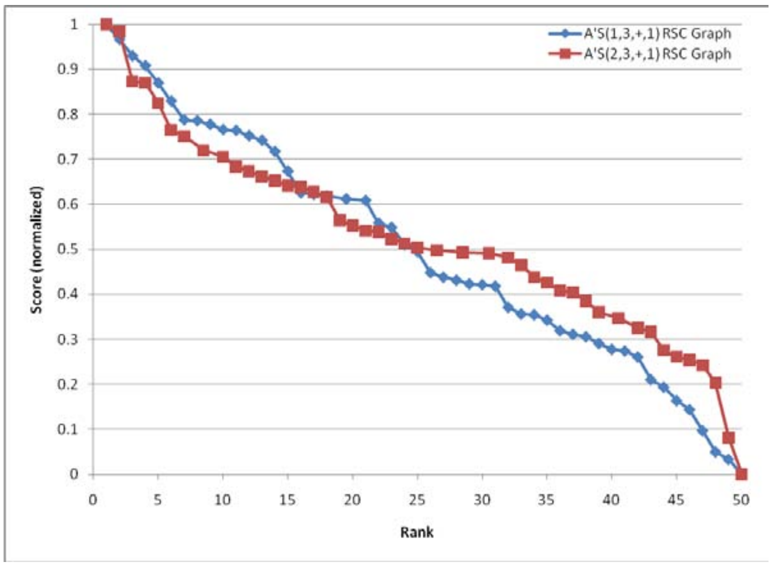

Figure 13 - RSC Graphs for male (blue) and female (red) faces when evaluated by male subjects under the mentalization task (Experiment 2).

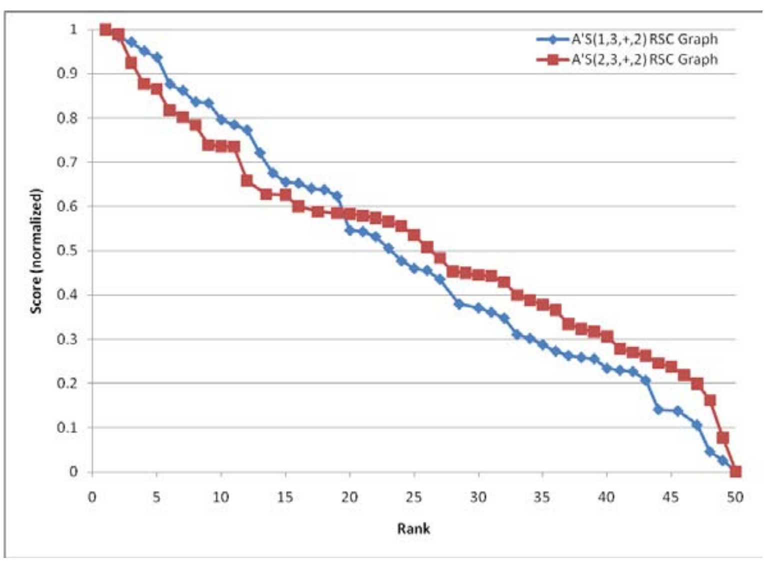

Figure 14 - RSC Graphs for male (blue) and female (red) faces when evaluated by female subjects under the mentalization task (Experiment 2).

3.3 Discussion

In our study, we use the Rank Score Characteristic function to measure the cognitive diversity between male and female subjects and between male and female faces. We have used the same technique to compare tasks among liking, beauty, and mentalization. This will be reported in the future. On the other hand, we have calculated rank correlation (Kendall's tau and Spearman rho) to study the variation between gender subjects and gender faces; this analysis will also be reported.

4 Conclusion and Remarks

4.1 Summary

In this paper, we cover brain systems, informatics, and brain informatics together with the new information paradigm: Combinatorial Fusion Analysis (CFA). CFA is then elaborated in more details using multiple scoring systems to score faces and the RSC function to measure cognitive diversity between subject genders and between face genders. We then describe the two experiments on facial attractiveness judgment and explore gender variation between male and female subjects and between male and female faces.

4.2 Further Work

Future work includes investigation into the relationship between the three tasks of liking, beauty, and mentalization for face judgment evaluation and experiments to determine what psychological and cognitive mechanisms lead to the evaluations subjects give in each of these tasks. We will develop and compare different diversity / similarity measurements, as well as compare our methods and findings to social psychology research.

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