Visualizing Mental Representations: Noise-Based Reverse Correlation Image Classification Techniques

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Abstract

Research in social psychology on the mental representation of images has long struggled to accurately characterize the content of mental activity. In the past decade, a novel psychophysical method—the "reverse correlation image classification technique"—has emerged. This technique assumes that observers' responses are correlated with visual noise, and that these responses are made according to observers' social judgment criteria rather than randomly; through performing weight calculations a sufficient number of times on the noise patterns corresponding to the responses and the emergence of visual codes, it thereby visualizes observers' internal evaluative characteristics. This technique has yielded some findings in domains such as trait research, racial bias, and intergroup prejudice, but future research must still address issues including excessive numbers of experimental trials, separating confounded noise, and participant performance in order to obtain more veridical mental representations.

Full Text

Visualization of Mental Representation: Noise-based Reverse Correlation Image Classification Technology

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Abstract

Studies of mental representation of images in social psychology have long struggled to accurately characterize psychological activity. Over the past decade, a new psychophysical method called "reverse correlation image classification technology" has emerged. This technique assumes a correlation between observers' responses and visual noise, with responses made according to observers' social judgment criteria rather than randomly. By performing a sufficient number of weight calculations on the corresponding noise patterns from observers' reactions and revealing visual codes, this method visualizes observers' intrinsic evaluation characteristics. The technology has achieved notable results in trait research, ethnicity, and intergroup bias. However, future work must address issues of excessive experimental trials, separation of confounding noise, and subjects' performance to obtain more realistic mental representations.

Keywords: face, mental representation, reverse correlation image classification technology

Mental representation, also known as psychological representation or knowledge representation, refers to the internal reproduction of external objects in psychological activities. Traditionally, research on mental representation has primarily focused on conceptual knowledge within cognitive psychology. In social perception, people must rapidly infer facial characteristics such as race, gender, age, and trustworthiness—attributes that cannot be directly observed. Therefore, the cognitive system must match perceptual input with mental representations to achieve this. However, due to limitations of traditional psychophysical methods, researchers have struggled to directly visualize how facial information is represented and encoded in mental activity, making the observation of mental representation consistently difficult.

Reverse Correlation Image Classification (RCIC) is a purely data-driven psychophysical method that has proven capable of directly visualizing the contents of mental representation and revealing people' s internal representations and decision-making strategies (Dotsch, Wigboldus, Langner, & van Knippenberg, 2008). After more than a decade of development, RCIC has become a "powerful tool" for revealing mental representations and studying high-level perceptual or cognitive processes (Ponsot, Arias, & Aucouturier, 2018). Based on this, the present study analyzes the research progress of RCIC, aiming to provide guidance on a visualizable psychophysical method for indigenous research on social perception of mental representation, and to offer a new research approach for future social psychology studies that begins from the content of mental representation.

1. Origins and Mathematical Foundations of RCIC

RCIC developed from reverse correlation technology, which has been widely applied to visual and auditory perceptual process research over the past four decades. Reverse correlation technology fundamentally follows signal detection theory but reverses the standard experimental procedure where subjects discriminate stimulus signals. In traditional signal detection paradigms, responses depend on meaningful manipulation of stimulus attributes, with the relationship between stimulus and response determined by fixed properties—identical stimuli can evoke different responses. In reverse correlation technology, however, the assumption is that different responses result from different patterns of stimulus inference, making stimuli variable rather than fixed, with subjects themselves determining whether a signal exists in the stimulus. This technique collects and combines noise fields that produce false alarms to infer the strategies employed to perform specific tasks. The term "reverse" refers to this inversion of the statistical relationship between stimulus and response. RCIC can generate intuitive visual image codes of representation content through random variation of stimulus noise parameters and estimation of the relative weight of each stimulus noise pattern in stimulus judgments.

The mathematical foundation of RCIC traces back to correlation in mathematics. In vision research, following the process of visual stimulus signals from retinal output neurons through the lateral geniculate nucleus to the primary visual cortex, the time-lagged correlation between stimulus and neural response signals can be expressed through an integral formula:

$$\int g(t)h(t+\tau)dt$$

where g and h represent stimulus and neural response signals respectively, and t represents time. For the t condition, the correlation between these infinite or finite-dimensional vectors can be further expressed as:

$$\sum_{i=1}^{n} g_i h_{i+\tau}$$

Through the Wiener-Hopf integral equation, variance estimation error for continuous-time stationary processes can be minimized to satisfy the necessary conditions for optimal filter impulse response functions. Based on this, the equation assumes two time series: stimulus x_i and neural response y_i, modeling y as a filtered version of x. The correlation formula can then be approximately expressed as:

$$y(t) = \int h(\tau)x(t-\tau)d\tau$$

By finding the optimal value of h, namely the kernel, this equation can be solved (Ahumada & Beard, 1998).

RCIC is a psychophysical method for discovering the kernel of linear systems and associating visual input with output. By applying Gaussian white noise to stimuli, it attempts to discover the linear system kernel of the visual system. Substituting Gaussian white noise x into the equation transforms the solution of the Wiener-Hopf equation kernel into:

$$\hat{h} = \frac{\sum y_i x_i}{\sum x_i^2}$$

To achieve this, the specific approach involves adding external filtered signals (visual noise) to the original stimulus in each trial of a traditional signal detection experiment. Through a large number of observation trials and calculating the collection of noise pixels selected by subjects (not the original stimulus), weighting them and displaying them as images achieves visualization of the kernel. This intuitive kernel is sometimes called a Classification Image (CI; Saegusa, Yamaoka, & Watanabe, 2015). Since this kernel image represents subjects' responses to external filtered signals and contains their social judgment criteria (trait evaluation), superimposing it on the original experimental stimulus can generate representation images reflecting observer expectancy effects (Dotsch & Todorov, 2012).

Moreover, by analyzing the intrinsic relationships among pixels in CI images, RCIC can also infer how observers make decisions. Its mathematical principle is based on Random Field Theory (RFT). RFT has two core elements: site and phase space. According to RFT, when a value from phase space is randomly assigned to each site according to some distribution, the entirety is called a random field. Adler and Hasofer (1976) derived that the expected Euler Characteristic (EC) deviation of fixed Gaussian random fields can serve as an estimator for the number of activated regions. EC essentially counts the number of clusters above a sufficiently high threshold in smoothed Gaussian random fields. By clustering pixels exceeding a fixed threshold, the visual code formed in space reflects people' s inference basis. Superimposing this visual code onto basic stimuli (such as faces) yields diagnostic regions for trait evaluation (Dotsch & Todorov, 2012).

In summary, RCIC' s technical principle can be summarized as: RCIC assumes a correlation between observers' responses and visual noise, with responses made according to observers' social judgment criteria rather than randomly. Through a sufficient number of weight calculations on corresponding noise patterns and visual code revelation, observers' intrinsic evaluation characteristics are visualized, and decision-making patterns can be inferred through mathematical logical operations. Scholars consider RCIC as an entry point for studying mental representation (Brinkman, Todorov, & Dotsch, 2017). The specific process of RCIC generating representation images and performing cluster analysis is shown in Figure 1 [Figure 1: see original paper].

The reverse correlation research paradigm mainly contains two processes: the generation process of random noise stimuli and the process of mental representation imaging. Along with the development of technical principles and investigation of mental representation effects, this paradigm has undergone three stages of evolution in the types of noise used and task forms.

1.1 Gaussian White Noise Research

Visual system research suggests that between early visual information acquisition and high-level cognitive processing, there must exist an intermediate process involving the construction of holistic visual scene representation. Inspired by using reverse correlation technology to simulate surface templates formed by subjects when solving specific tasks, scholars discovered that averaging the noise patterns selected by subjects during experiments yields a CI image. This classification image maps subjects' internal "template" for processing random noise stimuli (Saegusa et al., 2015). To avoid mental representation images being artifacts residual in stimuli, Gosselin, Bacon, and Mamassian (2004) designed a purely data-driven image representation experimental paradigm using reverse correlation technology. They first randomly generated texture images with 700 black dots on a white background, which were presented as stereograms through a stereoscope. The position and depth of each texture image were completely randomly determined, so the stereograms contained no signal components. The experimental task required subjects to report whether they detected a "+" or "-" symbol anywhere on the screen, though no such image actually existed. By integrating all responses, researchers confirmed that subjects could "pull out" a clear "+" or "-" image from random noise, thereby revealing subjects' internal representation estimation of symbols. Since the entire experimental process contained no structural visual processing stages yet did not affect visual recognition of symbolic elements, this paradigm could span early low-level and other high-level processing stages. Using reverse correlation technology, scholars achieved simulation and depiction of mental representation, confirming that a psychological-like intermediate process exists between visual signal processing and high-level cognitive processing (Gosselin et al., 2004). Gosselin et al.' s research made exploring mental representation content possible.

Notably, the noise superimposed on experimental stimuli in the above task used Gaussian white noise, projecting information onto linear space through weighted summation of white noise pixel intensities. Some researchers have questioned this approach, as such linear evaluation has only proven effective in low-level visual neurophysiology and psychophysics research, while its role in social cognitive activities remains unknown. Moreover, this paradigm did not manipulate basic images (blank backgrounds), resulting in excessively large stimulus space and requiring enormous numbers of trials. For example, Gosselin et al.' s (2004) study required 20,000 trials, greatly increasing subject burden.

1.2 Sinusoidal Noise Research

Mangini and Biederman (2004) adopted randomly varying sinusoidal noise instead of Gaussian white noise, which offers several advantages. First, sinusoidal curves better approximate preferred stimuli in early cortical visual areas. Second, the noise spectrum resembles signal distribution, making observers more likely to interpret noise as stimulus variation. While power spectrum can be achieved by filtering white noise, sinusoidal noise requires four times fewer parameters. More importantly, with fewer experimental trials (e.g., less than 1,000), sinusoidal noise estimates converge more accurately than white noise, undoubtedly beneficial for reducing experimental trials and subject burden.

Based on this, Mangini et al. (2004) improved reverse correlation research by replacing white noise with sinusoidal noise. They used truncated sinusoidal curve image fragments based on 6 orientations (0°, 30°, 60°, 90°, 120°, and 150°) × 2 phase variations (0, /2). These 12 images were fused to obtain random noise units, which were then arranged according to spatial scales (2, 4, 8, 16, and 32 cycles per image), finally forming original random field materials by superimposing a series of randomly contrasted images. This created 40,092 random noise images containing sinusoidal function parameters (see Figure 2 [Figure 2: see original paper]). The period parameter settings of sinusoidal noise well accommodate different levels of social cognition needs—lower frequencies can transmit shape and expression information, while complex social information (such as personality) requires higher frequency transmission. This indicates that sinusoidal curves not only match well with tuning at early cortical stages but also flexibly and effectively reflect processing results of different facial positions and spatial scale information according to task requirements.

Although Mangini et al.’ s (2004) paradigm could transform subjects’ random pixel matrices for different decisions into intuitive classification images with significant differences, its application to constructing social cognition models appears limited. First, the basic faces in this paradigm were synthesized from two images with different attributes representing two target categories, meaning two different categories were preset before stimulus presentation. However, researchers studying social dimensions assume these images do not actually represent two categories; rather, the categories are what researchers aim to discover, creating a potential contradiction. Second, this paradigm initially used 1-4 level forced-choice tasks but only screened “highly probable” responses for generating mental representation images, ignoring less probable judgments, resulting in relatively low experimental efficiency.

1.3 Two-Image Forced-Choice Task Research

Based on this, Dotsch et al. (2008) improved previous task paradigms by adopting a Two-Image Forced-Choice Task (2IFC). They continued using sinusoidal noise as random noise but selected average faces from face databases as basic images. This classification image was the result of subjects’ own mental representation, effectively eliminating experimenter preset categories. Moreover, these average faces, with their relatively blurred contours, made other features (such as mouth, nose, eyes) the focal point, making them very suitable for superimposing random noise. More importantly, they adjusted the rating task format to a two-image forced-choice format. This improvement enhanced data utilization: on one hand, more experimental data benefited imaging clarity; on the other hand, by averaging both selected and unselected noise patterns, a single experimental study could obtain both expected classification images (CI) and unexpected classification images (anti-CI), effectively improving experimental efficiency. Furthermore, the two images were generated by superimposing random noise patterns and opposite negative noise patterns on basic faces, creating visual effects similar to photographic negatives or medical positive/negative films. This provided better visual contrast while maximizing differences between the two presented images, minimizing stimulus pair numbers and reducing experimental trials. The 2IFC dual-image generation process and experimental task format are shown in Figure 3 [Figure 3: see original paper].

Dotsch et al. (2008) divided the experimental paradigm into four components: generating random noise stimuli, performing two-image forced-choice tasks, producing classification images, and performing pixel cluster analysis. Scholars believe this paradigm separates face stimulus generation from trait inference processes, objectively revealing mechanisms underlying face representation (Ratner, Dotsch, Wigboldus, van Knippenberg, & Amodio, 2014). Currently, it has been widely applied in social perception research (Karremans, Dotsch, & Corneille, 2011; Paulus, Rohr, Dotsch, & Wentura, 2016).

2. RCIC' s Technical Advantages

Since mental representation is an internal psychological construct, traditionally researchers could only rely on indirect methods to infer its content. To study how complex social stimuli are recognized, researchers must first determine which stimulus features perceivers use in judgment and how they combine these varying cues. More specifically, before subjects make stimulus judgments, researchers need to grasp the weights of different components, features, or regions of complex stimuli. Only by measuring and testing weighted stimulus patterns can researchers infer the content of mental representations and decision strategies influencing individual social perception.

The limitation of traditional data-driven techniques lies in their reliance on artificial manipulation of stimuli used to build models, systematically manipulating stimulus features to examine bases of social judgment. However, when structural features important for social attributes remain unchanged across a series of judgments, this method cannot identify these important features (Todorov et al., 2015). Additionally, people are inadequate at defining stimulus features —some features cannot be identified, and researchers and perceivers may be unaware of these features' influence on social perception.

In contrast, RCIC, as a new purely data-driven technique, possesses stronger methodological advantages. Benefiting from engineering and neurophysiological system identification techniques (such as fMRI), RCIC incorporates principles from psychophysics, experimental psychology, and computer science. This method' s investigation of stimulus-response relationships relies on analysis of each specific experimental trial rather than manipulation of stimulus features. Through numerous experimental trials, RCIC classifies noise patterns from subjects' responses, and averaging selected noise samples yields classification images.

Comparing empirical classification images with mental representations derived under different model assumptions allows discrimination of which theoretical model better explains subjects' decision-making behaviors in tasks. The general principle behind this technique is: across multiple experiments, analyzing statistical relationships between randomly perturbed parts of a stimulus ("noise") and corresponding responses provides direct insight into mental representations used by subjects in perceptual tasks, thereby identifying which perceptual decision strategies regulate task performance. Its purpose is to identify quantitative relationships between high-dimensional variables (such as face images) and behavior (such as perceptual decisions) with minimal bias.

Although RCIC is constrained by judgment and stimulus types used in specific experimental paradigms, its visualization approach to stimuli reflecting social cognition is unconstrained. By requiring subjects to judge basic images superimposed with random noise, and since random noise distorts basic images (such as faces) at the pixel level, resulting stimulus variations are less constrained than those in traditional psychophysical methods. The ultimate goal is calculating classification images to visualize psychological features driving social judgments. Notably, RCIC' s visualization effect fundamentally differs from eye-tracking research—eye-tracking only identifies partial images formed by subjects' fovea when viewing complete images, while RCIC identifies the entire stimulus visual region that provides potential information for classification.

2.1 Ecological Validity Advantage

Another advantage of RCIC is its high ecological validity. When signal features are unknown or when investigating classification representations, the absence of any a priori assumptions about image bias makes this paradigm less susceptible to social desirability or demand characteristics. RCIC has consequently become an ideal method for mining spontaneously used information in high-level psychological processes.

Although RCIC requires selecting a constant original stimulus as a basic image when generating mental representation images, the original stimulus does not affect RCIC' s ecological validity because the technique operates through the correlation between responses and visual noise. Therefore, whether selecting human faces or bodies as basic images (Johnson, Iida, & Tassinary, 2012; Lick, Carpinella, Preciado, Spunt, & Johnson, 2013; Nunnari & Heloir, 2017), or non-human images such as baboon heads (Martin-Malivel, Mangini, Fagot, & Biederman, 2010) and spider images (Young, 2014), the final classification representation images remain unaffected. This is because superimposed random noise completely changes the appearance of basic images visually, enabling multiple interpretations of basic images and creating opportunities to "shape" result images according to features in mental representation rather than basic images. Scholars believe randomization of noise provides ecological validity assurance for RCIC (Paulus et al., 2016).

Taking human faces as basic images, current basic face selections include Caucasian male faces (Dotsch & Todorov, 2012), Indian male faces from yellow races (Dunham, Srinivasan, Dotsch, & Barner, 2014), and mixed white and black male faces (Brown-Iannuzzi, Dotsch, Cooley, & Payne, 2017). Dotsch et al. (2008) showed that RCIC can visualize subjects' thoughts in different contexts—even using white faces as basic faces, it can generate mental representations of non-white faces such as Moroccans and Chinese (see Figure 4 [Figure 4: see original paper] left). Martin-Malivel and colleagues (2010) further expanded RCIC' s research scope from humans to animal groups through comparative studies on baboon information classification using baboon heads as basic images. These studies demonstrate that RCIC methodology itself is reliable and can provide evidence for mental representations of different objects. RCIC can also apply in more natural contexts (Paulus et al., 2016).

3. Research Applications of RCIC

3.1 Trait Evaluation

Oosterhof and Todorov (2008) used data-driven techniques to construct face models, finding that people primarily evaluate others based on two dimensions—trustworthiness and dominance—when forming first impressions. However, this trait attribution model requires verification. Benefiting from RCIC' s advantage of requiring no a priori assumptions, Dotsch and Todorov (2012) not only reconfirmed the validity of the trait attribution model but also discovered that trustworthy face representations appear more feminine with smiling expressions, while untrustworthy face representations appear more masculine with angry expressions, providing evidence for both emotional generalization explanations and gender differences in trustworthiness. Subsequently, Imhoff et al. (2013) used RCIC to further explore the relationship between these two dimensions in the trait attribution model, finding they exhibit compensatory relationships (Imhoff, Woelki, Hanke, & Dotsch, 2013). However, recent RCIC research indicates people cannot use these two dimensions to form self-images (van Driel, 2017), providing new considerations for trait research development.

Additionally, Nunnari and Heloir (2017) used an RCIC paradigm based on body basic images, employing virtual characters containing 14 body attributes (including face and body images) as basic images to examine relationships between three personality traits (trustworthiness, dominance, agreeableness) and body attributes. They attempted to construct a linear relationship model between traits and attributes system, making new attempts for trait research.

3.2 Intergroup Relations

Ratner et al. (2014) investigated the role of visual representation in intergroup relations. Using RCIC, researchers obtained typical visual representation images of ingroup and outgroup members, finding that trait evaluations of ingroup classification images were more positive than outgroup classification images, confirming visual representation as a powerful mechanism for transmitting group bias. This discovery also provides important visual representation evidence for explaining intergroup relations within the social identity theory framework. Moreover, even ordinary facial expressions are affected by group membership. Paulus et al. (2016) used RCIC to discover that visual representation images of ingroup smiling faces convey more social meaning (benevolence), demonstrating ingroup favoritism.

However, recent RCIC research also confirms that people can exhibit both ingroup and outgroup favoritism, potentially challenging the explanatory power of social identity theory. A study evaluating Indian children' s religious and caste representations showed that Dalit children evaluated Brahmin classification images more positively in terms of caste, yet simultaneously showed strong evaluation preferences for lower-class Muslims rather than upper-class Hindus in terms of religion (Dunham et al., 2014).

3.3 Prejudice

Dotsch et al. (2008) used RCIC to explore prejudice in high-level social cognition. Existing research shows that prejudice causes biases in cognition, emotion, and behavior toward racial outgroups (Fiske, 2015). This implies that due to preset motivations or specific knowledge, people may distort outgroup face representations when observing outgroup face stimuli. Based on this speculation, Dotsch et al. (2008) examined whether mental representations of outgroup members were affected by underlying prejudice, using a highly stigmatized immigrant group in the Netherlands (Moroccans) as the target group. Classification image results showed that the higher subjects' implicit prejudice toward Moroccans, the more they tended to represent their prototype as objectively less trustworthy and more criminal-looking. That is, more prejudiced individuals showed greater distortion in outgroup mental representation, producing more negative outgroup classification images. This result reveals that outgroup mental representation images may be closely related to prejudice levels (see Figure 4 right).

Additionally, in gender research, scholars have used body-based RCIC technology to intuitively depict internal representations of male and female bodies. Image processing results revealed varying degrees of gender bias toward women compared to men (Johnson et al., 2012; Lick et al., 2013).

3.4 Psychotherapy

Research shows that spider phobia patients have abnormal cognition of spiders, noticing spider images more quickly, experiencing stronger anger emotions, and higher anxiety states. Young (2014) used spider-based RCIC technology to examine and evaluate spider phobia patients' spider mental representation images, finding that their typical spider mental representations were more threatening and fear-inducing. This confirms that spider phobia patients' fear of spiders may be related to abnormal representations of fear-related stimuli, pointing to new directions for future phobia intervention and treatment.

Furthermore, scholars have used RCIC to explore facial emotion recognition deficits in schizophrenia, finding that compared to normal people, schizophrenia patients over-utilize nose and mouth regions while under-utilizing eye region information, and ignore lowest spatial frequency information. These findings provide direct evidence for abnormal patterns of visual information use by schizophrenia patients in distinguishing facial emotions (Clark, Gosselin, & Goghari, 2013).

Beyond these applied studies, RCIC has also been applied to emotion expression (Jack, Caldara, & Schyns, 2012) and intimate relationship research (Gunaydin, & Delong, 2015). This technology also has predictive power for judgments of race, age, gender, and other characteristics. For instance, it can explore which facial features make people appear more Caucasian or Black (Krosch & Amodio, 2014), older or younger (van Rijsbergen, Jaworska, Rousselet, & Schyns, 2014), male or female (Dotsch, Wigboldus, & van Knippenberg, 2011).

4. Technical Limitations and Future Prospects

Although RCIC aims to establish visualizable mental representation content and possesses high ecological validity, it can only provide approximations of real mental representation. This is because classification images generated by this technique contain not only real mental imagery but also superimposed noise, while subjects' performance also affects classification image generation. Separating these confounding factors to obtain real mental representation remains an issue worthy of continued in-depth exploration. Additionally, there are differing opinions on basic image settings—some scholars argue that composite faces obtained through face averaging technology can reduce differential details between individual faces and have more similarity with individual faces, making them more representative (Bijvank, 2014), while others believe RCIC technology based on computer-generated three-dimensional faces may be better as stimulus materials (Chen, Garrod, Schyns, & Jack, 2017).

Furthermore, as a "molecular" psychophysical method, RCIC' s investigation of stimulus-response relationships relies on statistical analysis of each specific experimental trial, requiring large numbers of trials (mostly exceeding 1,000) to complete calculations of random noise pattern regularities (Lick et al., 2013). This makes the research paradigm face practical difficulties in operation, and determining reasonable experimental trial numbers remains a methodological issue requiring resolution.

Over the past decade, RCIC technology has been adopted by social psychologists and has evolved from initial application in simple psychological process research to advanced psychological processes such as prejudice, stereotypes, and cultural-level studies. It has proven to be an important tool for exploring mental representation and will have greater application prospects in the future.

First, in terms of research methods, RCIC can be combined with advanced cognitive neuroscience. RCIC provides intuitive, visualizable mental representation images, while eye-tracking technology can clearly capture people' s eye movement trajectories. Future integration of these two technologies can achieve complementary advantages, better revealing high-level visual cognitive mechanisms. Additionally, how high-level cognitive activities execute social judgments through diagnostic regions of mental representation remains unclear regarding corresponding psychological and neural processing mechanisms. Given RCIC' s shared mathematical foundation with fMRI and their respective research advantages on mental content and processes, future attempts to combine with neuroimaging technology may more systematically reveal mental representation processing mechanisms.

Second, application areas can continue expanding. In clinical psychotherapy: (1) RCIC can be applied to emotional training for special children (such as those with alexithymia or autism), as it can effectively evaluate generated representation images, making it highly operational in actual interventions. (2) It can be applied to systematic desensitization therapy for phobias. Existing research shows phobia causes distortion in mental representation images of fear-related stimuli (such as spiders). Guiding patients to manipulate mental representation images to gradually restore normal representation images may achieve systematic desensitization therapy for phobias. (3) It can also be applied to body image shaping, using imagined ideal body images to assist in treating patients with anorexia nervosa. Additionally, in the judicial field, since RCIC can form subjects' desired face images while ignoring basic images, this technology can also be applied to eyewitness portrait depiction of criminals.

Notably, as a new technology, RCIC still requires improvement. Future exploration of noise parameter improvements and expansion of basic images from faces to bodies and even non-human images will be worthwhile, helping RCIC paradigms apply to more social cognition research areas. In summary, RCIC technology can help extract meaningful mental images and visualize mental representation content, providing a new approach for research in high-level social cognitive processing fields.

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Author Contributions

HOU Chun-Na: Proposed research ideas, structured research logic, wrote the paper, revised and finalized the manuscript
LIU Zhi-Jun: Collected and organized literature, revised and finalized the manuscript

Note: Figure translations are in progress. See original paper for figures.