Social Intention Recognition Based on Cost-Minimizing Information: Evidence from EEG and Behavior

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Abstract

Unlike previous research that focused on examining how to identify object-directed intentions (actions targeting physical objects without involving other people), this study investigated how people recognize social intentions (actions directed toward social agents to influence the other' s interactive behavior). Based on the analysis that two interacting agents should follow utility maximization at the holistic level, we propose that when the cost for A to assist B in achieving a goal state is less than the cost for B to achieve that goal state alone (referred to as cost-minimization information), it can be recognized as having social intention. By manipulating cost-minimization information through the method of placing a barrier in front of B, and using the degree of EEG mu suppression indicating different intention types and sensitivity to different changes (discriminability) as metrics, this hypothesis was tested. The results showed that, compared to the control condition of object-directed intention (i.e., A placing the target object apple in front of a stone), when A placed the target object apple in front of B who was blocked by a barrier, and this action could reduce the action cost for B to obtain the apple alone—i.e., when it met the cost-minimization condition—mu suppression was greater (Experiment 1), and discriminability for structural changes (swapping of agents serving the same role in two animations) was stronger, but discriminability for role exchange (exchange of roles between two agents in an animation) was weaker (Experiment 3a); however, when the barrier was absent, although A' s movement path was the same as in Experiment 1, the cost for A to place the apple in front of B was greater than the cost for B to obtain the apple themselves, i.e., it did not meet the cost-minimization condition, the difference in mu suppression between conditions disappeared (Experiment 2), and discrimination of changes across different action patterns was comparable (Experiment 3b). Given that previous research has shown that social intentions elicit stronger mu suppression than

object-directed intentions, and that people more easily discriminate structural changes between two agents when social intentions are present but are insensitive to role exchange, the above results reveal that whether the behaviors of two individuals satisfy cost minimization influences people' s recognition of action intentions, supporting the view that cost-minimization information serves as a cue for social intention recognition.

Full Text

The Recognition of Social Intentions Based on Cost-Minimization Information: Evidence from EEG and Behavior

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Abstract

Unlike previous research that focused on recognizing object-directed intentions (where actions target physical objects without involving other people), this study investigated how people recognize social intentions (where actions target social agents to influence their interactive behavior). Based on the analysis that two interacting agents should follow utility maximization at the collective level, we proposed that when the cost for Agent A to assist Agent B in achieving a goal state is less than the cost for Agent B to achieve that state alone (referred to as cost-minimization information), this can be recognized as a social intention. We manipulated cost-minimization information by placing a fence in front of Agent B and tested this hypothesis using two indicators: the degree of EEG mu suppression and sensitivity (discriminability) to different types of changes. The results showed that compared to the control condition of object-directed intention (i.e., Agent A placing the target apple in front of a stone), when Agent A placed the apple in front of Agent B who was blocked by a fence—thereby reducing B' s action cost to obtain the apple and satisfying the cost-minimization condition—mu suppression was greater (Experiment 1), discriminability for structural changes (swapping agents serving the same role across two animations) was stronger, but discriminability for role exchanges (swapping roles between two agents within an animation) was weaker (Experiment 3a). However, when the fence was absent, although Agent A' s movement path was identical to Experiment 1, the cost for A to place the apple in front of B exceeded the cost for B to obtain the apple alone, violating the cost-minimization condition. Under these circumstances, the difference in mu suppression between conditions disappeared (Experiment 2), and discriminability for different types of changes was comparable (Experiment 3b). Given that previous research has shown that social intentions elicit stronger mu suppression than object-directed intentions, and that people more easily detect structural changes but are insensitive to role exchanges when social intentions are present, these results reveal that whether the behaviors of two individuals satisfy cost-minimization influences how action intentions are recognized, supporting the view that cost-minimization information serves as a cue for social intention recognition.

Keywords: intention recognition, object-directed intention, social intention, cost minimization, mu suppression

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Humans establish connections with physical objects and social individuals through rich actions or behaviors to satisfy various needs (Miller, 2001). When observing these complex behaviors, the human visual system not only perceives physical-level motion information but also infers and recognizes their intentions, representing them as purposeful action patterns (Blakemore & Decety, 2001). Action intention recognition involves considerable uncertainty (Ullman et al., 2009). For example, when a hand approaches a teacup, the cup could be interpreted as either the target of the action (reaching for the cup to drink) or an obstacle to be bypassed (reaching over the cup to grasp another object). What information about the relationship between actions and objects does the human visual system use to achieve effective recognition of action intentions?

Previous researchers have conducted extensive studies on the recognition of non-social intentions directed at physical objects to satisfy needs (i.e., object-directed intentions, which do not involve others) (Heineman-Pieper, 2009). They proposed that the visual system decomposes behavioral scenes into three basic elements: action, goal (or resulting state), and contextual factors. Individuals' interpretation of the relationships among these three elements follows the fundamental rational principle that actions achieve goal states at minimum cost under contextual constraints (Csibra et al., 2003; Gergely & Csibra, 2003). Jara-Ettinger et al. employed a utility function (Utility = Reward - Cost) to describe the relationship between action and goal, arguing that because behavioral agents possess rationality as a fundamental characteristic, actions follow utility maximization to achieve goals. Therefore, when other conditions remain constant, if the behavior and the currently approached object have the maximum utility value, they have a goal-directed relationship (Jara-Ettinger et al., 2015). However, action intentions include not only object-directed intentions that target physical objects but also social interaction intentions that target social agents and influence others' behaviors (Canessa et al., 2012; Hobbs & Spelke, 2015), referred to as social intentions. Regarding the recognition of social intentions (primarily referring to interactions between two people), some researchers have proposed that the contingency between the two parties' behaviors is a key determinant, suggesting that as long as one individual' s action causes immediate and synchronous changes in another' s behavior, the two may be perceived as having an interaction-directed relationship (see review in De Jaegher et al., 2010), such as handshaking. However, subsequent studies have shown that when the target being jointly pursued by two individuals is invisible, even if behavioral contingency exists between them, people struggle to recognize their mutual intention; only when the pursued target is visible is the behavior recognized as having social intention (Yin et al., 2013). Such studies suggest that beyond behavioral contingency, people may rely on other cues or information to recognize social intentions (Auvray et al., 2009). Therefore, this study further examines what other cues or information can be utilized in this recognition process.

Although social intentions and object-directed intentions target different objects, the agents executing the behaviors are rational intelligent individuals, so the recognition of interactive intentions can also be analyzed based on the rational principle of action utility maximization (Gergely & Jacob, 2012). Social interaction behaviors are directed at another rational social agent, and analyzing the action utility of a single individual may not be suitable for situations involving multiple behavioral agents. Research indicates that people represent interactive behaviors holistically, suggesting that the visual system may compute utility maximization at the collective level, considering the rewards and costs of all interacting parties comprehensively (Török et al., 2019). Accordingly, when the following condition is met—when the cost for Agent A to assist Agent B in achieving a goal state is less than the cost for Agent B to achieve that state alone (referred to as cost minimization, such as delivering items that are difficult for others to obtain)—collective-level utility maximization is achieved, and this action pattern can be inferred to be recognized as having social intention. That is, cost-minimization information can serve as a cue that the visual system uses to recognize social intentions. However, this hypothesis does not exclude the possibility of other cues in social intention recognition, such as the contingency mentioned above; it only assumes that cost-minimization information is a sufficient but not necessary condition for social intention recognition.

This paper uses the EEG mu rhythm (8-13 Hz) as an indicator to indirectly measure whether social intentions are recognized (as shown in Figure 1 [Figure 1: see original paper]). The mu rhythm is located in the sensorimotor cortex (C3 and C4 electrodes) and is believed to originate from the mirror neuron system, an important functional area responsible for action intention processing. Stronger mirror neuron system activity corresponds to greater mu suppression (Muthukumaraswamy et al., 2004; Oberman et al., 2005). Research has found that because social intention processing requires considering the behaviors of both agents simultaneously, this processing places higher demands on the mirror neuron system than non-social intention processing involving only a single individual, resulting in stronger activation (Centelles et al., 2011). Since mirror neuron system activity is reflected in mu rhythm suppression, the strength of mu suppression can indicate whether observed behavior is recognized as having social intention (Oberman et al., 2007; Yin et al., 2020). Specifically, if a behavior produces stronger mu suppression than non-social object-directed intention behavior, it can be concluded that the behavior is recognized as having stronger social intention. This indicator has been successfully applied in relevant research on social intention recognition (Oberman et al., 2007; Yin et al., 2020).

To test the above hypothesis, this study adopted Heider and Simmel' s (1944) method of using animations to depict different behavior patterns (as shown in the stimulus scenes in Figure 2 [Figure 2: see original paper]), with behavioral agents simplified as geometric-shaped agents. This approach can simulate real interactive scenarios while conveniently controlling the action costs introduced by behaviors (Jara-Ettinger et al., 2015; Ullman et al., 2009). In this study' s animations, Agent B was always kept stationary while Agent A transferred the target apple. We manipulated the cost for Agent B to obtain the target apple by placing an obstacle (i.e., whether B was enclosed by a fence) in front of B. In this setup, if Agent A placed the apple in front of Agent B, and since objects in front of an agent are understood to belong to that agent (Tatone et al., 2015), Agent B obtained the target apple. When a fence was present in front of Agent B, making it difficult to cross the obstacle, the action cost for Agent A to place the target in front of B was less than the cost for Agent B to obtain the target through its own actions. However, when no fence was present in front of Agent B, the cost for Agent B to obtain the target through its own actions (path length) was less than the cost for Agent A to place the target in front of B. Since the fence condition satisfied the cost-minimization condition, Agent A should be recognized as having social intention in this scenario. In contrast, the no-fence condition should be recognized as non-social object-directed intention or weaker social intention. Because these two scenarios differ physically (presence or absence of a fence), direct comparison of mu suppression differences could be explained by physical-level differences. Therefore, we compared each experimental condition with its respective control condition, where Agent A used the same movement pattern but placed the apple in front of a stone enclosed by a fence. This behavior was unrelated to Agent B and represented a typical non-social intention behavior pattern (Tatone et al., 2015; Yin et al., 2020). If people can indeed use cost-minimization information as a cue to recognize social intention, then when Agent B is enclosed by a fence, Agent A placing the apple in front of B (satisfying cost minimization) should be recognized as having social intention, showing stronger mu suppression than the control condition where Agent A places the apple in front of a stone (Experiment 1). However, when Agent B is not enclosed by a fence, neither placing the apple in front of B nor any other action satisfies cost minimization. Therefore, Agent A placing the apple in front of B should be recognized as object-directed intention or weaker social intention, and we predicted that mu suppression would show no difference or a smaller difference from the control condition compared to the fence scenario

(Experiment 2).

To further test our hypothesis, this study also employed a behavioral indicator (as shown in Figure 1) to examine whether participants recognized social intention by measuring their sensitivity to different changes (i.e., discriminability). The experiment used a change detection paradigm, requiring participants to memorize a series of animations with identical action patterns (memory items) and then judge whether the animation in the test phase (test item) had appeared among the memory items (as shown in Figure 7 [Figure 7: see original paper]). Changes in test items included role exchange (where Agent A placing the apple in front of Agent B becomes Agent B placing the apple in front of Agent A) and structural change (where Agent A placing the apple in front of Agent B and Agent C placing the apple in front of Agent D becomes Agent C placing the apple in front of Agent B). Previous research has confirmed that, similar to Gestalt organization, two individuals with social interaction intentions are organized together in working memory and stored as an integrated unit (Stahl & Feigenson, 2014; Vestner et al., 2019; Ding et al., 2017). Since memory grouping can enhance discriminability across whole structures but cause confusion among elements within a structure (Papeo, 2020; Sedikides et al., 1993; Sherman et al., 2002; Suzuki & Cavanagh, 1995), we hypothesized that when Agents A and B have interactive intentions, they would be integrated into a memory group with interactive relationships. Consequently, people would more easily detect structural changes but be insensitive to role exchanges, showing a memory confusion effect (Experiment 3a). Conversely, discriminability would be comparable (Experiment 3b).

Experiment 1

This experiment used parietal mu rhythm as an indicator, presenting animations where Agent A placed an apple in front of Agent B enclosed by a fence or in front of a stone enclosed by a fence, to examine whether the former was recognized as having social intention.

Participants

Twenty-one university students voluntarily participated in this experiment. One participant was excluded due to poor EEG data quality caused by electrode detachment or excessive movement during data collection. Valid data were obtained from 20 participants (8 males, 12 females) aged 17-24 years (M = 19.5, SE = 0.4). All had normal or corrected-to-normal vision, no color blindness, and no physical or mental illnesses. Participants received 50 RMB as compensation after the experiment. This sample size referenced previous studies using mu indicators to investigate action processing, particularly interactive behavior processing, which typically had around 20 participants and yielded medium effect sizes (f between 0.25-0.46; Kourtis et al., 2019; Yin et al., 2017). To maintain consistency in sample size across experiments, 20 valid participants were recruited for subsequent experiments. The experiment was approved by the Ningbo University Psychology Research Ethics Committee, and all participants were fully informed of the experimental requirements and signed informed consent forms before the experiment.

Apparatus

The experiment used a 19-inch CRT monitor with a resolution of 800×600 and a refresh rate of 100 Hz. Participants were seated approximately 60 cm from the screen. All stimulus presentation and experimental procedures were controlled using the Psychophysics Toolbox (Brainard, 1997) in MATLAB.

Stimuli

Experimental stimuli were computer animations created using 3D animation modeling software Blender 2.78a, displayed at a size of $11.1°\times8.3°$. All animations were presented from a viewing distance of 12.2° and a 3D perspective angle of 73°. Each animation lasted 2 seconds and included two distinct animated characters (a moving agent, referred to as "Agent A," and a stationary agent, referred to as "Agent B"), a stone, and an apple. The appearance of the agents differed in each animation, with each trial randomly selecting from 36 different combinations (pairwise combinations of 9 different agent shapes). The stone and Agent B were positioned on opposite sides of the scene, 2.8° from the center, both enclosed by insurmountable fences with a small opening in the middle (through which agents could not pass) for Agent A to place the apple. At the start of each animation, the apple was located exactly between the stone and Agent B, and Agent A was positioned 1.6° above the screen center. Only Agent A moved during the animation: first moving vertically downward to the apple's location (0.5 s), then turning left or right toward Agent B or the stone (0.1 s), moving toward Agent B or the stone and placing the apple in front of B (0.5 s), and finally returning to its initial position (0.9 s). Two experimental conditions were created based on whether the apple was placed in front of Agent B (Figure 3a [Figure 3: see original paper]) or the stone (Figure 3b). These two conditions had identical kinematic properties except for the destination where Agent A placed the apple. When Agent A placed the apple in front of Agent B, the action cost was less than the cost for Agent B to obtain the target alone (which would require bypassing the nearly insurmountable fence), thus satisfying the cost-minimization condition and should be recognized as having social intention. Example animations can be viewed at https://osf.io/jfvxu/?view_{only}=c76000bc9a4b4f009151638441e79c99.

In addition to these two animation types, filler animations were created to require participants to count their occurrences, ensuring attention remained focused on the screen animations. These filler animations were essentially identical to the experimental animations except that Agent A randomly and continuously disappeared for 0.8 s between 0.3-1.7 s.

Procedure

The trial procedure is shown in Figure 4 [Figure 4: see original paper]. First, a dynamic fixation point was presented at the screen center for 480 ms, followed by a blank screen for 300-400 ms. Then, the first frame of the animation was presented. After 300 ms, the animation began playing for 2 s. The inter-trial interval was 900-1100 ms. Participants were instructed to watch the animations carefully and count the number of filler animations, reporting the count after each block.

The experiment consisted of two blocks, each containing 72 formal trials, with 36 trials per condition. The agent combinations in the 36 animation trials for each condition were all different, but the combinations were identical across conditions. Thus, aside from the context, all other physical information was consistent across conditions. In addition to the aforementioned settings, each block included 8-12 filler animations for attention checking. If participants' reported filler counts did not match the actual number, it indicated they may not have watched all videos attentively. Based on this attention check criterion, all participants accurately reported filler counts.

Data Recording

EEG was recorded using a NeuroScan Synamps 2 system (Compumedics NeuroScan Inc.) with an internationally standardized 10-20 64-channel Ag/AgCl electrode cap. The left mastoid electrode served as the reference, and the ground electrode was located midway between FPZ and FZ. Vertical eye movements (VEOG) were recorded from two electrodes placed above and below the left orbit, and horizontal eye movements (HEOG) were recorded from two electrodes placed 1.5 cm lateral to the outer canthi of both eyes. EEG signals were acquired with a gain of 500, a sampling rate of 500 Hz, and a band-pass filter of 0.05-100 Hz. Impedance between electrodes and scalp was maintained below 5 kΩ.

Data Analysis

Data were analyzed using the EEGLAB and Fieldtrip toolboxes in MATLAB. Preprocessing was conducted with EEGLAB. First, the left mastoid reference was converted to an average of left and right mastoids, followed by filtering the data from 0.1-100 Hz (fir1). Next, electrodes recording eye movements were removed, and independent component analysis (ICA) was performed. The ADJUST plugin in EEGLAB was used to identify and remove ocular and noise components from the independent components. Finally, EEG data were segmented from 500 ms before movement onset to 2000 ms after movement onset (animation end point).

Following preprocessing, Fieldtrip was used for spectral analysis. Specifically, for each segmented dataset, Morlet wavelet analysis was performed on rhythms from 4-30 Hz in 0.5 Hz steps with a bandwidth of 3 Hz. The energy value from the 500 ms period before movement onset was used as the baseline (this duration ensured at least three complete cycles of the target analysis frequency band). Energy values for each segmented dataset (from 500 ms before to 2000 ms after movement onset) were baseline-corrected. Finally, data were averaged across trials for each participant.

Consistent with previous research, the mu frequency band in this experiment was 8-13 Hz (Fox et al., 2016; Muthukumaraswamy et al., 2004; Ulloa & Pineda, 2007). Numerous studies have shown that the mu band related to action processing primarily appears in parietal motor areas, with C3 and C4 electrodes commonly selected in EEG research (Duan et al., 2018; Pomiechowska & Csibra, 2017). Therefore, this experiment also selected C3 and C4 electrodes to analyze activation patterns in the mu band. Since individual differences in scalp thickness and impedance can cause variations in mu band activation across participants (Pineda & Oberman, 2006), we followed previous studies (Cuevas et al., 2014; Pfurtscheller & Silva, 1999) by subtracting baseline energy values from mu band energy values during animation presentation, dividing by baseline energy values, and multiplying by 100% to obtain mu energy values. That is, for each participant, the dependent variable = (mu band energy during animation presentation - mu band energy during baseline) / mu band energy during baseline × 100%, with values less than zero indicating suppression. To further verify that mu band activity was not a generalization of occipital alpha activity, we conducted similar analyses on alpha at occipital O1 and O2 electrodes, following previous research (Klimesch et al., 2007; Perry et al., 2011). The results showed no differences in occipital alpha activity across different animation types in both experiments (see Appendix, available at https://osf.io/jfvxu/?view_{only}=c76000bc9a4b4f009151638441e79c99). Since the dynamic agent (Agent A) approached different objects between 600-1000 ms after movement onset—a time window where movement patterns differed across conditions—the average energy in this time window was used as the dependent variable.

Before conducting the between-subjects design experiments reported here, we also collected data from 10 participants using a within-subjects design (results in Appendix). However, all participants reported that the contrast between fence-present and fence-absent scenarios was obvious and that the experimenter' s placement of the fence was purposeful, leading us to adjust to a between-subjects design. More importantly, the fence-present and fence-absent scenarios for Agent A placing the apple in front of Agent B differed physically (different fence presence and occlusion of Agent B), so mu suppression differences found through direct comparison could be explained by physical-level differences. Therefore, we compared the fence-present and fence-absent conditions where Agent A placed the apple in front of Agent B with their respective control conditions, resulting in the current between-subjects design.

Results and Discussion

The 8-13 Hz band energy evoked under different conditions at different electrodes and the difference topographies are shown in Figures 5 [Figure 5: see original paper] and 6. A repeated-measures ANOVA on mu relative energy values with 2 (electrode: C3 vs. C4) × 2 (placement destination: agent vs. stone) revealed only a significant main effect of placement destination, $F(1, 19) = 8.71$, $p = 0.008$, ^{2}p = 0.31, 95% CI of the difference = [-15.1%, -2.6%]. When the dynamic agent placed the apple in front of the static agent (Agent B), mu band energy (M = -17.3%, SE = 3.6%) was significantly stronger (greater suppression) than when placing it in front of the static stone (M = -8.5%, SE = 4.6%). The main effect of electrode was not significant, $F(1, 19) = 0.80$, $p = 0.382$, ^{2}p = 0.04, 95% CI = [-9.5%, 3.8%], and the interaction between electrode and placement destination was not significant, $F(1, 19) < 0.01$, $p = 0.975$, ^{2}p < 0.01.

For 8-13 Hz band energy across all electrodes, cluster-based permutation tests (permutation test; Maris & Oostenveld, 2007) were conducted using Monte Carlo simulation with 500 sampling iterations, requiring at least two adjacent electrodes to show significant differences in 8-13 Hz band energy when the apple was placed at different destinations. The results again showed significantly greater mu suppression at C3 and C4 electrodes when the apple was placed in front of the agent compared to the stone condition, while no differences were found at O1 and O2 electrodes. Electrodes showing significant differences are illustrated in Figure 6c [Figure 6: see original paper]. Thus, the ANOVA results cannot be explained by the specific selection of electrodes.

These findings show that when Agent B was enclosed by a fence, Agent A placing the apple in front of Agent B produced stronger mu suppression than the control condition of placing the apple in front of a stone. This effect was not due to generalized alpha activity and supports the hypothesis that cost-minimization information is an important cue for social intention recognition.

Experiment 2

In Experiment 1, when Agent A placed the apple in front of Agent B, Agent A' s action reduced Agent B' s action cost to achieve the goal, satisfying the cost-minimization condition, and mu suppression was significantly greater than the control condition recognized as object-directed intention. However, it is possible that merely approaching another agent, rather than cost-minimization information, led to the recognition of social intention. This experiment tested this alternative explanation by removing cost-minimization information. Agent A maintained the same movement characteristics as in Experiment 1, but the fences enclosing Agent B and the stone were removed, making Agent B' s cost to obtain the apple less than Agent A' s cost to place it in front of B (i.e., violating cost minimization). If people indeed recognize social intention based on cost-minimization information, then when Agent A places the apple in front of Agent

B without a fence (violating cost minimization), the effect from Experiment 1 should disappear. Conversely, if the effect persists, it would suggest that social intention recognition between agents depends on other cues, such as the behavior of approaching an agent.

Participants

Twenty university students voluntarily participated in this experiment (8 males, 12 females). Participants were aged 17-24 years (M = 19.9, SE = 0.4), with normal or corrected-to-normal vision, no color blindness, and no physical or mental illnesses.

Methods

The experimental design and procedure were essentially identical to Experiment 1, except that the fences in front of the target objects (agent or stone) were absent (as shown in Figures 3c and 3d). Data collection and analysis were the same as in Experiment 1.

Results

The 8-13 Hz band energy evoked under different conditions and the difference topographies are shown in Figures 5 and 6. A repeated-measures ANOVA on mu relative energy values with 2 (electrode: C3 vs. C4) × 2 (placement destination: agent vs. stone) revealed no significant main effect of electrode, $F(1, 19) = 2.96$, $p = 0.101$, $^2p = 0.14$, 95% CI = [-10.3%, 1.0%]; no significant main effect of placement destination, $F(1, 19) = 0.18$, $p = 0.677$, $^2p < 0.01$, 95% CI = [-7.0%, 10.5%]; and no significant interaction, $F(1, 19) = 0.49$, $p = 0.494$, $^2p = 0.03$. Using the same cluster-based permutation test as in Experiment 1, no electrodes showed significant differences in 8-13 Hz energy between conditions.

To further verify that the results of Experiment 1 were indeed due to differences in action recognition, we combined data from C3 and C4 electrodes to form a 2 (experiment: Experiment 1 vs. Experiment 2; between-subjects variable) × 2 (placement destination: agent vs. stone; within-subjects variable) design and conducted an ANOVA on parietal mu band energy. The results showed no significant main effect of experiment, $F(1, 38) = 1.33$, $p = 0.257$, $^2p = 0.03$; no significant main effect of placement destination, $F(1, 38) = 1.90$, $p = 0.176$, $^2p = 0.05$; but a significant interaction between the two factors, $F(1, 38) = 4.27$, $p = 0.046$, $^2p = 0.10$. When Agent A placed the apple in front of Agent B, mu suppression was significantly stronger with the fence present (M = -17.3%, SE = 3.6%) than without the fence (M = -4.8%, SE = 5.6%; $t(38) = 1.89$, $p = 0.034$, Cohen' s d = 0.60, one-tailed test). This difference disappeared when Agent A placed the apple in front of the stone ($t(38) = 0.28$, $p = 0.390$, Cohen' s d = 0.09). These results suggest that the experimental manipulation modulated parietal mu band energy across different action patterns, further supporting that Experiment 1' s results were indeed due to differences in action recognition outcomes.

Experiment 3a

This experiment presented the same animations as Experiment 1 but used a change detection paradigm to measure participants' discriminability for different changes based on signal detection theory, examining whether a memory confusion effect would occur to further test our hypothesis.

Participants

Consistent with the sample size of previous studies, 20 university students voluntarily participated (7 males, 13 females). Participants were aged 17-24 years (M = 21.2, SE = 0.3), with normal or corrected-to-normal vision, no color blindness, and no physical or mental illnesses.

Methods

The stimulus materials were identical to Experiment 1, but the procedure was changed to a change detection paradigm (as shown in Figure 7). Specifically, a dynamic fixation point was presented at the screen center for 480 ms, followed by a blank screen for 300-400 ms. Then, four identical-pattern animations were sequentially displayed as memory items within a white frame (11.1°$×$8.3°), each lasting 2000 ms with a 1000 ms blank interval between them. Subsequently, a single animation was presented with the white border turning red to alert participants that this was the test item, lasting 2000 ms. After the test item disappeared, participants were asked to judge as accurately as possible whether the test item had appeared among the memory items. If the test item was identical to a memory item, participants pressed the "J" key; otherwise, they pressed the "F" key. If no key was pressed within 2000 ms, the program automatically advanced to the next trial. The inter-trial interval was 1500 ms.

In each trial, all memory and test items had the same action pattern (i.e., movement path and whether the apple was placed in front of an agent or stone), but each memory item featured a pair of agents with different appearances. In test items, three conditions were distinguished based on changes in agent appearance, as shown in Figure 8 [Figure 8: see original paper]: (1) No change, presenting a pair of agents identical to a memory item with consistent agent roles (i.e., randomly selecting a memory item as the test item); (2) Role exchange, where the agents in the test item came from a memory item but their roles were swapped (i.e., Agent A placing the apple in front of Agent B became Agent B placing the apple in front of Agent A); (3) Structural change, where agents occupying the same role across two animations in the memory items were swapped (i.e., Agent A placing the apple in front of Agent B and Agent C placing the apple in front of Agent D became Agent C placing the apple in front of Agent B). Since the action patterns were identical in memory and test items, participants only needed to judge changes based on the appearances of the two agents in the animations, allowing us to detect whether participants had formed memory groups of the two agents in the animations.

To balance trial numbers across change types, the number of trials in the no-change condition equaled the sum of trials in the role exchange and structural change conditions. For no-change trials, half were treated as no role exchange and half as no structural change. In fact, there was no difference between no-role-exchange and no-structural-change conditions; they were simply distinguished for subsequent data analysis. All change conditions appeared in both the agent-placement and stone-placement conditions. Each condition had 20 trials, resulting in 160 total trials divided into 4 blocks, with a 5-minute rest after each block. All trials were presented in pseudo-random order, with no identical condition repeated across three consecutive trials.

Data Analysis

To test the memory confusion effect—that is, whether placement destination (agent vs. stone) would modulate participants' sensitivity to different changes—we calculated sensitivity index d' (discriminability) for each change type based on signal detection theory, using "test item different from all memory items" (i.e., change) as the signal and "test item identical to a memory item" (i.e., no change) as the noise (Yin et al., 2018). To avoid infinite values when calculating d' , we followed Snodgrass and Corwin' s (1988) recommendation by adding 0.5 to the frequencies of hits, misses, false alarms, and correct rejections for each change type, then dividing by N+1 (where N is the corresponding frequency). This yielded discriminability values for a 2 (change type: role exchange vs. structural change) × 2 (placement destination: agent vs. stone) within-subjects design, which was analyzed using repeated-measures ANOVA. Additionally, decision criterion β values calculated based on signal detection theory are reported in the Appendix.

Results

Discriminability values under different conditions are shown in Figure 9 [Figure 9: see original paper]. A repeated-measures ANOVA on discriminability with 2 (change type: role exchange vs. structural change) × 2 (placement destination: agent vs. stone) revealed no significant main effect of change type, $F(1, 19) = 1.12$, $p = 0.304$, $^{2}p = 0.06$; no significant main effect of placement destination, $F(1, 19) = 0.11$, $p = 0.746$, $^{2}p = 0.01$; but a significant interaction between change type and placement destination, $F(1, 19) = 8.03$, $p = 0.011$, $^{2}p = 0.30$. Simple effects analysis revealed that in the agent-placement condition, discriminability for role exchange ($M = 1.38$, $SE = 0.24$) was significantly lower than for structural change ($M = 2.04$, $SE = 0.21$; $t(19) = 2.78$, $p = 0.012$, Cohen' s $d = 0.62$). In contrast, in the stone-placement condition, discriminability for role exchange ($M = 1.97$, $SE = 0.25$) was significantly higher than for structural change ($M = 1.51$, $SE = 0.23$; $t(19) = 2.26$, $p = 0.036$, Cohen' s $d = 0.50$). More importantly, in the role exchange condition, discriminability was significantly higher when the placement destination was the stone (M = 1.97, SE = 0.25) than when it was the agent (M = 1.38, SE = 0.24; t(19) = 2.33, p = 0.031, Cohen' s d = 0.52). Conversely, when the change type was structural change, discriminability was significantly higher in the agent-placement condition (M = 2.04, SE = 0.21) than in the stone-placement condition (M = 1.51, SE = 0.23; t(19) = 3.21, p = 0.005, Cohen' s d = 0.72), demonstrating a memory confusion effect.

Experiment 3b

To further test the role of cost-minimization information, Experiment 3b removed this information (as in Experiment 2) to observe whether the effects from Experiment 3a would disappear.

Participants

Twenty university students voluntarily participated (7 males, 13 females). Participants were aged 17-24 years (M = 20.1, SE = 0.4), with normal or corrected-to-normal vision, no color blindness, and no physical or mental illnesses.

Methods

The experimental design and procedure were essentially identical to Experiment 3a, except that the fences in front of target objects (agent or stone) were absent. Data analysis was the same as in Experiment 3a.

Results

Discriminability values under different conditions are shown in Figure 9. A repeated-measures ANOVA on discriminability with 2 (change type: role exchange vs. structural change) × 2 (placement destination: agent vs. stone) revealed a significant main effect of change type, F(1, 19) = 8.14, p = 0.010, ^{2}p = 0.30, with higher discriminability for role exchange (M = 2.09, SE = 0.25) than structural change (M = 1.42, SE = 0.22). The main effect of placement destination was not significant, F(1, 19) = 0.48, p = 0.495, ^{2}p = 0.03, and the interaction between change type and placement destination was not significant, F(1, 19) = 0.64, p = 0.434, ^{2}p = 0.03.

General Discussion

This study addressed the question of what information the visual system uses to recognize social (interactive) intentions. We proposed that when the cost for individual A to assist individual B in achieving a goal state is less than the cost for individual B to achieve that state alone (cost-minimization information), the visual system recognizes the action as having a social intention directed from the actor to the beneficiary. To test this hypothesis, we presented animations where Agent A placed an apple in front of Agent B or a stone, manipulating cost-minimization information by placing an obstacle (i.e., whether B was enclosed by a fence) in front of Agent B. Using four experiments, we investigated whether cost-minimization information serves as a cue for social intention recognition. The results showed that compared to the control condition recognized as object-directed intention (i.e., Agent A placing the target apple in front of a stone), when Agent A placed the apple in front of Agent B blocked by a fence—thereby reducing B' s action cost to obtain the apple and satisfying the cost-minimization condition—mu suppression was greater (Experiment 1), discriminability for structural changes (swapping agents serving the same role across two animations) was stronger, but discriminability for role exchanges (swapping roles between two agents within an animation) was weaker (Experiment 3a). However, when the fence was absent, although Agent A' s movement path was identical to Experiment 1, the cost for A to place the apple in front of B exceeded the cost for B to obtain the apple alone, violating the cost-minimization condition. Under these circumstances, differences in mu suppression between conditions disappeared (Experiment 2), and discriminability for different types of changes was comparable (Experiment 3b).

Regarding possible reasons for the differences in mu suppression, this study established strict control conditions to ensure they could only be explained by differences in intention recognition outcomes. First, because the fence-present and fence-absent conditions for Agent A placing the apple in front of Agent B differed physically (different fence presence and occlusion degree of Agent B), differences in mu suppression could reflect physical-level differences. Therefore, we compared each condition with its respective control condition—Agent A placing the apple in front of a stone. This design better excluded physical difference explanations: since the only difference participants saw was Agent A' s movement direction, which was balanced across conditions through randomization, differences in mu activation could only result from the special information conveyed by placing the apple in front of Agent B. Additionally, the control condition of Agent A placing the apple in front of a stone represented a typical object-directed intention, providing a baseline for interpreting the experimental condition of Agent A placing the apple in front of Agent B: if the latter' s mu activation was comparable to the control condition, it would indicate recognition as object-directed intention; if mu activation was stronger than the control condition, it would indicate recognition as social intention. Furthermore, we directly manipulated cost-minimization information (Experiments 1 and 2). The results showed that when cost-minimization information was absent (no fence), the experimental condition of Agent A placing the apple in front of Agent B showed mu activation comparable to the control condition of Agent A placing the apple in front of a stone. This reveals that the differences in mu activation between conditions in Experiment 1 were indeed due to different intention recognition outcomes. These results not only replicate Yin et al.' s (2020) finding that mu activation increases with stronger social intention but also extend their research by revealing a new cue applicable to social intention recognition.

In Yin et al.’ s (2020) study, the apple was in front of Agent A, and the costs for A to transfer the apple and for B to obtain it were identical. The key cue triggering social intention recognition was Agent A “transferring one’ s own item to another.” Our study did not include this “transferring one’ s own item to another” animation setup but instead manipulated the cost-minimization cue.

In addition to using EEG indicators to examine perceived intention types, this study also employed a change detection paradigm and signal detection theory to measure participants’ sensitivity to different changes. For memory of two agents with social interaction intentions, previous research has demonstrated that they can be integrated into a memory group unit (Stahl & Feigenson, 2014; Vestner et al., 2019; Ding et al., 2017). Therefore, people more easily detect structural changes but are insensitive to role exchanges, showing a memory confusion effect. This memory effect appeared when Agent A placed the apple in front of Agent B enclosed by a fence, suggesting recognition as social intention and further validating the EEG-based conclusions. When the fence was removed—eliminating cost-minimization information—only higher discriminability for role exchange than structural change was observed, comparable to discriminability for different changes in the control condition of Experiment 3a. The reason may be that in the animations, the actor (Agent A) was moving while the recipient (Agent B) remained stationary. When no social intention or weak social intention existed between agents, they were not grouped in memory but stored as individual agents. Thus, when the moving agent became stationary, the physical state changed substantially, making it easier for participants to detect. However, this phenomenon weakened or even reversed in the cost-minimization condition (Agent A placing the apple in front of Agent B enclosed by a fence), further indicating that it was recognized as having social intention, thereby producing memory grouping.

Our finding that an agent placing an apple in front of another agent (without cost-minimization information) was not recognized as having social intention seems to contradict everyday experience. Empirically, contact between two people is highly likely to be interpreted as having social intention. However, this experiential interpretation often has prerequisites: both parties must show overt behavioral responses, or even if one party shows no behavioral response, internal psychological changes are attributed (e.g., “he harbors resentment inwardly”). Everyday experience typically involves interactive parties with overt responses (e.g., handshaking), which includes another important cue in social intention recognition—contingency—so it is interpreted as having social intention. Regarding the first possible prerequisite, our study only had one party showing behavioral response (movement) while the other remained permanently stationary, making it difficult to satisfy. Regarding the second prerequisite, in Experiment 2, Agent A placing the apple in front of Agent B could indeed be interpreted as A wanting to interact with B, but B being unwilling. However, this interpretation strongly depends on experiential speculation about others’ mental states and personal experience, lacking stability in inference outcomes because different people have different interpretations. In fact, deeper analysis reveals that placing an object in front of someone does not necessarily represent social intention (e.g., students placing books in front of a teacher before an exam begins). Why do different levels of explanation emerge? This relates to the cognitive systems humans use to understand behavior, which are believed to consist of mentalistic representation and teleological representation (Gergely & Csibra, 2003). The former explains others' actions based on speculation about their possible mental states, relying on thoughtful consideration of mental states through experience, such as interpreting someone' s seemingly friendly behavior toward others as having malicious intent inwardly. This is difficult to become a universal cue in social intention inference because it varies across individuals. The latter explains others' action intentions based on directly observable elements—such as contextual constraints, action costs, and benefits—following the principle of utility maximization. This process has automatic processing characteristics, does not require task instructions, and the observed information can become one of the important cues for action recognition (Buon et al., 2013). In our study, participants did not need to deliberately reason about observed actions but passively observed while counting possible filler trials, relying more on teleological representation of actions. Based on this representation, they detected a reliable cue—the sufficient condition for social intention recognition, namely cost-minimization information—and recognized it as having social intention. However, when cost-minimization information is missing in this recognition process, people may search for other reliable cues or even be influenced by personal experience in speculating about others' mental states—questions for future research.

This study used animations to simulate actions, allowing effective manipulation of action contexts and strict control of extraneous variables—a method widely applied in action understanding research. However, this method abstracts human actions to some extent, and the ecological validity of its findings needs to be tested with real human actions. Additionally, to effectively control the action costs of interactive parties, our manipulation of cost-minimization information primarily relied on varying the path length for Agent B to obtain the target. Future research could further manipulate the path length for Agent B to obtain the target and use psychophysical methods to obtain subjective equivalence points where costs and benefits are equal, thereby testing the generalizability of our conclusions.

Conclusion

By manipulating whether the cost for individual A to assist individual B in achieving a goal state was less than the cost for individual B to achieve that state alone—i.e., whether cost-minimization information was present—this study used mu suppression and discriminability for different changes as indicators to investigate whether people use cost-minimization information to recognize social intentions. The following conclusion was reached: Whether the behaviors of two individuals satisfy cost-minimization influences how action intentions are recognized, revealing that cost-minimization information is an important cue for recognizing social intentions.

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Appendix

1.1 Experiment 1

Occipital alpha band energy under different conditions is shown in Supplementary Figure 1. A repeated-measures ANOVA on occipital alpha band energy with 2 (electrode: O1 vs. O2) × 2 (placement destination: agent vs. stone) revealed no significant main effect of electrode, $F(1, 19) = 0.47$, $p = 0.500$, $^2p = 0.02$; no significant main effect of placement destination, $F(1, 19) = 0.01$, $p = 0.920$, $^2p < 0.01$; and no significant interaction, $F(1, 19) = 0.67$, $p = 0.423$, $^2p = 0.03$. These results indicate that differences in mu energy evoked by different animation types were not due to generalization of occipital alpha activity.

1.2 Experiment 2

Occipital alpha band energy under different conditions is shown in Supplementary Figure 1. A repeated-measures ANOVA on occipital alpha band energy with 2 (electrode: O1 vs. O2) × 2 (placement destination: agent vs. stone) revealed no significant effects. Specifically, the main effect of electrode was not significant, $F(1, 19) = 0.24$, $p = 0.628$, $^2p = 0.01$; the main effect of placement destination was not significant, $F(1, 19) < 0.01$, $p = 0.957$, $^2p < 0.01$; and the interaction was not significant, $F(1, 19) = 0.97$, $p = 0.337$, $^2p = 0.05$.

2.1 Experiment 3a

Regarding decision criteria (Supplementary Figure 2), a repeated-measures ANOVA with 2 (change type: role exchange vs. structural change) × 2 (placement destination: agent vs. stone) revealed no significant effects. Specifically, the main effect of change type was not significant, $F(1, 19) = 3.60$, $p = 0.073$, $^2p = 0.16$; the main effect of placement destination was not significant, $F(1, 19) < 0.01$, $p = 0.953$, $^2p < 0.01$; and the interaction was not significant, $F(1, 19) = 0.13$, $p = 0.718$, $^2p < 0.01$.

2.2 Experiment 3b

Regarding decision criteria (Supplementary Figure 2), a repeated-measures ANOVA with 2 (change type: role exchange vs. structural change) × 2 (placement destination: agent vs. stone) revealed no significant effects. Specifically, the main effect of change type was not significant, $F(1, 19) = 3.24$, $p = 0.088$, $^2p = 0.15$; the main effect of placement destination was not significant, $F(1, 19) = 0.26$, $p = 0.618$, $^2p = 0.01$; and the interaction was not significant, $F(1, 19) = 0.16$, $p = 0.693$, $^2p < 0.01$.

3. Preliminary Within-Subjects Design Results

Regarding the within-subjects design, preliminary data were collected from 10 participants. The results showed that with the fence present, activation when placing toward the agent was significantly stronger than when placing toward the stone (Wilcoxon $W = 5.00$, $p = 0.020$, Cohen' s $d = 0.82$). Without the fence, no significant difference in activation was observed (Wilcoxon $W = 34.00$, $p = 0.557$, Cohen' s $d = 0.24$). When Agent A placed the apple in front of Agent B, activation with the fence present showed a trend of being significantly stronger than without the fence (Wilcoxon $W = 9.00$, $p = 0.064$, Cohen' s $d = 0.67$).

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

Source: ChinaXiv —Machine translation. Verify with original.