Decoding Virtual Agent's Emotion and Strategy from Brain Patterns

Eunkyung Kim, Sarah I. Gimbel, Aleksandra Litvinova, Jonas T. Kaplan and Morteza Dehghani
{eunkyung; sgimbel; alitvino; jtkaplan; mdehghan}@usc.edu
University of Southern California, Los Angeles, CA 90089 USA

Abstract

Recent advances in technology have paved the way for human-agent interactions to become ubiquitous in our daily lives, and decades worth of research on virtual agents have enhanced these interactions. However, for the most part, the effect of different types of agents on the human brain is unknown, and the neuroscience of human-agent interactions is rarely studied. In this study, we examine the underlying neural systems involved in processing and responding to different types of negotiating agents. More specifically, we show that different brain patterns are observed for various types of virtual agents; consequently, we can decode the strategy and emotional display of the agent based on the counterpart's brain activity. Using fMRI data, we analyzed participants' brain activity during negotiations with agents who show three different emotional expressions and use two different types of negotiation strategies. We demonstrate that, using Multi-Voxel Pattern Analysis, we can reliably decode agents' emotional expressions based on the activity in the left dorsal anterior insula, and also agents' strategies based on the activity in the frontal pole.

Keywords: Human-Agent Interaction; Negotiation; Emotion; Decision-Making; fMRI

Introduction

Virtual agents have become a part of our daily lives. From commercial websites that make use of chat agents for answering users' questions in personalized settings to educational and training software that incorporate virtual agents to provide better learning experiences, our numbers of interactions with virtual agents have dramatically increased in the past couple of years.

Parallel to this increase, various lines of research have studied the interactions between humans and virtual agents. For example, research has examined the contributing factors to user engagement (Bickmore, Schulman, & Yin, 2010; Castellano, Pereira, Leite, Paiva, & McOwan, 2009) and establishment of bonds with virtual agents (Cassell & Thorisson, 1999; Wang & Gratch, 2009). Bickmore et al. (2010) showed that people engage more with life-like virtual agents, such as a relational agent who remembers past history and relates to that history when communicating. Moreover, Wang and Gratch (2009) demonstrated that virtual agents who give non-verbal immediacy feedback, such as eye contact and gestures, are found to establish rapport with human partners.

Related to our research, the effects of emotion and strategies are among the most widely explored topics in human-agent interaction research (Maldonado et al., 2005; Kim, Dehghani, Kim, Carnevale, & Gratch, 2014; Van Kleef, De Dreu, & Manstead, 2004). These factors are particularly important because they are central in providing clues about the internal states and the intentions of the counterpart in any type of interactions (Jurafsky, Ranganath, & McFarland, 2009; Rafaeli & Sutton, 1987). Previous studies on the effect of emotion include the work of Maldonado et al. (2005) where they demonstrated that people who interact with an emotional agent perform better on a test than those who interact with an emotionless agent in a web-based learning environment. Van Kleef et al. (2004) argue that automated agents who express emotions, such as anger or happiness, elicit different levels of concessions based on the type of expressed emotions. Also, several researchers have examined the effects of different types of negotiation strategies during human-agent interactions. For example, Das, Hanson, Kephart, and Tesauro (2001) demonstrated that the agreed trade prices from human-agent interactions are different for two types of agent strategies; one strategy is to maximize its expected surplus using trade history and the other strategy is to make small random adjustments to the trade price continuously. Similarly, Grosz, Kraus, Talman, Stossel, and Havlin (2004) demonstrated that there are particular agent strategies that elicit more concessions during negotiations.

These, along with numerous other studies, have helped the field establish sets of features that influence the quality of human-agent interaction, resulting in a more enhanced and realistic experience for the human user. However, with a few exceptions (e.g., Sanfey, Rilling, Aronson, Nystrom, and Cohen (2003)), the majority of these studies have for the most part treated the process and the mechanism through which these features affect the human counterpart as a black box; they demonstrate that a particular type of agent, with particular emotion and strategy, enhances a user's experience (e.g. performance on a test). However, the question of how these features affect the underlying neural mechanisms of the user that result in such enhancement still remains unanswered. For instance, even though it is established that interacting with an emotional agent results in better performance on a test than interacting with an unemotional agent (Maldonado et al., 2005; Karacora, Dehghani, Krämer-Mertens, & Gratch, 2012), the neuroscience of these interactions are not fully understood.

In this paper, we investigate the underlying neural systems that are activated when participants interact with agents who show different emotional expressions and apply different negotiation strategies. As various emotions and strategies have been related to diverse reactions in previous studies, we assumed that we could find differences between the neural processes that are activated when these factors are manipulated. To examine these differences, we studied people's neural activation while they were interacting with a virtual agent. We hypothesize that distinct patterns of brain activity would be observed for each agent type.

To study brain activity during human-agent interaction, we used functional magnetic resonance imaging (fMRI). We used a human-agent negotiation platform for the experiment in order to capture active interaction between a participant and a virtual agent while they are trying to reach an agreement. The virtual agent was designed to display three different emotional expressions and apply two fixed negotiation strategies, for six combinations of emotional expression and negotiation strategy. During the experiment, we had participants engage in several rounds of negotiations with the virtual agent inside the fMRI scanner. We then analyzed their brain patterns during the decision-making period using Multi-Voxel Pattern Analysis (Norman, Polyn, Detre, & Haxby, 2006).

We focused our analyses on the anterior insula and the frontal pole. Anterior insula is a well-known emotion-related brain region that is consistently activated when processing basic emotions such as anger and sadness, as well as social emotions such as empathy and vicarious emotions (Kober et al., 2008; Lamm & Singer, 2010). It has been repeatedly reported that both observing the emotional facial expression and feeling the emotion activate the anterior insula (Zaki, Davis, & Ochsner, 2012). On the other hand, the frontal pole is one of well-known decision-making-related brain regions. It has been shown that frontal pole plays a significant role in thinking about the future (Okuda et al., 2003), and people with frontal pole impairment make disadvantageous decisions (Anderson, Bechara, Damasio, Tranel, & Damasio, 1999).

We hypothesize that an agent's negotiation strategy can be predicted based on the activity in the frontal pole, and an agent's emotional expression can be predicted based on the activity in the anterior insula. To validate these hypotheses, we compared participants' brain activities in these regions during negotiations in terms of an agent's emotional expression (angry, neutral, and sad), and an agent's negotiation strategy (conceding and non-conceding).

Our research contributes to a fast growing field of human-agent interaction, and is one of the first lines of work that investigates the underlying neural systems involved in the process of human-agent negotiation. This paper is organized as follows. First, we introduce our negotiation platform, the Objects Negotiation Task. Next, we explain our experimental settings and the design of our virtual agent. Then, we describe the parameters used to record fMRI data and how this data were analyzed. Finally, we show our results and discuss our findings.

Objects Negotiation Task

The Objects Negotiation Task is a multi-round human-agent negotiation platform (Dehghani, Carnevale, & Gratch, 2014) where a human negotiator and a virtual agent can negotiate diverse items over multiple rounds. We used a modified version of this task tailored for use in the fMRI. Common fruits were used as negotiation items, and the payoff for each item for both players were explicitly specified on the screen. In order to make sure all participants had the same goal during negotiations, they were asked to focus on maximizing their total payoffs. To ease the calculation of total payoffs, the system automatically calculated the player's total payoff as well as the agent's total payoff, and displayed whenever the items are redistributed.

When the negotiation starts, items are placed in the middle row indicating that they do not belong to anyone. After the participant distributes all the items, the 'Go!' button on the right bottom corner is enabled and the participant can propose his/her offer by clicking the button. The participant is then asked to wait until the virtual agent accepts or rejects the offer. If accepted, both parties get the proposed items and the negotiation ends. If rejected, the participant is asked to wait for the virtual agent to propose a counteroffer. Next, the virtual agent's offer is shown and the participant reviews the offer for five seconds. During this time, the participant simply observes the counteroffer and cannot relocate the items. For the fMRI version of the task, this review time was introduced to make sure that we can separate brain activity between the offer-making period and the non-offer-making periods. After the review, the participant decides whether to accept or reject the virtual agent's offer. If he/she accepts the virtual agent's offer, the negotiation ends. If rejected, the participant is again asked to wait for five seconds and then is redirected to the first step. Figure 1 shows an example of the timeline of the Objects Negotiation Task.

In our study, we used six types of agents characterized by the three types of emotions they expressed and the two types of offer sets representing their negotiation strategies. More details about these features are described in the following two sections.

Agent's Emotional Expressions

The role of emotional displays in negotiation has been extensively documented (Lerner, Li, Valdesolo, & Kassam, 2015). To find the neural mechanisms involved in processing different emotional displays in human-agent interactions, we used three types of facial expressions to express agents' emotions; angry, neutral (no emotion) and sad. Figure 2 shows agents' emotional expressions that were used in the experiment. In angry and sad conditions, the virtual agent's face starts as neutral and changes to the emotional expression for five seconds on the first, third, and fifth rounds of negotiation. In the neutral condition, the agent's face starts as neutral and does not change.

Agent's Negotiation Strategies

We used two sets of pre-programmed agent offer strategies: non-conceder and conceder. In the non-conceder strategy, the agent starts with no concession and continues with gradually increased concession. In the conceder strategy, the agent starts with some concessions and keeps conceding further in the next rounds.

When the virtual agent decides whether to accept or reject a participant's offer, the agent calculates the summed payoffs and compares it with its next offer. If the summed pay-

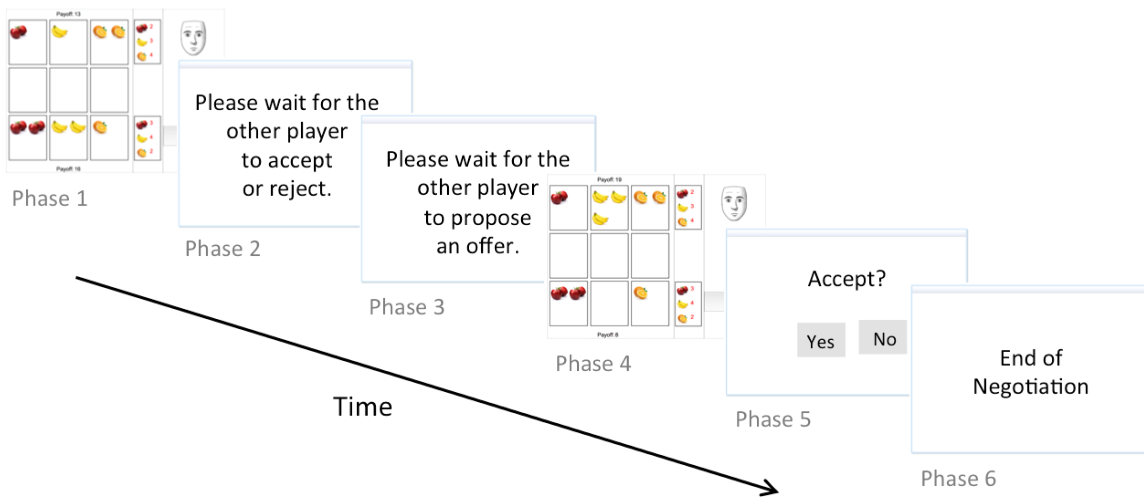

Figure 1: Timeline of the Objects Negotiation Task used in the fMRI experiment. During a negotiation, a participant and a virtual agent take turns in making a proposal. If the proposed offer is accepted, the negotiation ends. If rejected, the player who rejected the offer makes a new proposal.

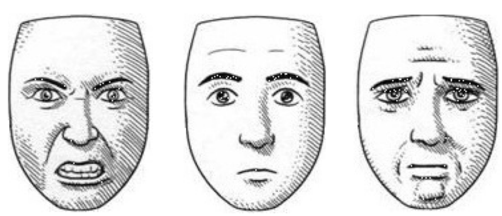

Figure 2: Agent's emotional expressions. Angry (left), neutral (middle), and sad (right).

offs are larger than the summed payoffs of the next offer, the agent accepts the offer. Otherwise, the agent rejects the offer and proposes a new offer. The same payoff matrix was used across all six negotiation tasks so that we could control for the potential effect of varying payoff values. However, we randomized the order of items shown on the screen in each task to give participants the impression that they were playing a new negotiation task every time.

Experiment

Participant

We recruited ten participants through an online bulletin board at the University of Southern California. Prior to the study, all participants completed a checklist to make sure they were eligible to take part in an MRI study. All procedures were approved by the USC Institutional Review Board and participants were provided with a written informed consent for the study. One participant's data was later excluded from the analyses because of technical problems with the obtained images.

Procedure

Upon arrival, participants completed the informed consent and each participant was asked to read the following hypothetical scenario:

> You are a restaurant owner in a small town. There has been a major fire in the market providing the necessary fruits for your restaurant and as a result only a limited number of fruits are available. Because of this you have to split the available fruits with another restaurant owner. You and the other owner value each fruit differently. In order to run your restaurant you need to get as many fruits as possible.
>
> In the task that follows, you will negotiate about how to distribute the fruits between you and the other restaurant owner.

After reading the scenario, participants were first invited to play a trial negotiation so that they got used to the interface of the task. Then participants performed six negotiation tasks inside an fMRI scanner. The total scan time for each participant was approximately 45 minutes.

Data Analysis

To study brain patterns during negotiations with various agents, we analyzed participants' brain activity using general linear models (GLM) analysis and multi-voxel pattern analysis (MVPA).

General Linear Model Analysis

To extract brain activity of the offer-making period from the whole negotiation period, we ran a general linear model (GLM) analysis using tools from the FMRIB's Software Library (FSL) (Smith et al., 2004). First, we pre-processed our fMRI data using FSL to reduce the noise of our dataset. Data pre-processing included the following mostly standard steps: (1) Motion-correction with MCFLIRT to fix head motion artifacts during scans, (2) Slice timing correction for interleaved acquisitions to compensate for timing difference between slices of functional images, (3) Non-brain structures removal with Brain Extraction Tool to remove non-brain regions, such as the scalp, (4) Spatial smoothing with a Gaussian kernel of full width at half maximum 5mm to increase statistical power by improving the signal to noise ratio, (5) High-pass temporal filtering to let high frequencies, such as activities relevant to experimental conditions, pass and to remove low frequencies such as signal drifts.

For each negotiation for each participant, changes in the blood-oxygen-level dependent signal were modeled with regressors for the offer-making period. Then the regressors were convolved with a double-gamma hemodynamic response function. The non-offer-making periods were modeled as baseline.

Multi-Voxel Pattern Analysis

When analyzing fMRI data, it is important to take into account the activity of the voxels, as well as the interactions between them because the activity in neighboring voxels is interdependent. However, given the univariate nature of GLM, the model fits to each voxel's time-course separately. To overcome this drawback, we used multi-voxel pattern analysis (MVPA) (Norman et al., 2006) which uses pattern-classification techniques to extract the pattern of response across multiple voxels.

We preprocessed the GLM analysis results and used them as inputs for the MVPA. The preprocessing included linear de-trending which removes any bias resulting from scanner drift over the acquisition time, and z-scoring which normalizes the range of each voxel. We used leave-one-participant-out cross-validation for MVPA, in which a classifier is trained on eight participants' data and then tested with the last participant's data.

Previous studies have shown that the anterior insula (AI) is activated when processing emotions (Kober et al., 2008; Lamm & Singer, 2010), and the frontal pole (FP) is activated when making a decision that affects the future (Okuda et al., 2003). We therefore hypothesized that the agent's negotiation strategy can be predicted based on the participant's brain activity in the FP, and the agent's emotional expression can be predicted based on the participant's brain activity in the AI. To test our hypothesis, we chose the AI and the FP as our regions of interest (ROIs), and performed ROI MVPA. In the following section, we explain the ROI MVPA approach.

Region of Interest Multi-Voxel Pattern Analysis To find the relationship between an agent's expressed emotion and brain activity as well as an agent's negotiation strategy and brain activity, we performed region of interest (ROI) MVPA with both the AI and the FP. The AI on each side of the brain can be divided into two subregions with distinct patterns of connectivity: dorsal anterior insula (dAI), connected to the dorsal anterior cingulate cortex; and the ventral anterior insula (vAI), connected to the pregenual anterior cingulate cortex (Deen, Pitskel, & Pelphrey, 2011). We ran ROI analyses for all four AI regions. On the contrary, the FP does not have widely accepted subregions (Moayedi, Salomons, Dunlop, Downar, & Davis, 2014). Thus, we ran ROI analysis for the whole FP labeled by the Harvard Center for Morphometric Analysis (Desikan et al., 2006).

To make sure brain activity in the AI or the FP is responsible either for agent's emotional expressions or negotiation strategies, we ran ROI analyses for both conditions, i.e., we calculated the prediction accuracy of agent's negotiation strategies using both the AI and FP as ROIs. We assumed that the prediction accuracy with their expected ROI would be significantly higher than the chance level, but the prediction accuracy with their unexpected ROI would be indistinguishable from chance.

We trained a linear Support Vector Machine (SVM) classifier using voxels from each of our ROIs separately using feature selection. Feature selection is a common approach used to reduce the number of features (voxels) by selecting only relevant features as input to a classifier. Classification performance improves with feature selection as it only picks features that vary significantly between categories (Guyon & Elisseeff, 2003). In our analyses, we used the GLM analysis results to compute the F-score for each voxel, and then used an analysis of variance (ANOVA) measure to select the top 10% of features with the highest F-scores.

Each participant's brain was transformed into standard MNI space (Evans et al., 1993) to have a brain that is more representative of the population. After performing this process for all participants, individual-level analyses were combined for a group-level analysis.

Results

As discussed previously, the AI is a brain region known to respond to emotional expressions, and it can be divided into two subregions with distinct patterns of connectivity. Therefore, we first ran ROI MVPA for all four (left/right $\times$ ventral/dorsal) AI regions separately. The prediction accuracies of emotional expression using our ROI MVPA with four AI regions indicate that ROI MVPA with the L-dAI has the best prediction accuracy (38.40%), while the prediction accuracy of other AI regions are indistinguishable from the chance level of 33%. A binomial test revealed that the prediction accuracy of the ROI MVPA with the L-dAI is significantly above chance ($p = 0.0566$). Therefore, we focus our analysis on the results of ROI MVPA with the L-dAI.

The prediction accuracy for decoding an agent's emotional expressions is higher for the L-dAI decoder (38.40%, compared to 33.87% for the FP ($p = 0.0960$) or chance ($p = 0.0566$). The prediction accuracy using the FP ROI MVPA was not different from chance ($p = 0.4266$). This supports our hypothesis that an agent's emotional expression can be

Table 1: Prediction accuracy on an agent's emotional expression and an agent's strategy from ROI MVPA. One-tail binomial tests were performed for each condition compared to the chance level, and significant results ($p < 0.05$) were marked with (*).

Region of Interest (ROI)	Condition	Prediction Accuracy	Chance Level
Left Dorsal Anterior Insula (L-dAI)	All Emotions	38.40% (*)	33.33%
	Angry	45.07% (*)	
	Neutral	29.60%	
	Sad	40.53% (*)	
Frontal Pole (FP)	All Strategies	58.96% (*)	50.00%
	Conceder	47.50%	
	Non-conceder	70.42% (*)	

reliably predicted using brain activity in the AI which is an emotion-related brain region, but not with information in the FP.

Similarly, the accuracies for predicting an agent's negotiation strategy using the ROI MVPA with the FP was 58.96%. A binomial test again confirmed that this performance is significantly higher than the chance level of 50% ($p = 0.0085$). The prediction performance was almost at chance (52.71%) for the L-dAI ($p = 0.2581$). This result validates our hypothesis that counterpart's negotiation strategy can be predicted based on brain activity in the FP, which is activated when people do active decision-making, but not with the insula, which is involved in emotion processing.

In order to examine these results in more detail, we broke down the predictions. Specifically, we analyzed the prediction accuracy for each agent's emotional expression and negotiation strategy from ROI MVPAs with anterior insular regions and frontal lobe (Table 1). Our results indicate that brain patterns in the L-dAI can predict angry and sad conditions but not neutral agent facial expressions. Also, brain patterns in the FP can predict the non-conceder negotiation strategy but not the conceder strategy.

Overall, our results confirm that negotiating with different types of agents results in activity in different brain regions, and these activity patterns can be used to further decode the specific type of interaction agent.

Discussion

The neuroscience of human-agent interactions is a rarely studied topic and the majority of studies treat the processes by which various agent features affect human participants as a black box. To answer the question of how these features interact with underlying neural mechanisms, we investigated brain activity during human-agent interactions. More specifically, participants engaged with virtual agents who showed three different emotional expressions (angry, neutral and sad) and used two different types of negotiation strategies (conceding and non-conceding). Using a human-agent negotiation platform, participants interacted with virtual agents in an fMRI scanner, and their brain activity during the interaction was recorded. We hypothesized that an agent's emotional expression could be predicted based on patterns in emotion-related brain regions, and an agent's negotiation strategy could be predicted based on patterns in decision-making-related brain regions. Therefore, we focused our analyses on the AI and the FP, as previous studies have shown that AI is activated when people engage in emotional tasks, and the FP is activated when people perform active decision-making tasks.

Our ROI MVPA results support our hypothesis; prediction accuracy of an agent's emotional expression based on brain patterns in the L-dAI, and that of agent's negotiation strategy based on brain patterns in the FP are well above the chance level. These results indicate that different features are likely processed in different brain regions. Finding which information is processed in certain brain regions would allow us to reliably decode the feature of the agent from users' brain activity. More detailed analyses revealed that brain patterns in the L-dAI could be used to predict angry (45.07%) and sad (40.53%) conditions, but not the neutral condition (29.60%). This indicates that there are clear differences in brain patterns in the L-dAI between angry and sad conditions. We hypothesize that the reason why the patterns in this region failed to predict the neutral condition is that the neutral facial expression is the default expression throughout the experiment. The facial expression of the agent only changes when it morphs into sad or angry. We plan to tackle this problem by only showing the agent's face during the decision making phase.

With regard to agent's negotiation strategies, predictions using brain patterns from the FP showed significantly higher accuracy compared to the chance level (50%) for the non-conceding condition (70.42%), but not for the conceding condition (47.50%). We assume that this is because participants expected to deal with a counterpart that acted like a conceding and fair agent, i.e. an agent who might start with a slightly unfair offer but over time it makes adjustments toward a fair offer. It is possible that the distinct patterns in the FP witnessed during negotiations with the non-conceding agent is because this agent acts in a very greedy and tough way that is not typical in social interactions. This could result in unique patterns of activity in the FP.

While our sample size could be considered small, we would like to note that sample size tends to be small in fMRI studies. Also, it is worth mentioning that the probability of finding the same effect as one found in the original experiment is not dependent on sample size, but dependent on p value (Killeen, 2005). This is because large effect sizes produce significant results, even with small sample size.

In conclusion, our results indicate that there is a link between an agent's emotional expression and brain activity in the L-dAI, and also between an agent's negotiation strategy and brain activity in the FP. Even though the results are preliminary, our work sheds light on the links between certain brain regions and different agent features. In future studies, we plan to continue investigating these links with other features such as voice tone and gestures, and hopefully over time construct a map of the brain regions activated by various agent features and compare these regions to human-human interactions.

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