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Machine Understanding of Human Implicit Intention

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Abstract:

We are trying to understand implicit (un-represented or hidden) human intention, which may be different from explicitly-represented one. Although the taxonomy of the implicit intention is not clear yet, we hypothesize that the implicit intention domain consists of two axes, i.e., the sympathy for one's represented intention and the sympathy for one's counterpart. The former had been studied in the framework of lie detection, while the latter is the new interest in this research. When the subjects read statements on computer screen, we measured fMRI, EEG, and pupil dilation. Also, the subjects were asked to reply as 'Yes' (Sympathy/Agreement to the statement) or 'No' (Non-sympathy/Disagreement).

For the fMRI experiments nineteen healthy right-handed Korean subjects (12 males and 7 females) were recruited from the student community in KAIST. Experiments were held with 3T MR scanner (Siemens Magnetom Verio, Germany) at KAIST Brain Science Research Center. The Sympathy cases have higher neural activation than the Non-sympathy cases in the left superior frontal gyrus and left anterior cingulated, which are known to be related with self-knowledge. Also, the Non-sympathy cases have higher neural activation than the Sympathy cases at the left fusiform gyrus, which is known to be related with unfamiliar words and faces. This fMRI experiments approve our hypothesis on the 2nd axis of the implicit intention space, i.e., Sympathy vs. Non-sympathy to the counterpart. We also conducted linear discriminant analysis (LDA) using pencil beam searching and identified brain areas with more than 70% classification for the Sympathy vs. Non-sympathy axis.

For the EEG experiments thirteen subjects (10 males and 3 females) were recruited and their EEG was recorded from 32-channel BrainAmp system (Brain Products GmbH, Germany). Twenty-nine electrodes were placed on the scalp according to the International 10-20 system. One electrode for recording eye movement (EOG) was positioned below subject's right eye. Two electrodes dedicated to the electrocardiogram (ECG1 and ECG2) were placed on subject's collarbones in both sides. Data were acquired with a sampling rate of 500Hz, along with 60Hz notch filtering. We work on two different electrode selection approaches, i.e., one based on the fMRI results (the left fontal electrodes such as F3 and Fp1) and the other with Fisher's linear discriminant analysis. Both ERP and frequency-band analysis are conducted. We had also trained Support Vector Machine (SVM) classifiers to classify single ERP from each channel, and obtained the maximum classification rate (78%) at the central frontal electrode, Fz.

In conclusion we had successfully tested a hypothesis on the implicit intention axis, i.e., Sympathy/Non-sympathy to one's counterpart, with fMRI experiments. Also, we showed that SVM classifiers are capable of classifying single-trial EEG on the axis.

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14. ABSTRACT

The project aimed at understanding implicit (un-represented or hidden) human intention. The implicit intention domain consists of two axes: the sympathy for one’s represented intention and the sympathy for one’s counterpart. This project focuses on the latter. The subjects were asked to read Korean statements on the screen and reply Yes (Sympathy/Agreement to the statement) or No (Non-sympathy/Disagreement). Korean has subject-object-verb structure and negation comes at the end. Thus, whether the statement is affirmative or negative is only known at the very end of sentence. The basic assumption is that the subjects make decision before reading to the end of sentence, which corresponds to the implicit intention. EEG, fMRI and pupil dilation signals were measured during this experiment. Experimental results indicate that there is clear difference between the activation levels of the measured signals, and it is possible to predict the subject’s response with the accuracy of about 80% by SVM.

15. SUBJECT TERMS

Brain Science and Engineering; Cognitive Neuroscience; Human-Computer Interface; Intelligent Systems

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Introduction:

Human-machine interface had been developed to understand explicitly-represented human intention such as speech, facial expression, and gestures. However, sometimes it may be too cumbersome to show all intention sequences explicitly. Also, there may be situations when people is reluctant to disclose his or her mind in daily social life. It may be especially true in Asian and military societies with strong vertical hierarchy. Therefore, it is desirable to understand implicit intention, both un-presented and hidden.

We are trying to understand implicit human intention, which may be different from explicitly-represented one. Although the taxonomy of the implicit intention is not clear yet, we hypothesize that the implicit intention domain consists of two axes, i.e., the sympathy for one's represented intention and the sympathy for one's counterpart. The former had been studied in the framework of lie detection, while the latter is the new interest in this research.

Experiment:

Two different types of recording experiments, i.e., EEG and fMRI experiments, were conducted with the same experimental paradigm and stimulus.

We had measured fMRI and EEG signals while showing somewhat personally-sensitive sentences to the subjects, and also asked to respond with a button as 'Sympathy" or "Non-Sympathy". Seventy-four stimulus sentences were selected for the experiment. Sentences were chosen from the list of Minnesota multiphasic inventory (MMPI) which is one of the most frequently used for psychological tests. Selected sentences were identified into two types; affirmative and negative sentences, which are all written in Korean.

Although the stimulus sentences may be given in any language, the subject-object-verb (SOV) structure of Korean language allows us to make a refinement on the experiment paradigm. In the SOV languages the subject, object, and verb of a sentence appear in sequence, and Korean, Japanese, Hindi, Latin are good examples of the SOV languages. An original English sentence "I read a book" may be re-structured in Korean as "I book read". In our experiments, only two existence verbs are used; to be("있다"), and not to be("없다") at the end of the sentences. Table 1 explains the difference of sentence structures between two languages. Translating into English, all sentences are in present perfect tense which is asking his/her experience. Due to the sentence order, it is uncertain whether or not this statement is affirmative or negative until the last word. Subject of sentence ("I") was omitted and unnecessary adverbs or adjectives were also left out. Also, some components which can imply negative form such as "any", "at all", "even once" etc. in contents block. Thus, subject cannot realize the type of sentences beforehand. Table 2 shows example of sentences which are translated into English. In the actual experiments, sentences were all given in Korean.

Table 1. Comparison between Korean and English Sentence Structures

Affirmative Statements				
Standard Korean	나는	물건을	훔친 적이	있다
Translation into English	I	something	have stolen	ever
Standard English	I have ever stolen things			
Negative Statements				
Standard Korean	나는	물건을	훔친 적이	없다
Translation into English	I	something	have stolen	never
Standard English	I have never stolen things			

Table 2. Example of Sentences in English

Affirmative Statements	Negative Statements
Had the same dream over and over Done anything dangerous for the thrill of it Been told that I walk during sleep Kept from stealing something Lost sleep over worry Worried about religion Had difficulty on urinating Heard so well it bothers to me Worried about my health	Never been in trouble because of my sex behavior Never worried over money and business Never had a fainting spell Never been in trouble with the law Never been in love with anyone Never had peculiar experience Never felt like swearing Never felt as if things were not real Never been afraid of my face becoming red

Experimental Paradigm

Type of sentences was classified according to the affirmative or negative sentence ending, but the order of presentation was random. Figure 1 shows the experiment paradigm. Starting with fixation cross, which is accompanied with beep sound, it was used to inform that next sentence will be shown soon and make them pay attention. One sentence consists of contents block and sentence end block. Each block is shown for 4 seconds. After a sentence is shown, an asterisk is presented also for 4 seconds. Subjects were asked to push the "Yes" button if he or she has been in those situations or agrees on those statements. Otherwise the subjects were asked to push the "No" button. All the button push should be made while the asterisk is shown. Subjects were asked to stay still and try not to blink too much during the task.

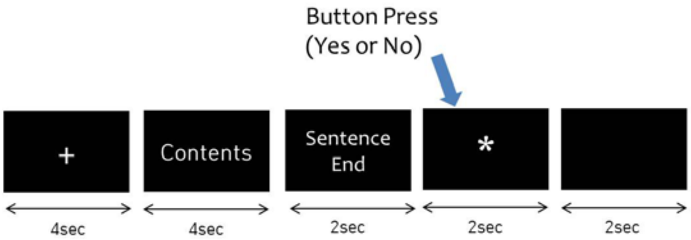

Figure 1. Experiment Paradigm

(1) EEG Experiment

Subjects

Nine healthy right-handed Korean subjects (6 men and 3 women) were recruited from the student community in KAIST. They are all KAIST undergraduate students, and voluntarily participated. All participants did not have a history of psychiatric disorder, significant physical illness, head injury, neurological disorder, and alcohol or drug dependence. After complete explanation of the study, written informed consent was obtained from all subjects. The study was submitted to the regular review in the KAIST institutional review board and approved.

Data Acquisition

Experiments were held at KAIST Brain Science Research Center (N23). The EEG was recorded from 32-channel BrainAmp system (Brain Products GmbH, Germany) and 32 electrodes of an EEG cap (BrainCap). 29 electrodes were placed on the scalp according to the International 10-20 system. One electrode for recording eye movement (EOG) was positioned below subject's left eye. One electrode dedicated to the electrocardiogram (ECG) was placed on subject's collarbones in the left sides. The impedance of each electrode was maintained below 10kOhm using gel.

Preprocessing

The raw EEG signals are highly contaminated with various noises. There are movement artifacts made by human such as eye blink, muscle, or heart beat as well as artifacts caused by electrical power lines. First, acquired EEG signals were high-pass filtered with a cut-off frequency at 1Hz and transition band width 0.2Hz in order to remove line noise. Movement artifacts cannot be eliminated easily because one artifact affected many channels simultaneously. Therefore, independent component analysis (ICA) was widely used to find artifact-related independent component [1-2]. ICA is a statistical method that maximizes the mutual independence of components. So ICA enables to select contaminated independent component, and reconstruct uncontaminated signals. In this study, extended ICA in EEGLAB was used to extract independent components [3], and artifact components were removed.

Feature extraction

EEG oscillations have been related to a variety of functions such as perception, cognition, sleep, etc. For a long time, researchers have found the sensory and cognitive processes are modulated by synchronous neural activity which is in turn induced by oscillations [24]. A variety of studies have demonstrated that neural oscillations like frontal midline theta are closely associated with memory processes. In this study, features were extracted from the neural oscillations during the task (reading sentence contents) and applied to the neural network algorithm to make a computational model for implicit intention decoding. To do so, 5 band powers were extracted from the spectrogram of preprocessed EEG signal, in delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30 – 40 Hz). With short-time Fourier transform (STFT), spectrogram of each single trial was obtained.

Then in each spectrogram, power spectral densities were summed up for the frequency range of each band and averaged for time domain in contents block, i.e., 4 seconds. Then 5 each representative band power value can be calculated for each sentence as well as each channel. Since we are interested in the higher cognitive function of brain, channels of interest are located at frontal area of the brain, which are 11 among 32 channels around whole brain. We selected 11 channels, extracted features, and applied to the classifier. We repeated this procedure for each channel. As an input feature, 5-dimensional feature vector was applied to an input of the classifier.

Classification

Input feature vectors are applied into the classifier. Classification has done into two steps: training phase and testing phase. In training, 80% of input samples are used to train classifier with known labels. After training, rest of 20% input samples is applied to the pre-trained classifier and predicts the labels of testing samples. Then classification accuracy can be obtained. This procedure is repeated for 5 times changing the dataset of training and testing for reliable performance evaluation. It is called 5-fold cross-validation. Classification performance is evaluated for each channel and each subject. There are many classifier for pattern classification, we selected support vector machine (SVM), and used LIBSVM tool [6]. The radial basis function (RBF) kernel is the most popular kernel function used in SVM classification. RBF kernel on two samples $\mathbf{x}_i$ and $\mathbf{x}_j$ is defined as,

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad (1)$$

but it is possible to make it simple using parameter $\gamma = \frac{1}{2\sigma^2}$,

$$k(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \quad \gamma > 0. \quad (2)$$

The objective function with soft margin also includes the question of selecting appropriate slack parameter C. As seen in Eq. 3, slack parameter, also called penalty parameter, C decides the contribution of ξ_i, which is the degree of misclassification, on the objective function.

$$\min_{\mathbf{W}, b, \xi_i} \frac{1}{2} \mathbf{W}^T \mathbf{W} + C \sum_{i=1}^{l} \xi_i \quad (3)$$

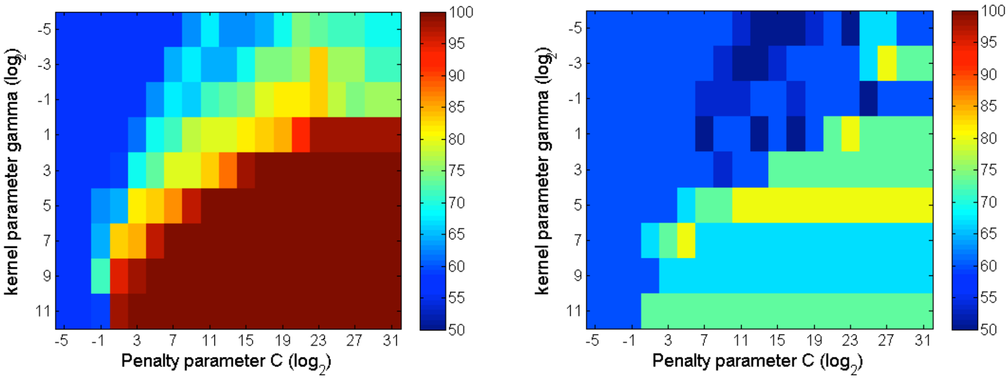

Figure 2 (a) Training accuracy (b) Testing accuracy

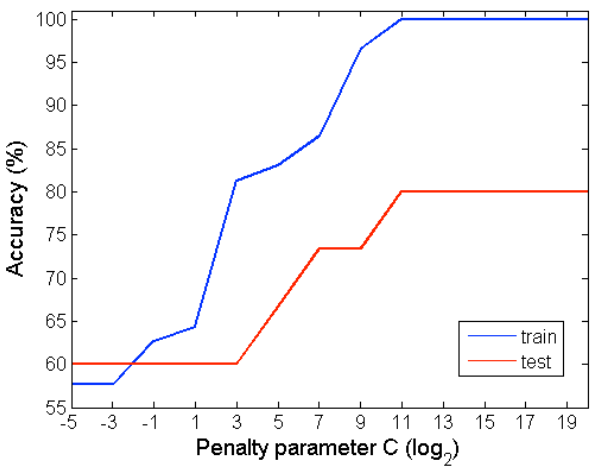

Figure 3 Training and testing accuracy versus C with $\gamma = 2^5$ for one subject at one channel

It is conventional to find optimal kernel parameter γ and penalty parameter C in training phase using grid search [26]. In this study, we also find the optimal γ and C which make high training accuracy and apply to the testing data. As shown in Fig.2(a) and (b), greater γ value shows higher training accuracy. Because the decision boundary becomes tightly fitting to the training data as γ increases. It means over-fitting, which is not as what we want it to be. When $\gamma = 2^5$, training accuracy gradually increases with C.

In Fig.3, training accuracy and testing accuracy are depicted in the same figure with varying C. Testing accuracy behaves similarly to the training accuracy with varying C. When $C = 2^{11}$, both accuracies goes to the maximum. In this manner, we find the optimal parameter (C,γ) for each classification procedure.

(2) fMRI Experiment

Subjects

Nineteen healthy right-handed Korean subjects (11 men and 8 women) were recruited from the student community in KAIST. They are all KAIST undergraduate or graduate students, and voluntarily participated. All participants did not have a history of psychiatric disorder, significant physical illness, head injury, neurological disorder, and alcohol or drug dependence. After complete explanation of the study, written informed consent was obtained from all subjects. The study was submitted to the regular review in the KAIST institutional review board and approved.

Image Acquisition

Experiments were also held at KAIST fMRI center (N23). Functional images were acquired on a Siemens 3 Tesla MR system with a standard head coil. The volumes consisted of 36 slices (thickness = 4mm, no gap) covering the whole brain. FOV = 220x220mm, matrix = 64x64, TE = 28, TR = 2 (Flip Angle = 90) GE EPI sequence voxel size 3.4mmx3.4mmx4mm.

Data Analysis

The data were analyzed with statistical parametric mapping software package (SPM8) (Wellcome Department of Imaging Neuroscience, University College London) running with MATLAB (Mathworks, Natick, MA). The imaging data were realigned to correct for movement, and normalized to the standard space defined by the Montreal Neurological Institute (MNI) template. Then the functional images were subjected to two different analyses, i.e., GLM and multivoxel pattern analysis. Among 19 subjects, two subjects' data were excluded for further analysis due to the unbalanced answer (over 70% in one class). The normalized images were then spatially smoothed with a 6-mm Gaussian kernel. The experiment had 2 event conditions (agreement and disagreement). For the GLM analysis we used SPM, and xjView toolbox (http://www.alivelearn.net/xjview) was also used to visualize the results and identify the region of activations as well as corresponding Brodmann areas. Experimental conditions were then contrasted to investigate the functional contributions of regions using standard t-test analysis.

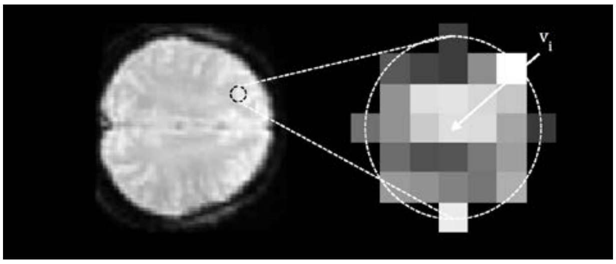

Figure 4: A spherical cluster centered on single voxel ($\mathbf{v_i}$) were defined for searchlight approach. Local spatial pattern surrounding each voxel $\mathbf{v_i}$ was extracted for pattern classification. Decoding accuracy was computed for single voxel and then moving on the whole volume of the brain.

For the *Multivariate pattern analysis (MVPA)* we used analysis technique to decode implicit intention. MVPA enables us to identify cortical regions then we can predict whether the subjects' intention was agreement or disagreement prior to their conscious decision to press button. Data samples were transformed from MRI signal intensity to units of percent signal change, calculated relative to the average level of activity for each voxel across all samples within a given run. Spatial smoothing has been highly controversial. Some of researchers had believed a MVPA with unsmoothed data could maximize sensitivity and extract full information in the spatial pattern [7-8]. However, others claimed that smoothing is nothing to do with classification performance and even improves the performance for some case [9]. We compared the classification performance with unsmoothed, 4mm FWHM, and 6mm FWHM smoothed patterns. Then we used a "searchlight" approach which examines the information in local spatial patterns of brain activity surrounding each voxel $\mathrm{v_i}$. A spherical cluster is defined at each voxel $\mathrm{v_i}$with radius of 3 voxels as shown in the figure 4. Local spatial patterns for single voxel $\mathrm{v_i}$ were applied to the classifier as an input, so decoding accuracy was obtained for every single voxel in the whole volume. For every subject, linear discriminant analysis (LDA) was used by training with 80% of feature samples and classification performance was calculated with the remaining features. We repeated this procedure by 5-fold cross-validation. Average decoding accuracy for each searchlight location was obtained after 5-fold cross-validation, then the results were investigated especially whether it is significantly above the chance.

Results and Discussion:

We focused on whether subjects agree (Sympathy to Others) or disagree (Non-Sympathy to Others) on the statements while seeing contents block. Before sentence end which indicates sentence type either positive or negative is presented, decision that agrees or disagrees on those statements may be determined in the contents block. “Yes” or “No” is only dependent upon existence verbs. We observed ERPs in contents block. If pre-decision occurs, and neural activities are different between agreement and disagreement, ERPs in contents block show a significant difference between two intentions. Each sentence is classified based on subject answer. If subject says “Yes” for affirmative sentence, it implies subject agrees on the contents. If subject says “No” for negative sentence, it also implies agreement on the contents. In the same way, if subject says “Yes” for negative sentence, it means subject disagrees on the contents. Also, saying “No” for positive sentence means disagreement. Let us assume subject sees the sentence “I have never been to Paris”. If he/she actually has been there before, subject’s answer will be “No”. Explicit answer is negative towards the sentence, but his/her intention towards the contents is positive. It is the same as saying “Yes” to the sentence of “I have been to Paris”. “Having been to Paris” is a common truth for the subject, answer can be either “Yes” or “No” according to the sentence type. Table 3 summarizes how to classify the intention. Now each condition is named to YY, YN, NY, and NN as in Table 3.

Table 3. Classification of Intention

Intention to the Contents	Sentence End	Answer	Condition
Agreement	Positive	Yes	YY
	Negative	No	NN
Disagreement	Positive	No	YN
	Negative	Yes	NY

Table 4 : 9 Subjects’ average recognition accuracy (%) of at 11 frontal EEG channels

Channel name	Recognition rate (%)
Fp1	72.8
Fp2	75.4
F7	76.1
F3	72.5
Fz	72.9
F4	74.7
F8	72.2
FC5	72.9
FC1	75.7
FC2	73.6
FC6	
Average	73.9

(1) EEG Experiments

Our experimental design has demonstrated and decoded implicit intention for each single trial using the selective attention algorithm. Recognition rate was obtained from the subject-dependent classification at 11 frontal EEG channels (Fp1, Fp2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, and FC6) with 5-fold cross validation for reliable performance evaluation. Table 4 shows the 9 subjects’ average recognition rate during 5-fold cross validation at 11 frontal EEG channels. In every channel, over 70% of classification accuracy is obtained. At channel F7, located at the leftmost position, has the highest accuracy among 11 channels, channel Fp2 and FC1 follow the next. Also, Table 5 shows the 5-fold average accuracy (%) for each channel in one subject. This subject shows **over 80% of recognition accuracy** at Fp2, and F4, which are located on the right side of frontal scalp. These results demonstrate the proposed approach works well in implicit intention decoding of the proposed experimental task.

Table 5 : One subject's average recognition accuracy (%) of at 11 frontal EEG channels

Channel name	Recognition rate (%)
Fp1	73.0
Fp2	82.3
F7	78.6
F3	73.0
Fz	74.5
F4	81.0
F8	79.7
FC5	71.5
FC1	74.4
FC2	78.5
FC6	74.4
Average	76.5

(2) fMRI Experiment

As defined in Table 3, agreement (Sympathy to Others) condition is a combination of YY and NN. In the same way, disagreement condition (Non-Sympathy to Others) is a combination of YN and NY. To ensure relative differences between activities associated with agreement and disagreement, random effect analysis of agreement minus disagreement were conducted. As illustrated in Figure 5, the relative activations between agreement and disagreement are mostly shown in BA9, dorsolateral prefrontal cortex, and BS24, anterior cingulate cortex. BA9 is involved in the motor planning, organization, regulation, working memory, etc. BA24 is related to the rational cognitive functions such as reward anticipation, decision-making, empathy, and emotion. However, disagreement minus agreement showed BA37 which is involved word recognition. These findings are showing that only when agreeing towards the sentence contents (before seeing the end of the sentences) brain activities related to the cognitive functions increased.

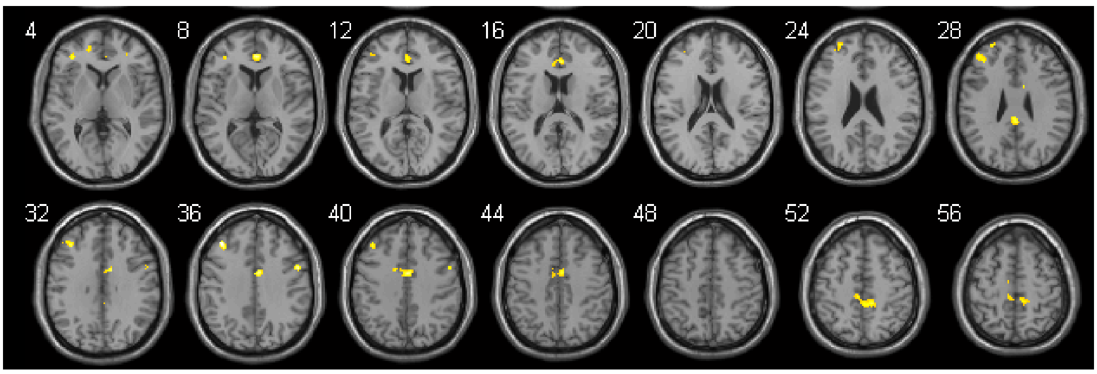

Figure 5. Agreement > disagreement contrast. DLPFC and ACC activities are shown.

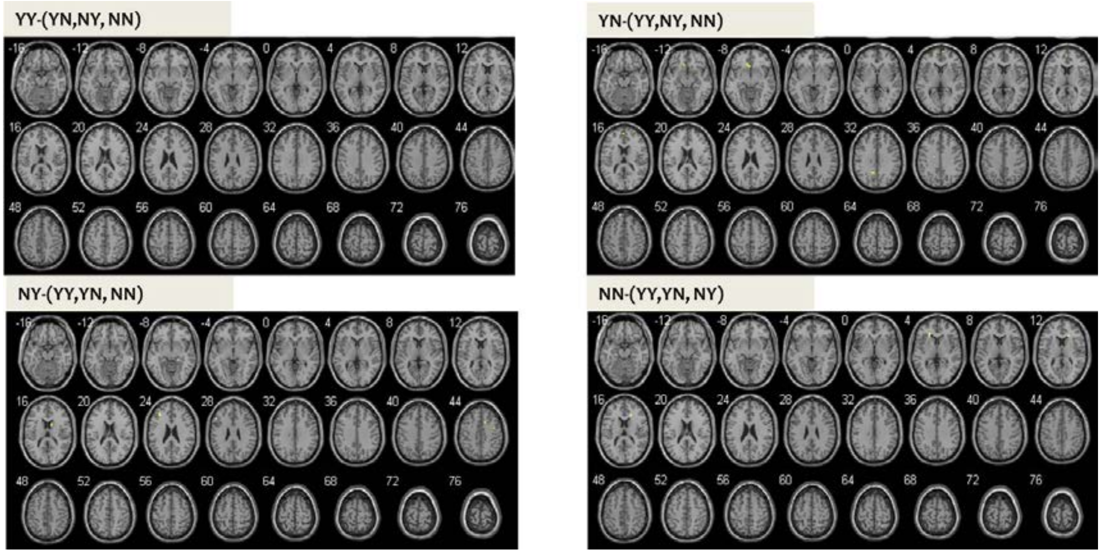

Figure 6. No Significant Activation in Sentence End Block.

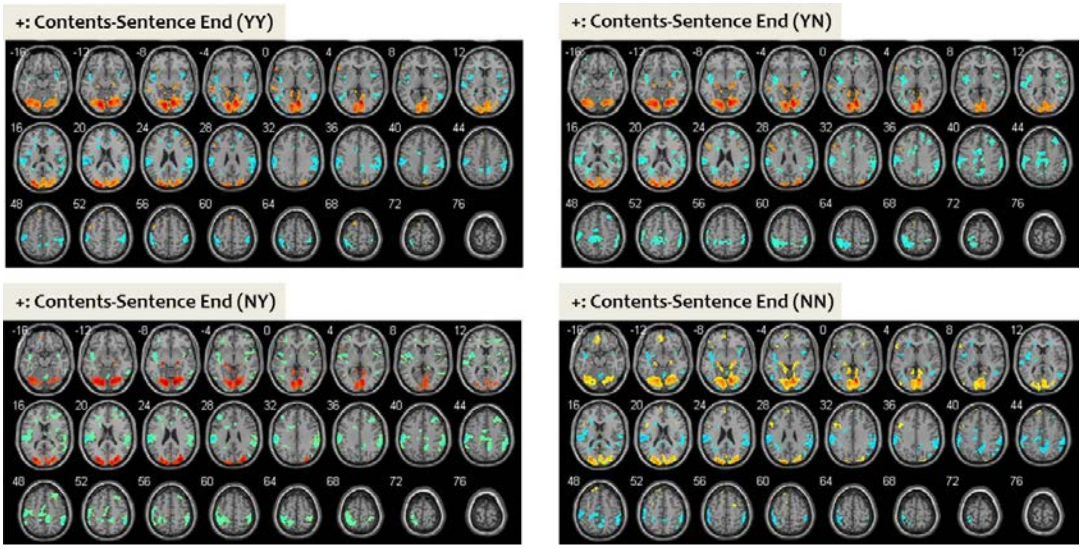

Figure 7. Activated Brain Region for each block in each condition

If we observe the 4 kinds of conditions in sentence end block, comparison to fixation showed motor and language related brain activities dominantly. Relative differences between conditions did not show anything. These results mean there is no cognitive process in sentence end block, only associated with button-press task. Table 6 summarizes activations in this task.

In this study, whether subject tells a truth or lie is not our concern. While decision-making related to the personal issue, his real intention may be revealed in EEG recordings. Thus, we examined the relationship of ERPs at the frontal sites and implicit intention. We defined implicit intention is an intention which can be observed in neural activities, but not explicitly found yet. In decision making of agreement and disagreement task, we found intention is generated in a brain before making an answer explicitly. We have also shown that ERP at Fz can be used to predict subject’s answer quite accurately in advance. Usually ERP analysis has been done by averaging all trials and all subjects in order to average out the random EEG noises and stress out the common activities in the same class. However, this study shows that it is possible to classify every single trial. In other words, it is not necessary to repeat many trials for each condition to find a common aspect. Thus, we can say this approach is applicable to the more natural situation.

Table 6 . Summary of Brain Activation

Block	Condition	Brain Region	Description
Contents Block	YYNN-FIX (Agreement -Fix)	Thalamus (Left)	kind of switchboard of information
		BA 9, BA 32	integration of sensory and mnemonic information and the regulation of intellectual function and action / rational cognitive functions, decision-making, attention
		BA 7	play a role in visuo-motor coordination (e.g., in reaching to grasp an object
	YNNY-FIX (Disagreement -Fix)	Medial Frontal Gyrus	Executive mechanism, decision-making
		Middle Frontal Gyrus	
		Thalamus (Left)	kind of switchboard of information
	YYNN-YNNY (Agreement–Disagreement)	BA 9, BA 32, BA 40	integration of sensory and mnemonic information and the regulation of intellectual function and action / rational cognitive functions, decision-making, attention / language perception and processing
	YNNY-YYNN (Disagreement-Agreement)	BA 37, Middle Temporal.Gyrus	word recognition, within-category identification / accessing word meaning while reading.
Sentence End Block	YY-FIX (Agreement)	BA 40	language perception and processing
		BA 6	primary motor cortex
	YN-FIX (Disagreement)	BA 40	language perception and processing
		Claustrum	Consciousness
	NY-FIX (Disagreement)	Insula	Consciousness, perception, self-awareness
		BA 4	primary motor cortex
		BA 40	language perception and processing
	NN-FIX (Agreement)	BA 4	primary motor cortex
		BA 40	language perception and processing

According to the results in fMRI experiments, activated brain regions were different during contents block and sentence end block. Figure 7 shows the difference between two blocks. This figure is not a proper contrast to see the condition characteristics, but for the block characteristics. This is why 4 images seem almost the same. Contrasts are given as contents minus sentence end for each condition, so red or yellow colored activities are associated to the response in contents block, while blue or green colored activities are associated to the response in sentence end block. As clearly seen in the figure, affected brain regions are different, which implies each block caused totally different processes. In detail, contents block is closely connected to the cognitive processes in prefrontal and anterior cingulate areas (BA9, BA24, especially agreement condition, see in Figure 5) as well as bigger activation in visual cortex which may be due to larger number of words or letters compared to the sentence end block. However, sentence end block seems related to the button press action which activities were shown in both sides of motor cortex.

These findings gave us an extended idea to the cultural studies. This experimental design can be applied only to SOV structured language natives. Also expression of agreement and disagreement is different according to the nations. Let us imagine the sentence “I have never been to Paris.” is presented on the screen. If subject is a Korean and he has been there before, “No” is his proper answer. However, if he is an American, then he will say “Yes”. In his case, agreement is no more combination of YY and NN, but YY and NY. Agreement and disagreement is only dependent upon the answer’s polarity regardless of the contents’ polarity. As shown in Figure 8, if we group each condition following English manner, we could not find any activation commonly associated with in agreement condition, and disagreement condition either except simple word recognition related activities. It is clearly seen if we compare with Figure 5, grouping as Korean shows us crucial responses related to the cognitive processes. We can expect that it might be observable in English-spoken subjects’ responses. We could let it as a further study and this study enables us to find cultural differences in implicit intention between Korean-spoken and English-spoken people.

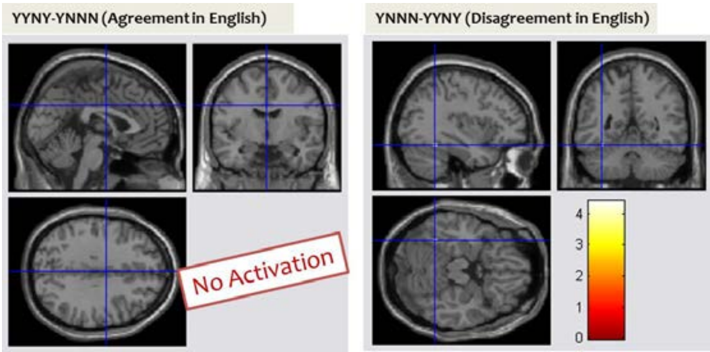

Figure 8. Grouping Conditions in English Way.

The observation of the frontal ERPs or fMRI images can be used to understand implicit intention. However, we use contact measurement in limited environment during experiment. There is no way to measure neural activities in a real environment such as moving situation for high cognitive tasks up to now. Human computer interface should understand real intention only using simple measurements in moving situation eventually like recent speech recognition system in smartphone does. Measuring device should be smaller and convenient to handle. There are two possible solutions; one is making portable devices which can measure one's neural activities. The other solution is investigating the relationship between neural activities and easily measured signals (e.g., speech, video, etc.) so as to predict the implicit intention only using non-contact measurement in a natural situation. Implicit intention study is also related to the mind reading, which enables control the machine by thinking. In a not too distant future, mind reading can also be a general aspect of future machine. Implicit intention study is standing at the start line of the mind reading research. Further improvements are required to make human computer interaction in a more natural way.

We also incorporated moving pencil beams with linear discriminant analysis, and identified discriminant areas for the Sympathy vs. Non-Sympathy brain responses. As shown in Figure 12, the left fusiform gyrus and inferior frontal gyrus are identified.

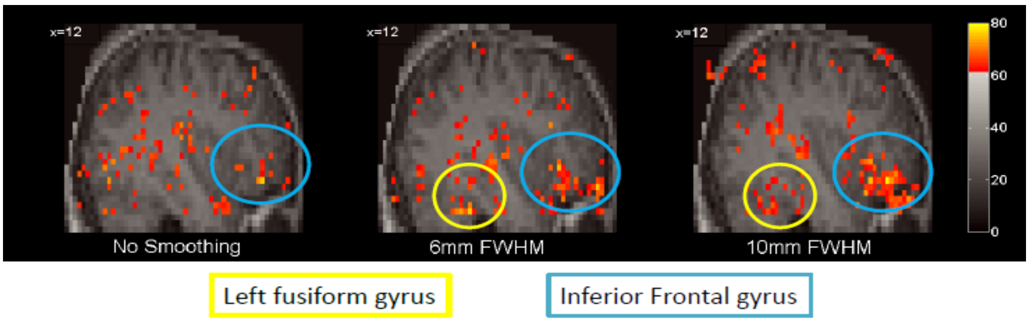

Figure 12. Pencil beam analysis to identify discriminant brain areas for the Sympathy vs. Non-Sympathy responses

List of Publications and Significant Collaborations that resulted from your AOARD supported project:

We had updated our experimental paradigms and the final results are currently under preparation for the submission to wee-cited peer-reviewed journals. Also, to stay way from "self-reproducing", we had presented papers at international conferences with "abstract only". However, we had presented plenary and invited talks at several international conferences.

d) conference presentations without papers (Abstract Only)

- Soo-Young Lee, Suhyeon Dong, and Dae-shik Kim, Understanding human implict intention from physiological and behavioral data, SPIE Defense, Security+Sensing, Conf. 8058: Independent Component Analyses, Wavelets, Neural Networks, Biosystems, and Nanoengineering IX April 25-29, 2011, Orlando, USA
- Soo-Young Lee, Artificial cognitive systems with active learning and situation awareness capabilities, 3rd International Conference on Cognitive Neurodynamics, Hokkaido, Japan, June 2011, Hokkaido, Japan **(Plenary Talk)**
- Soo-Young Lee, Implicit Intention Recognition and Hierarchical Knowledge Development for Artificial Cognitive Systems, 17th International Conference on Neural Information Processing (ICONIP), Shanghai, China, November **2011 (Plenary Talk)**
- Soo-Young Lee, Understanding human implicit intention from EEE and fMRI data, NeuroBiology and NeuroInformatics (NBNI), Dec. 17-20, 2011, Okinawa, Japan (By Invitation Only)
- Soo-Young Lee, Active Learning and Implicit Intention Understanding: Two New Functions for Artificial Cognitive Systems, 22nd Italian Workshop on Neural Networks, Salerno, Italy, May 2012 **(Plenary Talk)**
- Suh-Yeon Dong and Soo-Young Lee, Understanding Human Implicit Intention Based on Frontal Electroencephalography (EEG), International Joint Conference on Neural Networks (IJCNN), Brisbane, Australia, 2012
- Suh-Yeon Dong, Byeong Yeol Kim, CheongAn Lee, Hyunah Song, and Soo-Young Lee, Implicit Intention Understanding and Hierarchical Knowledge Development for Artificial Cognitive Systems, East-Asian University Workshop, Feb. 2012, Daejeon, Republic of Korea (By Invitation Only)
- Suh-Yeon Dong, Medial Prefrontal Cortex and Self-relevance: An fMRI Study, NeuroBiology and NeuroInformatics (NBNI), Nov. 21-23, 2012, Seoul, Korea (By Invitation Only)

e) manuscripts in preparation

- Suh-Yeon Dong and Soo-Young Lee, Understanding Human Implicit Intention based on the Electroencephalography (EEG)
- Suh-Yeon Dong and Soo-Young Lee, Understanding Human Implicit Intention :An fMRI Study

f) provide a list any interactions with industry or with Air Force Research Laboratory scientists or significant collaborations that resulted from this work

- Prof. Riccardo Monzatti, ILUM University, Milan, Italy: Cross-cultural study on implicit intention for Italian

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Attachments: Publications a), b) and c) listed above if possible.

DD882: As a separate document, please complete and sign the inventions disclosure form.