Discrimination of Lies in Communication by using Automatic Measuring System of Nonverbal Information

Yoshimasa Ohmoto, and Kazuhiro Ueda
Department of General Systems Studies
University of Tokyo
Tokyo, Japan
Ohmoto9@dolphin.c.u-tokyo.ac.jp,
ueda@gregorio.c.u-tokyo.ac.jp

Takehiko Ohno
NTT Department II
NTT Corporation
Tokyo, Japan
ohnot@acm.org

***Abstract*—In the near future, it is expected for us to communicate with robots and computer agents in a natural way. In daily life, we usually speculate about partner's intentions from diverse nonverbal information expressed unconsciously. We thus need to investigate the method of speculating partner's intentions by using nonverbal information and to implement it with a robot or agent to realize the smooth communication. However, there is not a system satisfying necessary conditions which we considered for the measuring nonverbal information in natural communication. Therefore, we made a real-time system for readily measuring gaze directions and facial feature points at a time. And then, we established an experimental setting for measuring multimodal nonverbal information that participants expressed during communication. We used the system and setting to make an experiment for discriminating lie, as an example which intentions were unconsciously expressed by nonverbal information. As a result, we found that we could discriminate lies by using diverse nonverbal information in the same way people did.**

Keywords—communication, nonverbal information, gaze measuring and lies.

I. INTRODUCTION

In these days, we have made noticeable progress in developing robots and computer agents, especially interactive robots and agents. An increasing number of studies have been thus made on human-robot interaction by using an interactive robot or agent. For example, Ono investigate correlations between body movements and utterance understanding in human-robot communications involving giving/receiving route directions ([9]). In the near future, an interactive and autonomous artifact will come into our daily life. At that time, it is highly expected for us to communicate with them in a natural way. In fact, we have some problems to realize such a natural communication with an artifact.

Let's think about human-human conversation. For communicating with a partner, it is not sufficient to understand only words and sentences which he/she utters. If people did not speculate about partner's intentions by using nonverbal information, they would have trouble in understanding even a meaning of interjection ([10]). Therefore, an artifact is needed to speculate about its partner's intentions by using nonverbal information that the partner expresses the same as people usually do. Many researchers have conducted research on speculating people's intentions based on their nonverbal information (for example, [11]). In most of the studies, a limited number of nonverbal information was used for speculating simple intentions. In our actual communication, however, we use synthetically multimodal nonverbal information for speculating communication partner's intentions.

We usually speculate about our partner's intentions from multimodal nonverbal information. On the other hand, we often express our intentions unconsciously by nonverbal information. For example, facial expressions, prosody and gaze tell us some truth of the speaker; their feeling, thinking, and so on. It is important to understand those unconscious expressions of our intentions by using diverse nonverbal information. We thus need to pay attention to diverse nonverbal information and to use it synthetically in order to investigate how we understand unconscious expressions of intentions. In addition, since we think the result of the investigation is applied to a robot or agent that comes into our daily life, we also need to investigate in a situation similar to actual communication.

In this paper, we focused on lie as an expression of deceptive intention. One of the reasons for focusing lie is that telling a lie is one of the typical behavior in which we often express our intentions unconsciously. Another reason is that it can be defined objectively; conversely, it is difficult to objectively define other intentions. In [8], Coleman and Kay state a prototypical lie. It was defined as following features: the speaker asserts something which is untrue; the speaker believes that it is untrue; and the speaker's intention is to deceive. On the other hand, there are some ways to deceive people besides a prototypical lie. For example, people are deceived when the truth is said like telling a lie. However, we were focused on this prototypical lie for objectively defining lie. In this paper, a "lie" means "linguistic statement deceived intentionally."

In our previous work ([1]), we confirmed that we could discriminate human's lies by the synthetic use of multimodal nonverbal information. We conducted an experiment using a game in which the communication of players resembled actual communication. We manually classified nonverbal information of every utterance in playing the game into the variables. To do so, we focused on 13 variables, gaze (three variables), prosody (nine variables) and facial expression (one variable). We then carried out a discriminant analysis to analyze the variables. As a result, we found the discrimination rate to be 75% - 85%. The rate reached about 80% even when the discriminant function of the first experiment classified a data set of the second experiment. However, it takes a great deal of time to measure nonverbal information from the recorded video manually. So, it is necessary to reduce the cost of measuring nonverbal information. Moreover, a method of automatic measurement is required when a robot or agent judges its partner's (i.e. a person's) intentions automatically.

For our purpose, a measuring system has to satisfy following three necessary conditions. 1) It must be able to measure both gaze directions and facial feature points at least. 2) It must allow a user's head position and orientation to move to a certain degree. 3) It is not necessary to put markers on a face and to make any model of a face manually before measuring. Some real-time systems to measure facial feature points satisfy 1) and 3). "Tobii" or a few other gaze tracking systems satisfy 2). Some real-time systems to measure head pose and gaze directions simultaneously ([3]) satisfy 1) and 2). However, no system satisfies the three necessary conditions at a time. If we use multiple systems at a time, we can satisfy the three necessary conditions. However, a great deal of labor will be required for us to operate their systems.

For this reason, we made a real-time system of measuring gaze directions and facial feature points simultaneously without making a model of a face ([2]). We then used the measuring system to investigate a method of discriminating lies.

This study has two purposes; one is to establish a setting for measuring multimodal nonverbal information of persons during communication for discriminating lies and the other is to confirm that it is necessary for discriminating lies in actual communication to pay attention to multimodal nonverbal information in the proposed setting. For these purposes, we conducted an experiment using a game in which participants can tell a lie spontaneously and intentionally, if necessary.

The rest of the paper is organized as follows. Section 2 explains the outline of the experiment conducted in this study. Section 3 describes the method of analysis and results. Section 4 contains a discussion. Finally, we conclude this study in Section 5.

II. Experiment

A. Revised "Indian Poker"

Indian poker is a kind of card game. One card is dealt to each player who cannot look at its face side. Each player must place the card dealt, on the forehead, so that all the other players can see the face side of the card. This means that the players can see every card except their own. The players are then asked to decide, from the number on the cards shown, whether or not to stay in the game by communicating with the other players. Finally all the players' cards are turned face up on the table and the player who has a card with the highest number wins. Exceptionally, one (A) is counted as 14. The point lost when a player quits the game is smaller than that when a player is defeated. However, a player who holds a top card loses big points when all players quit the game (TABLE I).

TABLE I. List of Points

Defeated.	-5 points.
Quit the game.	-3 points.
Quit despite holding a top card.	-10 points.
Winner.	Gets all of the other players' lost points.

Under these normal rules, the probability of winning or defeat is easily estimated from the number on the other players' cards. Therefore, we add the following rule; "Players can change their cards." By adding this rule, a player can change his/her card if the player estimates that he/she will lose. The game of normal Indian poker plus this rule is called "Revised Indian poker". This added rule is expected to encourage players to communicate with one another for getting information of their own cards. In this communication, a player tries to tell a lie in order to make the other players quit the game or change cards.

The reason for using the revised Indian poker is that participants can tell a lie spontaneously and intentionally, if necessary. So we can observe lies in a situation similar to actual communication.

B. Face-Gaze measuring system

We used a system that enables to measure gaze directions and facial feature points for getting nonverbal information of participants. If we are forced not to move our head or if markers are put on a face to measure them, it is very concerned that we cannot communicate naturally. Therefore, we made a real-time system for measuring both gaze directions and facial feature points without markers, which impose not so much on restriction of user's action and required no model of a face to be manually made before measuring (see [2]).

The software for facial feature points and gaze direction consists of four major parts, 1) face tracking, 2) facial feature detection, 3) head pose detection and 4) gaze detection. First, in the face tracking stage, the system searches the eye positions in the whole 2D image using a SSR algorithm and eye blinks ([4], [5]). Second, the system starts facial feature detection in each 2D image. If the facial feature detection is not successful, the system regards a face to be lost and it jumps back to the face tracking stage to find a face again. If the facial feature detection is successful, the system then calculates a head pose in the head pose detection stage. The head pose detection is followed by that the system calculates directions of gaze in the gaze detection stage. The 3D eye model is used to determine the 3D

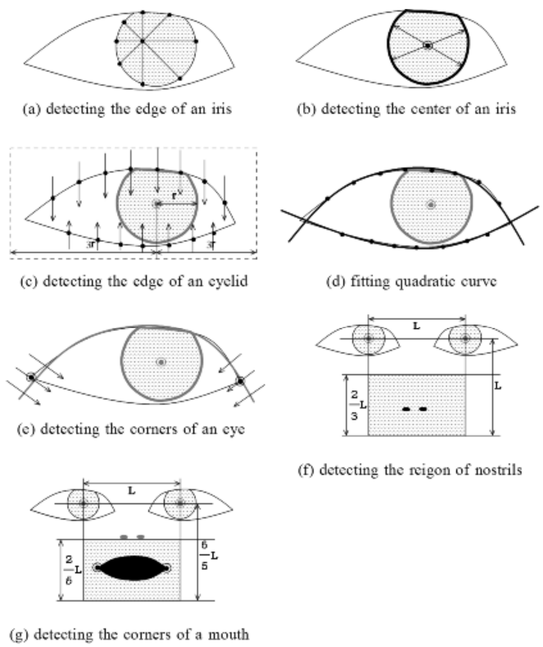

Figure 1. The detection sequence of facial feature points.

gaze vector. Finally, the system jumps back to the facial feature detection stage in the next frame.

In the facial feature detection stage, the system searches 10 feature points and eyelids in the current frame. The 10 feature points are two centers of irises, four corners of the eyes, two centers of the nostrils, and two corners of the mouth. They are detected by light and shadow in the 2D images. Figure 1 (b) (d) (e) (f) (g) illustrates the 10 feature points and eyelids. After the facial feature points are detected in each 2D image, the system performs stereo matching to calculate the 3D coordinates for each feature. Then, a face model is made from recent 100 sets of the facial feature points.

In the head pose detection stage, the system calculates the 3D pose of the head by using the facial feature points except the centers of the irises and the corners of the mouth. The reason is that those features move very often in communication. We adopted a simple gradient method using virtual springs for the estimation of the head pose. In the relative coordinate so that the origin is the midpoint of the nostrils, the face model is rotated gradually and iteratively to reduce the elastic energy of the springs toward the measured facial feature points.

In the gaze detection stage, the eyeballs are regarded as spheres. Gaze direction is determined on the basis both of the head pose and of the center of the irises of the eyes. The 3D eye model consists of the relative position of the center of the eyeball respect to the head pose and radius of the eyeball. The relative position of the center of the eyeball is defined as a 3D vector from the midpoint of the center of the nostrils to the center of the eyeball. These parameters and the relative positions of the centers of the eyeballs are currently determined by the manual adjustment through a personal calibration where the gaze point of a person is known. The 3D position of the eyeball can be determined from the pose of the head and the relative position of the center of the eyeball. Since the centers

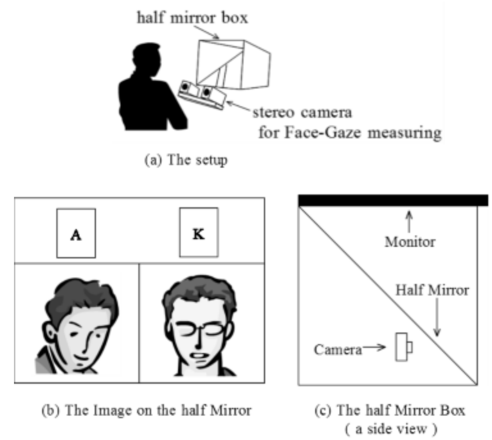

Figure 2. The setup of the experiment by using the system.

of the irises are already detected, the system calculates the gaze direction from the relationship between the iris center and eyeball center. Two gaze directions are detected independently. However, each measurement is not sufficiently accurate, mainly due to the resolution of the image. The field of view of the camera is set to capture the whole face in the image, then the radius of the iris is only about 15[pixel] in a typical situation. Therefore, it is hard to determine the "gaze point" in a 3D scene by calculating the intersection of the detected gaze lines. Therefore, those two vectors are currently averaged to generate a single gaze vector for reducing the effect of noises.

We use a personal calibration method [6]. In this calibration method, the user gazes at least two points on the screen for the calibration. Once a calibration matrix is calculated, it is possible to compute the calibrated vector of the user. Many existing gaze tracking systems need to be calibrated before every measurement session even for frequent users. In addition, the calibration put a heavy strain on users since users must watch 5-20 calibration points.

The whole process takes approximately 50 [ms], 20 [FPS]. In [1], we could discriminate lies by using 15 [FPS] video data. Therefore, this speed is enough to analyze in our experiment. The accuracy of the measurement of the facial feature points is approximately ±2 [mm] in translation, ±1 [deg] in head pose rotation. The accuracy of the gaze direction is approximately ±2 [deg]. The accuracy of the gaze direction is evaluated through experiments, in which two participants were asked to gaze at nine markers on a monitor.

C. *Experimental settings*

We designed the setup of an experiment for discriminating lies by using our Face-Gaze measuring system. Figure 2 shows the setup of the experiment. Participants were asked to communicate with each other by using a half mirror box shown in Figure 2 (c). Three participants (players) participated, in a group, in the experiment, which will be referred as "triad" in the rest of the paper. The monitor of the half mirror box displayed the other two user's faces taken by a network camera. Cameras were set, behind the middle of the each participant's eyes, inside the half mirror box, so that they could catch the eyes of each other. The reason why we used the half

TABLE II. VARIABLES IN OUR EXPERIMENTS

Nonverbal Information.	Independent variables.
Gaze (Three variables)	The rate of gazing at the partner of conversation.
	The rate of gazing at the useful object for communication.
	The transitional rate of gazing at the object.
Prosody (Six variables)	Pitch, (the first half, the second half, change.)
	Power, (the first half, the second half, change.)
Facial feature (One variable)	Whether the mouth moved earlier than the eyelids.

mirror was that a gaze direction was shown to be important for discriminating lies in our previous research ([1]). Participants talked with each other through a microphone and speakers.

In this setting, participants were asked to play a game of Indian poker repeatedly after they were briefly provided instructions on the rules and strategies of the game. Participants played a game through the monitor of each half mirror box. The behavior and utterances of participants playing the games were recorded by our system and voice recorder. The participants' utterances and actions were not controlled; they were allowed free communication. Each triad consisted of two graduate students and the experimenter. The two graduate students were acquainted with each other. The reason why the experimenter participated in the game was that it was difficult for only beginners of the game to communicate smoothly. This experimenter behaved like a usual player.

D. Procedure

The experiment was conducted in the following manner.

1) Each of a triad sat in front of each half mirror box.

2) The experimenter briefly provided instructions on the rules and strategies of the game.

3) The experimenter dealt a card to each participant through software.

4) Each participant communicated, through monitor, in order to make the other participants to quit, to stay in the game or to change their cards.

5) Each participant showed his/her card to the others through software, after deciding on whether to stay in or quit the game.

6) After the winner was decided, the losers paid the points to the winner.

The procedures of 3–6 were defined as a trial. This trial was repeated about 20 times.

In addition, we conducted the same experiment by the same participants a month after the first experiment had been made.

III. ANALISIS AND RESULTS

A. Method

We used a discriminant analysis to classify the discrimination rate of lies.

Utterance, a unit of analysis, was taken out from the data, which was recorded during the experiment. This “utterance unit” was defined by the time span from the utterance start to the utterance end.

Multimodal nonverbal information in every utterance unit was measured and recorded by using our system and voice recorder. Measured information was a direction of gaze, pitch and power of prosody, and 3D positions of upper and lower eyelids and corners of a mouth. The variables for discriminating lies were elicited from that information. The variables are shown in TABLE II.

Below, we explain how to elicit those variables from measured information. In [1], we manually carried out this procedure by watching recorded videos of the experiments.

The three variables of gaze row in TABLE II are estimated by a direction of gaze. The definition of "the rate of gazing at the partner of conversation" is the proportion of time, during which a participant gazed at his/her partner of conversation, to the total time of an utterance unit. The definition of "the rate of gazing at the useful objects for communication" is the proportion of time, during which a participant gazed at the object that had useful information for communication, to the total time of an utterance unit. For example, when a participant talks about objects on a table, other participant's faces and the objects on the table are regarded useful objects. The experimenter himself now judges whether an object is useful or not. In this experiment, the candidates of useful objects were faces and cards of other participants. The definition of "the transitional rate of gazing at the objects" is the value of the number of the gaze shifts divided by the total time of an utterance unit.

The averages of pitch and power of an utterance are coded as any of the following three categories. I explain about the procedure of coding the variable of pitch in the first half of an utterance. First, the average and standard deviation of pitch in all the first half of an utterance calculated, which will be referred as "total pitch average in the first half" and "pitch SD in the first half". If a pitch average in the first half of an utterance > ("total pitch average in the first half" + "pitch SD in the first half"), the variable of pitch in the first half is coded to +1. If a pitch average in the first half of an utterance < ("total pitch average in the first half" - "pitch SD in the first half"), the variable of pitch in the first half is coded to -1. Another is coded to 0. The variable of pitch in the second half is coded in a similar procedure. The variables of power in the first half and the second half are also coded in a similar procedure. When the variable of the second half is higher than the variable of the first half, the value of the variable of change is set to +1, when low, the value is set to -1, and when no change, the value is set to 0 (a prosody row in TABLE II). The reason to adopt this method is to remove the noise due to the directivity of a

TABLE III. RESULTS OF THE DISCRIMINANT ANALYSIS

Experiments	The number of utterances.	Discrimination rate.	The number of variables.	The main variables. (Coefficient of discriminant function).
First	Total utterances: 136 Lie utterances: 27 Other utterances: 109	Lie utterances: 74% Other utterances: 69%	4	The Rate of Gazing at the Partner of Conversation. (-0.84) The Transitional Rate of Gazing at the Object. (-5.9) Power (the first half) (-1.3) Power (change). (-0.69)
Second	Total utterances: 119 Lie utterances: 19 Other utterances: 100	Lie utterances: 74% Other utterances: 67%	3	The Rate of Gazing at the Partner of Conversation. (1.5) Pitch (the first half) (-1.3) Pitch (change). (-1.8)

microphone and the change of distance between a microphone and a participant.

3D positions of upper and lower eyelids and corners of the mouth are used to identify whether a smile is forced one or not. It is difficult to pick up subtle changes in facial expressions. We have noticed that people forced a smile while telling a lie in many cases. It is reported that there is a time difference between the start of the reaction of the eyes and that of the mouth in a forced smile ([12]). Therefore, "whether the mouth moved earlier than the eyelids" is regarded as a typical feature of facial expressions (a facial feature row in TABLE II). The value was set to 1 (truth) when the mouth moved earlier than eyes. Otherwise, it was set to 0 (false). The variable was also set to 1 when only the corners of the month moved.

B. *Procedure*

We classified utterances into two groups according to the definition of lie explained in Section 1. One was "an utterance which is a lie" (hereafter, “lie utterance” for short) and the other was "other utterances." We defined an "equivocal utterance" as an utterance that is neither a truth nor a lie; for instance, an ambiguous statement and a noncommittal answer. “Equivocal utterances” accounted for 10-20% of the whole utterance, which “equivocal utterances” were classified into “other utterances.”

A linear discriminant analysis was applied to the data sets of variables in TABLE II. The method of selecting the variables was as follows. First, an experimenter elicited pairs of variables with 0.8 or more correlation coefficients and, in addition, removed variables with a lower F-value from the elicited variables. Next, the variables were reduced by backward elimination. The finally selected variables by this series of operations were regarded as the main variables that contributed to discriminating whether an utterance was a lie or not.

C. *Results*

We conducted one experiment. Three persons participated as a triad, in the experiment. Out of the three, one participant’s behavior could not be recorded because of the troubles of the measuring system. The proportions of utterances which could not be measured nonverbal information by the system were below 10%, 14/150 in the first experiment and 12/131 in the second experiment. We could get enough data for applying the above-mentioned method of discriminating lies. The result is shown in TABLE III.

TABLE IV. THE RESULT OF THE DISCRIMINATION RATE

The discrimination rate by the discriminant function of the first experiment.	Lie utterance.：63% Other utterances.：65%

In all the results, the number of finally selected variables was at most four and the average discrimination rate was 69%. According to the research of [7], a proportion of correct answers are at most 70% when people judge whether an utterance was a lie or not. Therefore, this result showed that the proposed setting could discriminate lies, by using diverse nonverbal information, almost as accurately as people do.

In all the results, both the variables of gaze and prosody were always included in the finally selected main variables, which imply that it is necessary to observe diverse nonverbal information. These finally selected variables or their contributions differed between the first experiment and the second experiment. However, if there had been no consistency in the contribution, we could not have been able to discriminate lies with relatively high discrimination rates. Then, we applied the discriminant function, which was derived from the data of the first experiment, to that of the second experiment as unknown data set. The result is shown in TABLE IV although it was not so high. The discrimination rate was higher than chance level in spite of a month interval between the first experiment and the second experiment. Therefore, it is suggested that the discriminant functions were almost the same among the results of the experiment.

TABLE V showed the results of discriminating lies by using the variables of a single modality, which were three gaze variables or six prosody variables. In the results of the first experiment, the discrimination rates were lower than the rates in TABLE III. In the results of the second experiment, the discrimination rate of either "lie utterance" or "other utterance" was high, and the other was low. TABLE VI showed the results which we applied the discriminant function, which was derived from the data of the first experiment by using the variables of a single modality, to the data of the second experiment as unknown data set. In the result by using the gaze variables, the discrimination rate was lower than the rate in TABLE IV. In the result by using the prosody variables, the discrimination rate of "other utterance" was high, and the other was low. These results showed that it is necessary to pay attention to multimodal nonverbal information.

TABLE V. RESULTS OF THE DISCRIMINANT ANALYSIS BY THE VARIABLES OF A SINGLE MODALITY

Experiments	**Discrimination rate. (three gaze variables)**	**Discrimination rate. (six prosody variables)**
First	Lie utterances: 67%	Lie utterances: 52%
	Other utterances: 57%	Other utterances: 59%
Second	Lie utterances: 84%	Lie utterances: 47%
	Other utterances: 48%	Other utterances: 75%

TABLE VI. RESULTS OF THE DISCRIMINATION RATES BY THE DISCRIMINANT FUNCTION OF THE VARIABLES OF ASINGLE MODALITY

Discrimination rate. (three gaze variables)	**Discrimination rate. (six prosody variables)**
Lie utterances: 56%	Lie utterances: 44%
Other utterances: 51%	Other utterances: 73%

IV. DISCUSSION

Many researchers have conducted research on detecting deception by using the variable(s) of single modality. For example, Fukuda presented data suggesting that the temporal distribution of blinks during the performance of a dual modality attention-focusing task can be useful in the detection of deception ([13]). Based on his results, he suspect that when subjects are attending to visual stimuli the presentation of relevant auditory information should lead to a peaking of blink rate following the processing of such stimuli. However, his method cannot be directly applied to the situation of actual communication. Actual communication is not controlled like a dual modality attention-focusing task. Many factors which are not related to the communication cause eye blinks. In the results shown in TABLE III, the finally selected variables or their contributions differed between the first experiment and the second experiment. This shows that the expressions of nonverbal information are changeable. On the other hand, in the results shown in TABLE III, there was not the variable of facial expression in the finally selected variables. That was selected in the result of our previous work ([1]). This also shows that the expressions of nonverbal information are changeable. Therefore, if we pay attention to a single modality, we could not detect deception in actual communication. In fact, there was less consistency in the discrimination rates in TABLE V as compared with the results of TABLE III. Moreover, the discrimination rate of either "lie utterance" or "other utterance" was low. The result in TABLE VI also shows less consistency in the variables of a single modality between the first experiment and the second experiment as compared with the result of TABLE IV. Then, we suggest that it is necessary for discriminating lies in communication to pay attention to multimodal nonverbal information.

The result of section 3 was only the result of one preliminary experiment, which was not enough to prove the effectiveness of our method. Also, the data of nonverbal information measured by the system was sometimes missing because of participant's behavior in measuring. We are now conducting experiments to clarify the effectiveness of our method in this setup.

V. CONCLUSION

We proposed a system and experimental setting for measuring multimodal nonverbal information of persons who communicate with one another, and we applied them for discriminating lies. We conducted an experiment by using the game that enabled participants to spontaneously tell a lie or not. We confirmed that we could get, by using automatic measuring system of nonverbal information, the result similar to that of our previous work. Moreover, we suggest that it is necessary for discriminating lies in communication to pay attention to multimodal nonverbal information. We are now conducting another experiment to clarify the effectiveness of our method in the proposed setting. This is a first step to propose the method of automatic discrimination of lies by using nonverbal information.

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