Supporting Negotiation Behavior with Haptics-Enabled Human-Computer Interfaces

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Abstract—An active research goal for human-computer interaction is to allow humans to communicate with computers in an intuitive and natural fashion, especially in real life interaction scenarios. One approach that has been advocated to achieve this has been to build computer systems with human-like qualities and capabilities. In this paper, we present insight on how human-computer interaction can be enriched by employing the computers with behavioral patterns that naturally appear in human-human negotiation scenarios. For this purpose, we introduce a two-party negotiation game specifically built for studying the effectiveness of haptic and audio-visual cues in conveying negotiation related behaviors. The game is centered around a real-time continuous two-party negotiation scenario based on the existing game-theory and negotiation literature. During the game, humans are confronted with a computer opponent, which can display different behaviors, such as concession, competition, and negotiation. Through a user study, we show that the behaviors that are associated with human negotiation can be incorporated into human-computer interaction, and the addition of haptic cues provides a statistically significant increase in the human-recognition accuracy of machine-displayed behaviors. In addition to aspects of conveying these negotiation-related behaviors, we also focus on and report game-theoretical aspects of the overall interaction experience. In particular, we show that, as reported in the game-theory literature, certain negotiation strategies such as tit-for-tat may generate maximum combined utility for the negotiating parties, providing an excellent balance between the energy spent by the user and the combined utility of the negotiating parties.

Index Terms—Human Factors; Experimentation; Haptic I/O; Haptic User Interfaces; Haptic Guidance; Dynamic Systems and Control; Multimodal Systems; Virtual Environment Modeling; Performance; Haptic Negotiation

1 Introduction

During everyday human-human sensory communication, we display and exchange cues through auditory, visual, and haptic channels. These cues not only support fluid and natural communication, but also facilitate our interaction. For example, imagine yourself carrying a table with another person. In this scenario, you would determine a joint course of action by exchanging spoken commands, interpreting facial expressions, observing each other's movements, and negotiating paths through forces. However, no currently available robotic system supports this sort of interaction with a human being, because the synthesis and the recognition of the aforementioned cues have largely been ignored in the context of human-robot interaction until recently. In this paper, we focus on the negotiation aspects of such interactions from the haptics point of view. In particular, we use a computer-driven haptic device that serves as a general purpose robotic interface to create a controlled virtual environment for studying force exchange dynamics in haptic negotiation.

1.1 Approach

In order to study how negotiation-related behaviors can be conveyed through sensory cues, we designed a test-bed application that allows users to interact with a computer partner in the context of a multiplayer computer game. The game is designed such that the human and the computer occasionally end up in situations where their interests would conflict. In effect, such conflicts force the parties to negotiate in real-time by trying out various alternative actions and observing the other party's response. In this dynamic environment, both the human and the computer players have to plan and update their actions continuously based on their interpretation of each other's actions. Our framework provides a multimodal platform where auditory and visual cues are supplemented with haptic enabled bilateral interaction. Hence, players need to react to the cues acquired from these communication channels.

Our model uses formal models of negotiation from the game theory literature for implementing three different styles of interaction for the computer, namely competition, concession, and a retaliatory tit-for-tat strategy. We study the utility of these strategies and their effect on the quality and end-result of interaction using our test-bed application.

1.2 Experiment and Results

The main goal of this study is to measure the effectiveness of haptic stimulus in conveying the negotiative character of the interaction within a game-theory framework. Therefore, our work brings to-

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gether elements from agent based negotiation, haptic collaboration, and multimodal interfaces research.

Our results illustrate that the individual and joint utilities of the players agree with the results predicted by the negotiation literature, which serves as evidence that the respective negotiation strategies are successfully implemented, and that the negotiation modes elicit the desired effects. We showed that subjects can successfully recognize different negotiation-related behaviors displayed by the computer player. Moreover, users can differentiate the negotiation behaviors of the computer more easily when haptic feedback is provided to them.

The rest of this paper is organized as follows: In Section 2, we present a brief overview of related work in haptic interaction and negotiation theory. In section 3, we introduce our haptic negotiation game, explain the physical model behind the game, and discuss how it can be used to study real-time negotiation in the presence of visuo-haptic cues. In section 4, we discuss the three negotiation strategies used in the game, and give necessary implementation details. Sections 5 and 6 describe the experimental setup used for evaluating various aspects of interaction, and summarize the objective and subjective results. Finally, we conclude with a summary of our main contributions and list possible future work in Section 7.

2 Background

In this study, we combine ideas from different research fields. In essence, to the best of our knowledge, our work is the first that combines concepts from the areas of negotiation, game theory, and haptic collaboration. In the rest of this section, we briefly review the relevant work in the related fields.

2.1 Haptic Interaction

Haptic interaction between a human operator and a computer controlled robot has been originally investigated in the domains of teleoperation and training. Virtual fixtures and guidance forces, which are displayed to a human operator through a haptic interface, have been used to help the operator to perform a teleoperation task by limiting his/her movements into restricted regions and/or influencing his/her movement along a desired path. The initial studies have shown that the task performance of the user during a teleoperation task can increase as much as 70% with the introduction of virtual fixtures [1]. Some other applications of virtual fixtures include training in virtual environments [2], robotic assisted surgery [3], and micro manipulation using optical tweezers [4]. As passive guidance displayed through virtual fixtures limits the learning of a task, progressive [5] and predictive [6] mechanisms, which alter the amount of guidance during the task, have been suggested for improved task performance and learning in the short term. Lee and Choi [7] suggested that long-term task learning occurs if haptic disturbance is used instead of guidance to teach the dynamics of a task.

Recently, there has been a growing interest in defining roles for the entities involved in collaborative haptic interaction and in investigating their contributions to the task. Haptic interactions between a human operator and a robot, as well as those between two human partners have been investigated in virtual and physical worlds. For example, Reed and Peshkin [8] investigated human-human haptic interaction and found indications of specialization between dyads: during the task some took the role of accelerators, and others decelerators. Similarly, Stefanov et al. [9] suggested executor and conductor roles for human dyads within haptic interaction, where the conductor acts as the decision maker, and the executor performs the desired action. Oguz et al. [10] proposed a role exchange model for dynamic dyadic interaction between a computer and a human, where the computer offers haptic assistance based on the intent of the human partner. Later, Kucukyilmaz et al. [11] further showed that explicitly displaying the role state to the partners improves the sense of collaboration and creates a stronger sense of trust towards the computer. Evrard and Kheddar [12] investigated human-robot haptic interaction and offered a model that allows the robot partner to switch between leader and follower roles during the execution of a task. Lawitzky et al. [13] investigated the roles of human and robot partners in a table-carrying task in terms of effort-sharing and concluded that the cooperation quality improves with an increasing degree of robotic assistance in the redundant direction. Wojtara et al. [14] investigated haptic interactions between human and robot partners during precise positioning of a large and long object through the decomposition of the task in the spatial domain; and based on force cues, they assigned weights to the partners' force contribution to the task.

However, all these studies on haptic interaction are based on the assumption that the computer (or robot) partners are in collaboration with their human partners. Hence, these models fail to offer necessary interactions where the dyads have their own interests, and short term goals that may possibly conflict. The most relevant line of haptics research in the context of our work is by Groten et al. [15]. They investigated the potential use of the haptic channel to negotiate intentions in collaborative manipulation tasks. They showed that feeling the interaction forces improves task performance, but negotiation over haptics results in increased effort. The authors have utilized task performance (i.e. RMS error) and physical effort (i.e. mean average power) as measures of negotiation. Our work carries the state of the art forward by introducing a formal model for haptics-enabled negotiation based on the game theory literature. Our experiments

as well as analyses are also carried out in the context of game theory.

2.2 Negotiation

Shell [16] defines negotiation as a form of decision-making where two or more parties jointly search a space of possible solutions to reach a consensus.

Although various models of agent-based negotiation have been suggested in the literature [17], [18], [19], [20], [21], only a few address multi-issue bilateral negotiation scenarios where a human is in physical interaction with a computer agent, as in our case. This is an important distinguishing point, because unlike virtual agents, humans do not necessarily follow equilibrium strategies [22], [23] or maximize their expected utility.

Similarly, there are lines of work that attempt to build computational models of negotiating agents using probabilistic and knowledge-based approaches [24], [19], [18], [25], [20]. Again, these make assumptions on rationality and utility, which do not match general human behavior. By contrast, we believe that when humans are in the loop, human factors should be considered carefully. Hence, although our computer models are inspired by the negotiation research, our experimental setup and evaluation are centered around user experience.

3 Haptic Negotiation Game

In this section, we describe the haptic negotiation game as well as the negotiation behaviors that we have implemented. We tested the system under three negotiation behaviors, namely concessive, competitive and a modified version of tit-for-tat. In the remainder of this section, we will also explain the general approach we adopted in implementing the negotiation behaviors, the physics based model used for the game design, and how sensory modalities are fused within the game.

3.1 Design Approach and Choice of Application

Unlike the common discrete bidding process, dynamic negotiation should allow the human player to change his/her bids continuously. In return, the computer player should actively respond to the human's new bid. Conversely, when the computer player makes a movement, the human should be able to identify the computer player's intent and react according to his/her own agenda. Such a dynamic interaction setting requires appropriate channels for relaying interaction cues. Moreover, since we are interested in measuring the effectiveness of different modalities on negotiation, we need to observe how dyads react to conflicting situations. With these concerns in mind, we implemented a dynamic and interactive virtual game. Our game consists of conflicting situations for the dyad where one party can choose to collaborate or behave selfishly and compete with the other party.

The haptic negotiation game is designed to create a dynamic environment, in which the human interacts with a computer in conflicting situations. The visual front-end to our game is shown in Figure 1. The screen shows a road divided into 3 lanes. On the left-hand side, the computer player controls the movement of the green ball to avoid obstacles and collect coins to increase its score. Likewise, on the right-hand side, the human controls the blue ball using a PHANToM® Omni haptic device to avoid obstacles and collect coins to increase his/her own score. During the game, the obstacles and the coins move towards the balls with constant velocity. The middle lane also has a coin, which can be collected by the red ball – referred to as "the Ball" in the rest of the text. In the game, each player's ball is restricted to move within the respective lane, i.e. the right or the left lane. On the other hand, the Ball can move freely, hence it can leave the middle lane. As a result, since the Ball can leave its lane freely, collecting the coin in the middle lane requires the players to collaborate. This design choice restricts the players and enforces them to form their own agendas. Hence, the dyads need to find a solution within their own spaces, even if that means impairing their initial interests.

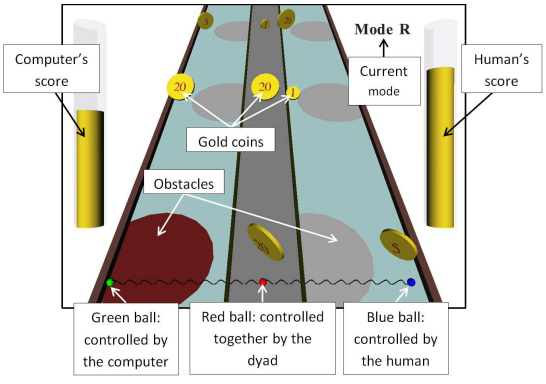


Fig. 1: A screenshot of the Haptic Negotiation Game.

The blue and the green balls in Figure 1 serve as interface points for the human and the computer, respectively. The position of the Ball in the middle is jointly controlled by the human and the computer as if the Ball is connected to the players' interface points via virtual springs. In order to let the users have a more solid understanding of this joint control mechanism, the visual setup includes two virtual springs between the Ball and each of the human's and the computer's interface points. These springs extend as the interface points move away, and compress as they come closer.

Separate scores are calculated for the human and the computer. The human's score is calculated by summing up the values of the coins that he/she

collects from the middle lane and from his/her own lane. Similarly, the computer's score is calculated by summing up the values of the coins collected from the middle lane and from the computer's lane. The scores for each player are visually indicated on the left and right sides of the screen, represented as bars that are filled with coins collected by the users (see Figure 1).

The models we used for implementing the computer player's strategies are based on models in the negotiation research. The game is designed such that both the computer and the human player have their own agendas, which at times may be in conflict. Since the main goal of the users in the game is getting higher scores, both parties pursue their own agenda of collecting coins from their own lanes. In addition, they collect coins from the middle lane with the Ball. When a coin is collected by the Ball, it gets awarded to both players as its value is added to both the human's and the computer's score. Since the Ball is controlled jointly by the dyad, the parties need to collaborate in order to ensure that the Ball collects the coins in the middle lane. However, certain layouts of the obstacles in the computer and human players' lanes cause conflicting situations where collecting the coin in the middle necessarily requires one of the players to hit an obstacle on his/her lane, hence miss the coin in that lane[1]. By design, players can collect coins in their lanes, but they need to cooperate in order that the coin in the middle is collected by the Ball. Otherwise, their movements conflict with each other, and the Ball fails to collect the middle coin. In other words, this conflicting situation might require one of the players to concede and help the other player to acquire his/her own coin as well as that of the Ball.

3.2 The Physics-Based Model

The model used for simulating the physics-based interactions in our game (Figure 2) is similar to the one presented in our earlier work [10], [11]. The human control is supplied to the system through a PHANToM® Omni device, which is used to control the Haptic Interface Point (HIP) in our physics-based model. The computer follows a rule-based policy for each negotiation behavior executed over a PD controller [10] through the control of a Computer Interface Point (CIP). Inputs of the user and the computer are fused together at the Negotiated Interface Point (NIP) as shown in Figure 2. As the name suggests, the Negotiated Interface Point represents the combined output of the user and the computer, and it is used to control the movement of the ball.

All connections between the interface points (IPs) are implemented as spring-damper systems. As a result, the forces due to the movements of HIP and CIP are summed up on NIP, and only then, they

1. 41 out of 45 obstacle combinations cause such conflicting circumstances.

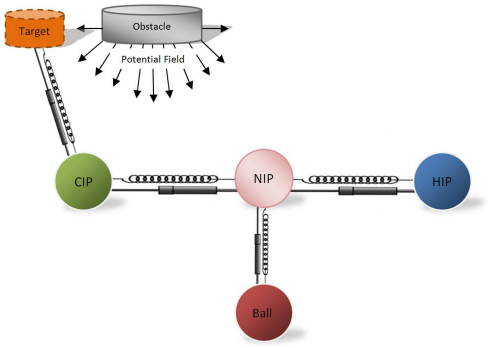


Fig. 2: The physics-based model for the haptic negotiation game. The Ball lies on the line between CIP and HIP, but for clarity of presentation, it is shown below NIP.

are reflected on the Ball with another spring-damper system.

The physics-based model used in this game differs from our previous work [10], [11] in two ways. First, players can control their IPs only on the x-axis. The coins and obstacles move in the positive z-direction (toward the IPs), and the players try to avoid the streaming obstacles only by moving left and right. Second, in order to implement obstacle avoidance, we incorporated a potential field around the obstacles that applies an external force on CIP. This potential field exerts a repulsive force inversely proportional to the distance between CIP and the obstacle (see Figure 2). The potential field of obstacles is a secondary means for helping CIP to avoid obstacles and reach its goal. It can be turned on and off according to the computer player's negotiation behavior and its current decision.

We use the haptic channel for conveying the negotiation dynamics. Hence, the users are provided with forces due to the Ball's deviation from the center of the middle lane. If the Ball moves into the right lane that belongs to the user, the user feels a leftward attractive force (i.e, in the negative x-direction). On the contrary, when the ball passes to the computer player's lane, then the user feels a rightward repulsive force (i.e., in the positive x-direction). This haptic information signals a collaboration opportunity to the user, but a conflict can still occur if the user does not accommodate the actions of the computer.

3.3 Presentation of the interaction cues

The dynamics of the haptic negotiation game as well as the dyad's negotiation state is displayed to the humans through visual, auditory, and haptic channels.

The springs visually rendered between HIP, CIP, and the Ball allow the physics-based model to be visually displayed to the humans. Another visual cue is displayed when the dyads fail to collaborate. In such a case, the Ball goes out of its lane, and the borders of the middle lane start flashing to notify the players about the conflicting behavior.

Auditory cues are displayed when the dyads collect coins. We played three different sounds based on the number of collected coins at a moment (i.e. either a single coin, 2, or all 3 coins). Hence, a perceptive subject is given the opportunity to understand whether the computer has collected its coin or not, using only audio signals.

In addition to providing auditory and visual cues, we also presented a proper way of communicating the negotiative nature of the game to the users through haptic feedback. We intended for the users to sense the conflicting behavior through the forces applied due to the Ball's deviation from the center of the middle lane. Clearly, when the partners collaborate, the Ball stays on a straight path in the center of the middle lane, which results in an equilibrium between the springs, and as a result the users do not feel any force, as intended.

4 Negotiation Behaviors

The behaviors associated with negotiation cover a spectrum between concessive and competitive behaviors [16]. Shell identifies five negotiation behaviors in this range, namely accommodating, avoiding, collaborating, competing, and compromising [16]. However, it is not feasible to convey all these behaviors with only visual and haptic cues. Hence, we narrowed down these five behaviors, and selected three for modeling the behavior of the computer player. These three behaviors lie on the spectrum of the aforementioned range of negotiation styles as shown in Figure 3.

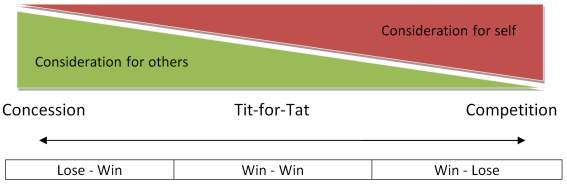


Fig. 3: Spectrum of computer player's negotiation behaviors. Concession and Competition stand on the two ends, and Tit-for-Tat lies in between.

Concession and competition lie on the two ends of the range of negotiation styles and they exhibit clear distinctions between action choices. On the other hand, our tit-for-tat strategy shares elements from both competitive and concessive behaviors. In other words, in tit-for-tat, the actions are formed by blending the other two behaviors' decision-making processes.

In order to implement the negotiation behaviors, we constructed a set of coin combinations and determined the set of actions for each combination (see Table 1). The coin combinations are a key part in designing an interactive setup with collaborative and conflicting components. In order to define payoffs for for different action choices, we selected 3 different coin values in the game: 1, 5 and 20. Note that different combinations for the coins will have different effects both on the human's and the computer player's motivation. We chose 9 out of 27 possible coin combinations, which allow us to create unique conflicting situations where the computer player would behave differently under distinct negotiation behaviors. Those 9 combinations are repeated 5 times during a trial, totaling 45 coin combinations for each dyad. The set of actions for the computer for each of the 9 combinations is listed in Table 1. This set helps us to implement the desired decision-making behaviors for the computer. Moreover, some variation within a given negotiation behavior is allowed in a deterministic fashion. For example, a concessive computer player does not always concede the actions of the human, whereas a a competitive computer player is allowed to accommodate the human if certain conditions hold.

TABLE 1: Chosen coin combinations and the corresponding decisions of the computer for each negotiation behavior.

Coin Values			Computer's Decision			
			Concede	Tit-for-tat		Compete
				Did the computer concede in the last decision?		
CIP's coin	Ball's coin	HIP's coin		Yes	No	
1	1	20	ball's coin	ball's coin	own coin	own coin
5	5	5	ball's coin	ball's coin	own coin	own coin
20	20	1	ball's coin	ball's coin	ball's coin	own coin
1	5	20	ball's coin	ball's coin	own coin	own coin
1	20	5	ball's coin	ball's coin	ball's coin	ball's coin
1	20	20	ball's coin	ball's coin	ball's coin	own coin
5	1	20	ball's coin	ball's coin	own coin	own coin
20	5	1	own coin	ball's coin	own coin	own coin
20	5	20	ball's coin	ball's coin	own coin	own coin

Before presenting the details of the negotiation behaviors, we define the following essential concepts in the context of our game:

- **Benefit** is considered to be an advantage in negotiation. In the haptic negotiation game, the score achieved by a player is that player's *individual benefit*. Also, for each party, *the benefit of making a concession* can be defined as the amount of increase in that party's earnings when he/she collects the Ball's coin instead of his/her own coin. Similarly, the *joint benefit* can be calculated by summing the scores of both players.
- **Cost**, on the other hand, is the element in negotiation, which entails losses. In the haptic negotiation game, we can talk about *the cost of conceding* for each player. When one of the players chooses to concede, he/she concedes to collect the Ball's coin, and in return fails to get the coin in his/her lane. In such a case, *the cost of conceding* is equal to that player's coin.

4.1 Concession

In negotiation research, concession, in its broad definition, is described as consideration for others. Co-

operation theory, which was proposed by Axelrod and Hamilton [26], puts concession as a key factor in negotiation, and focuses on the exchange of concessions. It is suggested that an agreement can be reached through a process in which negotiators cooperate by matching each other's concessions, and the compromises of a person yield benefits to his/her opponent [27]. However, there can be negative side effects of making concessions. When one of the parties makes an offer that supports the other party's interests, he/she would have to face an accompanying reduction in his/her own benefit. In such a case, even though one of the parties benefits from the other's concession, excessive consideration for the opponent may lead to a lose-win situation since the reciprocity is not achieved [27].

When designing our concession strategy, we made use of the definitions and properties as specified in the negotiation research. Essentially, with some exceptions, the computer player makes concessions for the benefit of the human by letting the Ball collect the coin in the middle. This movement eventually allows the human to collect his/her own coin without any compromises. As a result, the benefit of the computer decreases for the sake of maximizing that of the human.

The concession protocol of the computer player depends on three conditions as summarized in Table 2. For each coin combination, if one of these conditions holds, the computer concedes and goes for the Ball's coin instead of collecting its own.

TABLE 2: Conditions and the resulting action for the computer playing with the concession strategy. If one of these conditions holds, then the computer makes a concession, and helps the Ball to collect the coin in the middle. c, b and h represent the values of coins belonging to the computer, the Ball and the human, respectively.

Condition	*Action*
1. $c \leq b$	Concede, and help the Ball to collect the coin in the middle.
2. $c < h+b$	
3. $2 * b \geq c + h$	

The computer first weighs the benefit of collecting its own coin against that of the Ball. If the value of the coin that the Ball can collect is larger than or equal to its own coin's value, collecting the Ball's coin will be beneficial for both the players. Secondly, the computer evaluates the difference between the human's individual benefit (i.e. the sum of the values of the coins the Ball and the human will collect) and the cost of conceding (i.e. the value of the computer's coin). If the human's benefit outweighs the cost of the computer, then the computer concedes. Lastly, the joint benefit is evaluated. If the dyad chooses not to collect the Ball's coin, they will collect the coins in their own lanes. If the sum of the values of the coins in the players' lanes do not exceed twice the value of the Ball's coin[2], then the computer player makes a concession. Since the value of the Ball's coin is added to both player's score, the concession is justified for the computer player. If none of these conditions are met, the computer player ignores the human player, and collects its own coin.

4.2 Competition

Guttman and Maes [28] describe competitive negotiation as the decision-making process of resolving a conflict between two or more parties over a mutually exclusive goal. In competition, each party has its own interests, which are in conflict. The Game Theory literature considers the competitive negotiation as a zero-sum game. From that perspective, the value of the item being negotiated over lies along a single dimension, and it shifts in a single party's favor. Consequently, one side is better off while the other is worse off. Hence, the game theory literature describes competitive negotiation as a win-lose type of negotiation [28].

Our competitive strategy for the computer player reflects these properties. The competitive computer player regards its interests more than those of the other party. With some exceptions, whenever a conflict occurs, the computer player collects its own coin and increases its own utility. However, its persistent, non-cooperative attitude may cause the other party to stop making further concessions. Hence, even though dyads increase their individual utilities, they may miss a win-win outcome.

The protocol for the competition strategy consists of two conditions as listed in Table 3.

TABLE 3: Conditions and the resulting action for the computer player adopting the competition strategy. If one of these conditions holds, then the computer player competes, i.e. it does not try helping the Ball to collect the coin in the middle; instead it collects its own coin. c, b and h represent the values of coins belonging to the computer, the Ball and the human, respectively.

Condition	*Action*
1. $c \geq b$	Compete, and collect the coin on your side.
2. $h \geq b-c$	

First, the computer compares the benefit of collecting the coin in its lane to that of collecting the Ball's coin. If the benefit of collecting its own coin is higher, then the computer collects its own coin. Secondly, it evaluates the benefit of making a concession (i.e. the amount of increase in its earnings when it collects the Ball's coin instead of its own). Unless this incremental benefit exceeds the value of the human's coin, the computer player carries on collecting its own coin. If none of those conditions holds, then the computer player accommodates the human user and helps the Ball to collect its coin in the middle.

2. In the worst case, both players go only for the Ball's coin, missing both coins in their own lanes.

4.3 Modified Tit-for-Tat

The dictionary definition for tit-for-tat is "equivalent retaliation". The strategy was firstly suggested by Anatol Rapaport for the Prisoner's Dilemma tournament, designed by Robert Axelrod. Axelrod and Hamilton [26] formulated the iterated Prisoner's Dilemma game to understand the achievement of mutual cooperation. Tit-for-tat was the winner, and since then, it has proved to be an effective strategy in simulations where cooperation was sought between dyads. Tit-for-tat is a cooperative negotiation strategy. Guttman and Maes [28] classify cooperative negotiation as a decision-making process of resolving a conflict involving two or more parties with non-mutually exclusive goals. Hence, the game theory literature describes cooperative negotiation as a non zero-sum game where there is a possibility for all parties to be better off. In that sense, cooperative negotiation is a win-win type of negotiation.

We incorporated some additional conditions into the original strategy for using it in the haptic negotiation game. In our experiment, the computer player adopting the modified tit-for-tat strategy starts with a cooperating move. In return, the computer expects similar concessions from the human, and unless the user defects[3], the computer player continues to cooperate as long as it increases the joint benefit of the partners. Hence, the parties share a non-mutually exclusive goal, which results in a higher joint benefit. For the computer player to accommodate or make a concession, the history of the process is critical. Table 4 summarizes the two conditions, both of which need to hold in order for the computer player to make a concession. If the computer player notices a defective action in the previous decision for the human's part, then it may retaliate. A retaliation decision is executed if the joint benefit will not increase (i.e. twice the value of the Ball's coin does not exceed the sum of the coins in the other lanes.).

TABLE 4: Conditions and the resulting action for the computer playing with the tit-for-tat strategy. If one of these conditions does not hold, then the computer player makes a concession by accommodating the actions of the human player in order to help the Ball to collect its coin. c, b and h represent the values of coins belonging to the computer, the Ball and the human, respectively.

Condition	*Action*
1. check if you conceded for the previous coin combination	If both conditions hold, retaliate, and collect the coin on your side.
2. $c + h \geq 2 * b$	

5 Experiment

The primary goal of this study is to investigate if the subjects can differentiate between different negotiation behaviors under different feedback conditions. In order to do this, we collected subjective data that reflects the subjects' perception of different playing strategies of the computer player. Moreover, we sought an indication of the effectiveness of different modalities on the recognition of the negotiation behavior. Finally, we evaluated the performance of the subjects on how effectively they can utilize these negotiation behaviors. The main hypotheses that we aimed to test were:

- H1 Subjects can differentiate between different negotiation behaviors in terms of the level of collaboration or conflict they experience during the task.
- H2 Haptic enabled bilateral communication will have a higher impact on the subjects' perception and awareness of the displayed negotiation behaviors.
- H3 Tit-for-tat strategy will help subjects to utilize the negotiation process better than the other two strategies.

5.1 Experiment

24 subjects (5 females, and 19 males) participated in our study. Twelve subjects were tested under the visual and haptic feedback (VH) condition, and the remaining twelve were tested under the visual only (V) condition. Under both feedback conditions, the subjects were asked to perform the task for three behavioral modes of the computer: concessive, competitive, or tit-for-tat. There are six combinations for the ordering of three different negotiation behaviors. In order to balance any ordering effects, each combination was played by two different subjects.

Each experiment took about half an hour, and we provided the same physical setting for all subjects. Since most of our subjects were unfamiliar with a haptic device, we introduced the haptic device to each subject verbally and through training applications. The subjects were presented with an instruction sheet explaining the rules and the goals of the game. They were informed about the existence of three different playing behaviors of the computer, and were instructed to pay attention to the computer's strategy in each mode. However, they were not told that the task was about negotiation. Before starting the experiment, the subjects were given the opportunity to practice with a test trial in order to improve their understanding of the game. During the test trial, the computer played with a preset random negotiation behavior so that the subjects would not acquire prior information about the negotiation behaviors. During the experiment, the subjects were not told what negotiation behavior the computer player had adopted. Instead, they could only see a reference to the mode of the computer player on the screen (i.e. Mode A, Mode B, or Mode C).

3. Defection of the human player means that he/she does not accommodate the computer player by letting the Ball collect the coin in the middle.

For the test trial, the computer player's mode was written as Mode R, for highlighting its random pattern. After the test trial, the actual trials began, in which the subjects played the game once in each mode of the computer (A, B, C) with short breaks between consecutive modes. Finally, each subject performed a short trial consisting all 3 modes (A, B, C) in succession in order for them to remember their sensations under each mode. At the end of the experiment, subjects were asked to fill out a short questionnaire regarding their experience. During the experiments, data was recorded at 1 kHz.

5.2 Metrics

To evaluate whether the subjects can recognize the behavior used by the computer or not, we defined a set of subjective evaluation metrics. Also, the forces exerted at the haptic device are used as indicators for recognizing the governing behavior of the computer player during game play. Finally, we adapted a utility metric from game theory literature for the haptic negotiation game.

5.2.1 Subjective Evaluation Metrics

After the experiment, the users were given a questionnaire, which is designed with the technique Basdogan et al. [29] used previously for investigating haptic interactions in shared virtual environments. The questionnaire consists of a total of 15 questions, 8 of which are included to collect personal information and user feedback. The remaining questions asks the users to specify their level of agreement or disagreement on a 7-pt Likert scale for the 3 negotiation behaviors they experimented with (concession, competition, and tit-for-tat). Some questions are rephrased and asked again within the questionnaire in random order.

For each of the three negotiation behaviors, the questionnaire is designed to measure the collaborative and competitive aspects of the negotiation strategies without knowing the actual behavior that the computer adopts. These ratings are used to assess whether or not the users can identify different behaviors employed by the computer and constitute what we call the "perception of negotiation behavior". To be more specific, in concession, the expected perception of negotiation behavior is towards being more collaborative or accommodating; whereas in competition the expected perception is towards being more conflicting.

Finally, the subjects rated the perceived effectiveness of the available sensory cues, which are given through auditory, visual, and haptic channels. These measurements indicate whether the effectiveness of any modality is higher than the others, and whether there are any significant differences between the effectiveness of modalities under different negotiation behaviors of the computer.

5.2.2 Forces

For each negotiation behavior, we calculate the average force values that were fed to the users by the haptic device. These forces are definitive indicators of the collaboration or the conflict between the dyad. Hence, they are mainly analyzed in order to verify our implementation of negotiation behaviors for haptics-enabled bilateral communication. Additionally, since we have no preconception on the general behavior of the computer for the tit-for-tat strategy, the average forces present valuable information on the dyad's tendencies.

5.2.3 Utility

We investigate how humans interact with the computer players that execute different negotiation strategies. We looked into whether the dyads were successful in utilizing these strategies by looking at the individual and the joint scores of the players. However, due to the chosen coin combinations, the maximum attainable scores by the players are subject to variation. Hence, normalization of the scores is needed to allow us to compare the utilities of the human users and the computer player. We normalize the individual scores by the maximum achievable score (which is deterministic given the coin sequence) in a single game:

$$\text{Individual Utility} = \frac{\text{Achieved Individual Score}}{\text{Max. Achievable Individual Score}} \quad (1)$$

Similarly, the overall utility of the game is calculated using the joint score of the players, which is the sum of their individual scores. We then normalize this joint score with the highest possible joint score in a game:

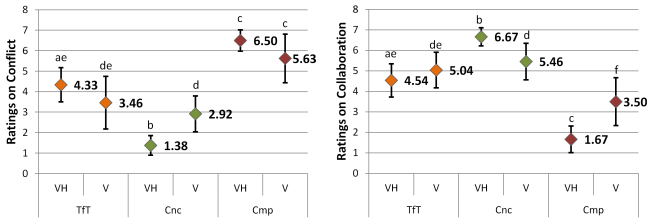
$$\text{Overall Utility} = \frac{\sum \text{Achieved Individual Scores}}{\text{Max. Achievable Joint Score}} \quad (2)$$

6 Results and Discussion

In this section, we present the results of the experiment in terms of the subjective and quantitative measures defined in Section 5.2.

6.1 Subjective Evaluation Results

Our results show that the subjects can successfully differentiate between the behaviors of the computer. As seen in Figure 4, in both visual only (V) and visual and haptic feedback (VH) conditions, the subjects are successful at identifying the characteristics of the computer player such as being collaborative or competitive. Specifically, regardless of the feedback condition, the subjects consistently think of the computer's behavior as being conflicting when the computer employs the competitive strategy, and as being collaborative when the computer plays with the concession strategy.



(a) (b)

Fig. 4: Average responses to the questions regarding the degree of a) conflict, and b) collaboration the subjects felt under V and VH. Different letters above the bars indicate a significant difference at p = .05

In order to shed light on the governing behavior for tit-for-tat, we investigated the average forces fed back to the subjects as an indicator of the ongoing negotiation state in our game. Under the competitive strategy, the computer player insists on collecting its coins, hence it is expected for the humans to frequently find themselves in conflict with the computer. Eventually, these conflicts result in higher force values to be displayed to the subjects. On the contrary, in concession mode, the computer player dedicates itself to accommodating the human. This strategy results in fewer conflicts, hence the subjects feel smaller forces. As shown in Figure 5, this expected behavior is confirmed by the data collected through the trials. Here, we observe that the forces generated for the tit-for-tat strategy fall in between the other two strategies, again indicating a mediocre level of conflict with a tendency towards being more collaborative, during the task. Upon closer inspection of Figure 4, we see that the subjects could successfully differentiate between all three behaviors.

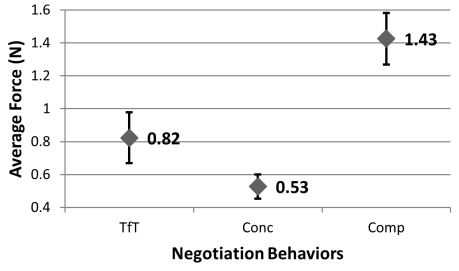


Fig. 5: Average force values that the users feel through the haptic device for each negotiation behavior under VH.

We used paired t-tests with Bonferroni correction to investigate the differences between the negotiation behaviors. The p-values for the t-tests are given in Table 5. Even though all the differences between the subjects's sensations for different behaviors are statistically significant under VH, the subjects cannot differentiate between the tit-for-tat and the concessive behaviors while evaluating how much the computer player worked against them under visual only (V) condition. These results suggest that, when visual cues are supported with interaction forces rendered by our negotiation mechanism, as in VH, the subjects perceive and identify the diversity of the computer player's negotiation behaviors with better precision.

We used the Mann-Whitney U-test to measure the effect of sensory cues on the perception of negotiation behaviors. In parallel with our previous conclusions, the results of this test, as seen in Table 6, also indicate an increased level of awareness under VH when compared to V. We observed that the sense of collaboration is significantly different between V and VH for concession and competition strategies. However, the sense of conflict is significantly different between V and VH only for concession. These results indicate that competitive and concessive playing behaviors, which are the extreme strategies in our negotiation behavior spectrum in Figure 3, are better perceived by the users in the presence of haptic cues.

TABLE 6: Bonferroni corrected p-values of the Mann-Whitney test for detecting the significant differences between the VH and V conditions.

Conflict			Collaboration		
TfT	Con	Com	TfT	Con	Com
0.155	0.000*	0.235	0.518	0.001*	0.001*

Modalities		
Visual	Haptic	Auditory
1.000	0.001*	0.468

* The mean difference is significant at p = .05 level.

Finally, we examined how effectively the three modalities support the subjects to differentiate between the behaviors of the computer player. Figure 6 presents the subjects' responses on the effectiveness of the displayed visual, haptic and auditory cues. We observed that the subjects do not find audio feedback useful in identifying the computer's behavior. On the other hand, visual feedback is effective almost to the same degree under both V and VH. Under V, no haptic feedback was available and the subjects tended

TABLE 5: Bonferroni corrected p-values of the t-test for detecting statistically significant differences between the responses to the questions regarding the level of conflict and the level of collaboration during the game.

	Experimental Condition					
	Visual & Haptic (VH)			*Visual Only (V)*		
	TfT-Cnc	TfT-Cmp	Cnc-Cmp	TfT-Cnc	TfT-Cmp	Cnc-Cmp
Conflict	0.000*	0.000*	0.000*	0.451	0.010*	0.001*
Collaboration	0.000*	0.000*	0.000*	0.131	0.012*	0.003*

* The mean difference is significant at p = .05 level.

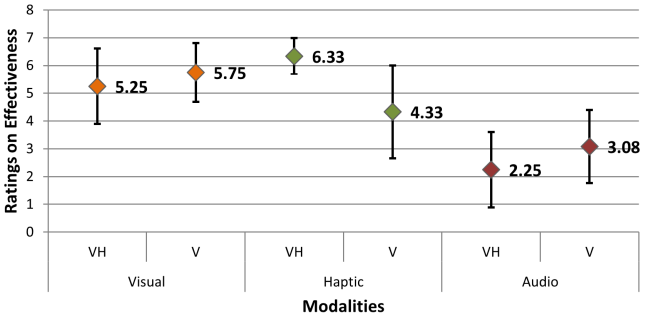


Fig. 6: Average responses to the questions regarding the effectiveness of the three modalities under V and VH conditions.

to remain neutral to the question. However, under VH, the effect of the haptic feedback is observed to be superior to the audio-visual channels. On the average, the subjects rate the effectiveness of the haptic channel as high as 6.33, whereas the visual and auditory channels only achieved the ratings of 5.25 and 2.25, respectively. These ratings indicate a statistically significant difference between the effectiveness of haptic feedback and the other two modalities. Hence, haptic feedback proves to be an effective indicator for the subjects to comprehend the cues of their negotiation with the computer player.

6.2 Utility Analysis

Upon closer inspection of the average overall utility values (See Table 7), we observe that the overall utility is the lowest when the computer player adopts a concessive strategy. On the other hand, it is maximized when the tit-for-tat strategy is adopted by the computer player. We applied paired t-tests to examine the statistical differences between the negotiation behaviors in terms of the overall utilities. The results indicate statistically significant differences between the tit-for-tat strategy and the other two strategies for both V and VH. Under VH, when the computer player makes use of the tit-for-tat strategy, the average overall utility of the game is maximized, and is significantly higher than the overall utilities of concession ($p < 0.01$), and competition ($p < 0.001$). Similarly under V, the highest utility is obtained with the tit-for-tat strategy, followed by the competitive and finally the concessive strategies. Once again, the overall utility in tit-for-tat is significantly higher than that of concession ($p < 0.05$) and competition ($p < 0.01$). Even though no significant difference is observed between V and VH, the games played under VH have slightly higher overall utility values than those played under V for all the negotiation behaviors.

One major outcome of this study is the existence of differences between the individual utility correlations of the players under different negotiation behaviors of the computer player. The concessive and competitive strategies tend to favor a single player's individual utility. For example, a computer player making

TABLE 7: Average overall utilities of the games for the three negotiation behaviors under V and VH.

Average Overall Utility					
Visual & Haptic (VH)			*Visual Only (V)*		
TfT	Concede	Compete	TfT	Concede	Compete
0.85	0.79	0.80	0.83	0.78	0.79

numerous concessions results in a higher individual utility for the human. In other words, the computer player sacrifices its interests for the sake of increasing human's individual utility when it adopts a concessive strategy. On the other hand, unlike a concessive player, the competitive computer player cares only about boosting its own utility, and thus, impairs the utility of the human user. In essence, these two strategies create either a win-lose or a lose-win situation. However, the tit-for-tat strategy allows the parties to balance the number of concessions and conflicts, and as a result of this behavior, favors the overall utility. Hence, the tit-for-tat strategy is beneficial for tasks where the maximized outcome of the joint work of two parties is targeted or valued more. Essentially, it may offer a win-win case and a fair utility distribution for both parties.

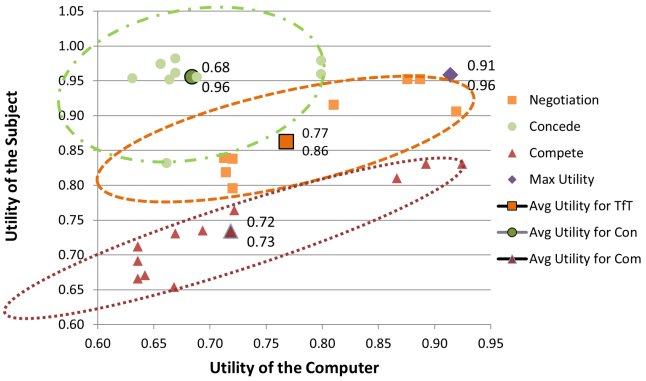


Fig. 7: Utility distribution of the subjects under VH condition. The clusters representing the utility correlations for different negotiation behaviors are marked with ellipses. The cluster centroids are indicated with bold markers.

The three behaviors of the computer player result in different individual utility values for each player. The correlations between individual utilities are shown in Figure 7. The clustering shown in this figure clearly indicates a distinction between the three negotiation behaviors regarding the correlations between individual utilities. The average correlation value for each negotiation behavior is also marked within the enclosing ellipses. To compare the effectiveness of the negotiation behaviors, we computed the maximum achievable individual and overall utilities in our game. The maximum individual utility values are 0.91 and 0.96 for the computer and the human, respectively. When we consider the distance between the cluster centers to the achievable maximum utility values, we observe

that the tit-for-tat strategy is the closest one to that value.

7 Conclusions

In the context of human-robot interaction, haptic negotiation has not been explored in sufficient detail yet. If a haptic task carried out together by a human and a computer-controlled robot involves not only collaborative but also conflicting components, then a haptic interaction model for negotiation is necessary. In this study, we developed such a model for enabling haptic negotiation between a human operator and a computer. Our experiments showed that subjects were more successful in differentiating 3 preprogrammed negotiation behaviors of the computer (concession, competition, and tit-for-tat) when haptic cues were displayed to them. Specifically, the subjects, who played the negotiation game with visual and haptic feedback (under VH), were significantly better at differentiating the negotiation behaviors than those who played with visual cues only (under V). The primary aim of our study was to investigate if haptics improves the recognition rate of machine displayed negotiation behaviors. Hence, score maximization through deliberate and careful identification of the computer behavior was not one of the goals of this study. In our experiments, we only instructed the subjects to pay attention to the different behavioral modes of the computer. However, they were not asked to punish/award the computer in return. On the other hand, in a real-life scenario involving a negotiation between two humans, each party may adaptively update his/her strategy in time depending on the behavior of the other party to maximize either his/her individual utility or the joint one. Hence, understanding the underlying mechanism of the adaptation is also an important component of a negotiation process and must be investigated in depth. In this regard, our game can be used to investigate the haptic interaction between two human players to discover the salient features of negotiation first, which then can be transferred to the computer to make it display more humanlike and adaptive behavior.

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