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GROUP NORM-AWARE ROBOT THAT OBEYS IMPLICIT RULES IN HUMAN GROUPS

理工学研究科総合理工学専攻
知能ソフトウェア工学領域

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博士論文要旨

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<<論題>>

GROUP NORM-AWARE ROBOT THAT OBEYS IMPLICIT RULES IN HUMAN GROUPS
（人間集団内の暗黙のルールに従う集団規範アウェアなロボット）

<<概要>>

今日，人間とロボットの共生社会の到来が予想される中，人間とロボットの間のやり取りに関する様々な研究が取り組まれている．人間とロボットの共生のためには，ロボットが人間と人間らしくやり取りできる上で，ロボットは周囲の状況からその場で期待される振舞いを推察するべきである．人間は直接的なやり取りや指示無しに，その場の状況に応じて他者にある特定の振舞いを期待することがある．その期待される振舞いは集団規範と呼ばれ，度々集団内で暗黙的に共有される．人間は他者を観察することのみから集団規範を推察でき，この能力が人間社会を維持する基礎となる．したがって，集団規範に適応できるロボットは人間とロボットの共生社会の発展に将来貢献することが期待できる．

本研究では人間が形成する集団規範に適応するロボットモデルを提案し，そのモデルを２つのシナリオで評価する．１つ目のシナリオでは人間とロボットの集団が明確な正解のないクイズを回答し，２つ目のシナリオでは自律移動可能なロボットと人間の集団が空間内で距離感を保ちながら移動する．

１つ目のシナリオでは人間集団内で暗黙的に発生する集団規範を推定する意思決定モデルの有効性を検証し，実験結果から人間とロボットの集団は集団規範を形成することが示された．加えて，その集団規範が一部の人間の意思決定に社会的影響を及ぼすことが示唆された．２つ目のシナリオでは人間とロボットが共存する集団で物理的な距離感の集団規範に従う自律移動ロボットの性能を仮想空間と現実空間において検証した．そのシナリオでは集団メンバがお互いに物理的な距離感を保ちながら空間を移動することが期待される．実験シナリオ内でのロボットの移動経路と印象調査の結果から，ロボットが物理的な距離感に関する暗黙的な集団規範に従って移動したことが示された．

以上のシナリオにおいて，本研究で提案されているロボットモデルによる意思決定は，人間とロボットの暗黙的な集団規範の形成に有効であることが示され，直接的なやり取りが無い中でのロボットの社会的な振舞いや人間とロボットの共生社会の実現に将来貢献することが期待できる．

<<各章の要旨>>

第１章では，研究の背景と先行研究を概説し，人間とロボットが共生する社会を実現するために求められるコミュニケーションロボットの社会性についての課題を述べている．そして，本論文の目的と全体の構成を紹介している．

第２章では，本論文で対象としている問題を理解するために，関連する主要な概念について論じている．特に，コミュニケーションロボットと人間の社会性や人間社会で形成される集団規範に関連する研究を紹介している．それらの関連研究の紹介を通じてリサーチクエスチョンを提示することによって，関連研究に対する本論文の位置づけを明確にしている．

第３章では，人間集団で暗黙的に発生する集団規範を推定するためのロボットの意思決定モデルを提案し，１つ目のシナリオである点の多さクイズによりその意思決定モデルの有効性を評価している．２人の人間と提案された意思決定モデルに従って振舞うだけの１人の人間で構成される集団内で，集団規範が形成されているかどうかを検証している．実験結果から，点の多さクイズにおいて意思決定モデルを含む人間集団内で集団規範が形成されることが示され，提案モデルが暗黙的な集団規範を推定して意思決定可能であることを明らかにしている．

第４章では，人間集団における集団規範を推定するロボットの意思決定モデルの改良版を提案し，１つ目のシナリオである点の多さクイズにおいて，そのモデルを搭載したロボット１台と人間２人で構成される集団内で集団規範が形成されるかどうかを調査している．実験結果から人間とロボットが混在する集団でも集団規範が形成されることが示され，点の多さクイズにおいて改良版意思決定モデルは集団規範に適応するロボットの振舞いを表出可能であることを明らかにしている．加えて，点の多さクイズを用いて，２台のロボットと１人の人間で構成される集団内で発生する集団規範が，人間の意思決定に与える社会的影響を調査している．実験中の人間の行動やアンケートから，集団規範発生前と発生後の人間の行動や思考に変化があるかどうかを検証している．実験結果から，点の多さクイズにおいてロボットが集団規範に適応することが人間の意思決定に社会的な影響を及ぼす可能性が示唆されている．

第５章では，人間とロボットが共存する集団で物理的な距離感の集団規範に従う自律移動ロボットを提案し，２つ目の実験シナリオである距離感タスクを仮想空間内で実施し，人間によって操作されるロボットと共に自律移動ロボットが距離感の集団規範に従って移動可能かどうかを評価している．実験被験者は実験シナリオに沿って仮想空間内を移動するロボットの様子を観察し，その後アンケートで仮想空間内の各ロボットの印象を回答している．ロボットの移動経路と印象調査の結果から，距離感タスクにおいてロボットが距離感に関する集団規範に従って移動したことが明らかになっている．

第６章では，複数の人間と１台の自律移動ロボットが共存する現実空間において距離感タスクを実施し，物理的な距離感の集団規範に従うロボットの性能を検証している．本実験では，実験シナリオ内において移動する人間に適応するために，１台の自律移動ロボットが物理的な距離感についての集団規範に適応しながら移動可能かどうかを調査している．集団内の人間がロボットに対して持った印象やロボットの移動経路から，現実空間における距離感タスクでも自律移動ロボットは物理的な距離感の集団規範に適応して移動可能であることを明らかにしている．

第７章は結論であり，本論文の成果を総括し，そこから導き出される将来の展望や将来の研究領域に貢献する可能性について述べている．

以上

Doctoral Thesis

GROUP NORM-AWARE ROBOT THAT OBEYS IMPLICIT RULES IN HUMAN GROUPS

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ABSTRACT

This paper summarizes studies on robots following implicit group norms in human–robot groups in experimental scenarios. Recently, there has been a surge in research to develop communication robots that will interact naturally with people. Optimistic predictions have been made that people will live along with robots in the future. Along such lines, many studies have demonstrated that robots can communicate with people using social behaviors, such as expressing emotions and gestures. However, robots still need to interact more human-like to be socially accepted by people in a human–robot symbiotic society.

To achieve symbiosis between humans and robots, robots should be able to not only communicate directly with others in a human-like manner, but also infer the required behavior from the surrounding situation. In human society, although humans have no direct communication or instruction, certain behaviors are expected from each other according to a given situation and context. The expected behavior is called group norms, which are shared implicitly within a group and are often not explicitly stated. Implicit expectations are also a type of group norm. However, humans can infer implicit group norms by observing others without direct communication with them; society is maintained by individuals who have this ability. Therefore, robots would be able to behave in accordance with implicit group norms, which will contribute to the realization of a society in which humans and robots live together.

In this paper, we propose a robot that adapts to group norms formed in human–robot groups, and evaluate the robot in two scenarios. The first is a scenario in which a group of humans and robots answer a quiz with no clear correct answer, and the second is a scenario on the norms of distancing shared by humans and autonomous mobile robots. The second scenario concerns the norms of distancing shared by humans and autonomous mobile robots.

As a result, we considered the three following research questions:

- Is the proposed model of a robot that learns group norms valid?
- Is the proposed model on a robot effective to estimate group norms in human–robot

groups?

- Do human–robot group norms have a social influence on humans?

In the first scenario, we proposed a decision-making model for the robot that learns group norms implicit in human groups, and tested the effectiveness of the model. The experimental results show that the human-robot group forms collective norms. In addition, the results suggest that the group norms have a social influence on the decision making of some humans.

In the second scenario, we tested the performance of an autonomous mobile robot that considered the dynamically fluctuating norms of distance to be maintained in a human-robot population in virtual and real space. The path taken by the robot in the experimental scenario and the results of the questionnaire revealed that the robot can move according to the group norm regarding the distance to be maintained in the group.

Thesis Outline

The thesis consists of seven chapters.

Chapter 1 introduces the reader to the motivations, contributions as well as overall structure of the thesis.

Chapter 2 provides an overview of the major terms and concepts relevant to understanding the theoretical foundations of the problem targeted in this thesis. In particular, it introduces past and current research related to communication robots, human sociability, and group norms formed in human society. By introducing these related studies, the research questions are presented and the position of this thesis is determined.

Chapter 3 proposes a decision-making model for robots that learn the group norms implicit in human groups and evaluates the model's performance. We form a group with two humans and one human who behave according to the decision-making model, and investigate whether or not the group norms, an implicit understanding to be followed in the group, are formed in the experimental scenario. The results reveal that statistically significant group norms were created in the human group in the experimental scenario, showing that the suggested model can estimate implicit group norms and make decisions.

Chapter 4 proposes enhanced decision-making model for robots that learns group norms in human groups, We test whether group norms arise in a group of one robot and two humans using the model. The experimental results statistically show that a mixed group of humans and robots create group norms and that the improved decision-making model can estimate group norms. In addition, we assess the social impact of group norms on human decision-making in a group of two robots and a human, learning group norms among humans. We explore the change in human participant behavior and thinking in the experimental scenario immediately after the commencement of the experiment and after the emergence of the group norm, based on human behaviors and a questionnaire. We reported that the robot's attempt to follow the group norm in the experimental situation could have a social impact on human decision making based on the results.

Chapter 5 suggests a mobile robot that considers the distance that should be maintained in a dynamic group of humans and robots coexisting in a virtual environment.After the group members move according to the experimental scenario, we conduct a questionnaire survey to evaluate the mobile robot's movement. We concluded that the robot could move around regarding the group distance norm in the experimental scenario based on the answers to the questionnaire and the robot's movement path.

Chapter 6 examines the autonomous mobile robot's performance in adhearing to the distance norm established by human group members. First, we test whether an autonomous mobile robot can move in real space alongside human beings while adhearing to the collective distance norm. The experimental scenario demonstrates that the robot can adjust to changing distance perception. Furthermore, we discovered from the findings of the questionnaire and robot's movement trajectories that the robot can adapt to the variable distance maintianed by group members in the trial.

Finally, Chapter 7 summarizes the thesis and discusses the prospects derived from this thesis and the potential contributions to future research areas.

Contents

Chapter 1

Introduction

Recently, robots have been used to care for the elderly, education, and guiding people in public spaces. With the advancement of science and technology, a society in which humans and robots coexist, is expected to emerge. Many studies have shown that robots can communicate with people by displaying social behaviors such as expressing emotions and making gestures [2, 3, 57, 58]. With the advancement of science and technology, we can anticipate a society where humans and robots coexist peacefully. Robots will need to have human-like behaviors familiar to humans as they are used in the future. Social behaviors such as emotional expressions and interactions using gestures are being studied. On the other hand, studies are being conducted to determine how much human judgment is influenced by robots when human-like robots interact with humans under social pressure. For humans and robots to have an appropriate relationship in a human–robot symbiotic society, there is a need to investigate the possibility of robots misrepresenting human cognition. In other words, robots that try to behave in a human-like way and the social impact of such robots on humans are under study.

In addition to facial expressions and movements, the nature of robots that attempt to follow the group's unspoken and unwritten implicit rules need to be considered. People in a group behave based on their perception of the unspoken rules specific to the group. Robots need to adapt to group norms shared by other group members. Group norms are the informal rules adopted by a group to regulate member behavior, shared value judgments, and behavioral standards [30]. The sharing of group norms provides fluidity in exchanging information among members, making it easier to predict the behavior of others. However, conventional robots output predetermined behaviors in response to human actions, giving humans the impression of being rigid. As a result, there is a limit to how a human-like robot can express itself using only conventional behaviors such as emotional expressions and gestures. Therefore, robots need to behave flexibly in their interactions with humans by adhering to group norms.

There has, however, been little research on robots that decide how to act based on group norms. The development of robot decision-making models that learn group norms is necessary, and their social influence on humans in the group needs to be investigated. Therefore, there is a limit to how human-like robots can express themselves using only conventional behavior, such as emotional expressions and gestures. It is necessary for robots to behave flexibly by following group norms in their interactions with humans. However, only a few studies on how robots behave based on group norms have been reported.

This research aims to propose a decision-making model for robots to estimate group norms in tasks they perform with humans. To solve the above problem, we propose a decision-making model for robots to estimate the value of selecting the action with the highest execution value from multiple feasible actions in the group to which the robot belongs. In addition, to verify whether the decision-making model works effectively and has social effects on humans, we conduct an experimental scenario, in which a robot equipped with the decision-making model and the human participants engage in a group task to analyze human behavior and impressions.

To propose and evaluate the effectiveness of a decision-making model according to group norms, we conduct validation experiments in two scenarios. The first scenario involves humans and a robot answering a quiz together in a group with no clear, correct answer. The second scenario involves distancing norms when a human and an autonomous mobile robot move through an experimental environment. Furthermore, in the first exploratory scenario, we investigate how the formation of human–robot group norms, in which a robot capable of making decisions based on group norms makes decisions alongside a human, affects human decision-making and thinking.

We develop scenarios in which group norms can emerge among group members, conduct basic experiments on group norms in human–robot groups, and apply robot decision-making models to norms shared by human groups. In the basic experimental environment, a quiz with vague correct answers in the first scenario is used. In the application-oriented experiments, a distance norm task maintained in a group is used in the second scenario. We assume a scenario in which humans and robots share space in a society where humans and robots coexist, and we test whether robots can move in the same way that humans do.

First, we propose a decision-making model for robots that learn the group norms implicit in human groups, and evaluate the model's performance. We form a group of two humans and one human who act following the decision-making model. we investigate whether or not group norms, an implicit understanding to be followed in the group, are formed in the experiment.

Following that, we propose an improved version of the decision-making model for robots that learn group norms in human groups, and test whether group norms emerge in a group of one robot and two humans equipped with the model.

Furthermore, we assess the social influence of group norms on human decision-making in a group of two robots and a human, learning group norms among humans. Finally, we investigate the change in the behavior and thinking of the human participants in the experimental scenario immediately after the start of the experiment and after the occurrence of the group norm using human behavior and a questionnaire.

Thereafter, in a continuously shifting group of people and robots coexisting in a virtual world, we present a mobile robot that considers distance rules. After the group members move according to the experimental scenario, we conduct a questionnaire survey to evaluate the mobile robot's movement.

Finally, we create an autonomous mobile robot that adheres to distance norms established by human group members. Humans have a sense of distance rules when sharing space with people that varies depending on the situation. We study whether the autonomous mobile robot can move around while adhering to group standards in an experimental scenario.

Chapter 2

Communication Robots and Human Sociability

2.1 Communication Robots

Recently, there has been a boom in the development of communication robots that can naturally interact with people. Optimistic forecasts have been made that in the future, people will live side by side with robots. Many studies have shown that robots can communicate with people by displaying social behaviors, including verbal and nonverbal communication such as expressing emotions and making gestures. However, it is worth mentioning that, to be socially accepted, robots still have to behave in more human-like fashion in their interactions with people. Therefore, there is a growing body of research that focuses on the development of robots that could physically assist humans and communicate with them through interaction.

For instance, robots can play an active role in various situations, such as companionship, healthcare, and education [14, 15, 36]. In the context of an aging population, social robots are expected to be an aid for social assistants, custodial caregivers in medical treatment, mental health therapists, physiotherapists, care facilities, and private homes [15]. Robots have also begun to show genuine promise in education as learning or teaching companions for children in classrooms or at home, for the elderly to retain cognitive and physical capacities, and for learners with disabilities to adapt content to their abilities [14].

Robots that play an active role in human society require designs and behavior acceptable to humans. Robots, for example, need to be able to verbally communicate with human(s), express emotions and make gestures. It is effective for robots to behave in a human-like or animal-like manner for humans to accept them, as humans tend to feel closer to robots that behave in such a fashion. The design and behavior of robots that make people feel close to them are expected to contribute to sustained interactions between humans and robots, thereby fostering the realization of a human–robot symbiotic society.

The above human-friendly way of interaction is one of the core requirements for human–robot interaction. In a society where humans and robots are expected to coexist in the future, it will also be even more essential for robots to belong to human groups and communities. In human society, humans live with one another while belonging to various groups, such as families, classes, clubs, and companies. Humans behave socially as group members to keep belonging to their groups. To create a human–robot symbiotic society, robots are expected to also exhibit the ability to behave like a member of a particular group or community, which is even much more complex than mere one-to-one interactions with humans.

2.2 Human Sociability and Social Norms

2.2.1 Human Sociability

Human society is made up of many different groups, each of which is a part of society. Humans live in groups and communities, and social intelligence, or the capacity to comprehend others and act effectively in social circumstances, is essential to build harmonious interactions [30]. Aside from humans, there are a plethora of other social creatures. Human sociality is unique in that it develops a wide range of social institutions, such as regulations [16]. A social institution is a set of behavioral characters controlled by various mutually accepted norms and rules [16]. Humans can construct large-scale collaboration based on social institutions formed by the integration of multiple norms and rules.

Social institutions shape the world's social reality, consisting of innumerable physical particles. Humans who live in a social world face various social entities such as currency, corporations, and states. "The piece of paper in my hand is a ten thousand yen bill," for example, is an understandable objective statement. However, this factual statement results from a set of human subjective attitudes. Although the bill is physically just a piece of paper with a historical person printed on it, the subjectivity of each individual makes the piece of paper socially valuable as a bill. Social entities are compatible with this physical world.

There have been efforts to explain how social reality may exist in this physical world owing to the subjectivity of each individual as described above [17, 18]. Individuals' devising and obeying of social rules result in the emergence of social reality when all individuals share a common understanding of the rules. Devising and obeying social rules are essential components of every human civilization in which humans live in harmony with one another.

2.2.2 Formation of Social Norms

When a person behaves in a group that he or she belongs to, he or she is aware of the group's social norms. There are two types of social norms: explicit and implicit social norms. Although explicit norms are shared among groups, unspoken and unwritten norms also exist. These unspoken and unwritten norms differ from one group or community to the next. Group norms are such distinctive regulations that are exclusive to each group or society. Such regulations rely on humans' social nature to remain homogenous. In addition, when a person joins a new group, he or she needs to learn the group's standards of proper conduct and thought for fitting in and being accepted as a member. Although such standards are frequently implicit, people need to adapt to each of the norms of the organizations that they belong to.

The adaptation of human behavior to social rules or group norms keeps organizations, communities, or the world in order. These norms determine informal rules created by groups to manage members' conduct [30]. Social interactions among group members are effective when group norms are shared, since group members expect orderly behavior from one another [30]. Hence, humans can live in harmony even with strangers, if group norms are shared and maintained [10].

Nevertheless, humans have individual differences in their decision-making criteria [19, 20]. As a result, they can respond differently to the same stimuli. Even though individuals have their own personalities that make them unique, people in a group are influenced by social factors. A change in an individual's beliefs, feelings, attitudes, or actions resulting from interacting with another person or a group is referred to as social influence [21]. Normative social influence and informative social influence are both types of social influence. These factors have an impact on a person's decision-making [20]. When people are unsure how to act in a new circumstance, they emulate the actions of others.

According to Sherif et al., developing a group norm in a human group takes only a few exchanges when group members attempt to answer ambiguous questions as part of an exam [13]. It was assumed that the influence of each participant in the group helped the other participants to imitate their answers [31], thereby forming a group norm about the quiz. However, some studies also noted the social influence of group norms in human groups to demonstrate an experiment about sociality [39, 40, 41]. In particular, Asch et al. experimented with investigating social pressure from a majority group [37]. They investigated whether most participants would follow the majority group's blatantly erroneous behavior. They found that the experimental participants in groups implicitly made social pressures to form group norms with no direct verbal communications.

To behave as member of a group or community, it is not only important to interact appropriately with other members on a one-to-one basis, but it is also vital to act in such a manner that one is recognized as a group member and the group members acknowledge the group's unity. For the sense of belonging to the same group, unity, and solidarity, individuals of the group are expected to follow the group's behavioral pattern.

2.3 Previous Works and Research Questions

2.3.1 Human–Robot Groups

Researchers have proposed numerous robots for different domains and purposes such as healthcare, therapy, education, and navigation in public spaces [2, 57]. Furthermore, some studies have established methods for human-robot collaboration in a variety of scenarios [58].

Considering the prediction that humans and robots will coexist in the future, it is necessary to investigate the impact of robot behavior on humans to build appropriate human–robot relationships. Ideally, humans need to maintain cordial relationships with robots without displaying excessive trust or handling excessive social pressure during mutual interactions in a human–robot group. Furthermore, several studies have investigated social influence in human–robot groups inspired by Asch's experiments. Robinette et al. reported that some individuals over-trusted a robot [32], and Salomons et al. demonstrated that some individuals changed their opinions because of the social pressure caused by robots' presence [33]. Meanwhile, Brandstette et al. observed conformity in human–robot groups in some scenarios [34]. Williams et al. and Vollmer et al. reported that some children changed their opinions or behaviors due to a robotic behavior [42, 43]. However, Beckner et al. showed that humans did not conform to humanoid robots in boundary tasks of linguistic imitation [44]. As a result, human compliance with robots and robot social effects on humans are situation-dependent. However, robots did not alter their attitudes or behaviors to impact human social pressure in these trials. Hence, it is uncertain whether changes in robots' behavior would have a societal impact on people.

Many researchers have investigated the role of social impact in human–robot interactions. In a human–robot group, humans should ideally maintain a suitable connection with robots while mutually participating in the group without overtrusting or imposing undue social pressure. However, in studies on social pressure, robots do not behave adaptively. Even if implicit group norms occur in the experiments within those studies, they may be caused by the subordination of only human participants. In a society where humans and robots live together, group norms need to be formed by the adaptive behavior of both humans and robots. For this purpose, developing a decision-making method for robots to behave adaptively by following group norms is necessary.

2.3.2 Methods for Robots Learning Sociable Behaviors

Humans have varied criteria for decision-making [19, 20] and respond differently to one another under the same conditions. Individuals in a group are subject to social influence, defined as a change in a person's thoughts, feelings, attitudes, or behaviors. Such social influence results from the interaction with another person or group [21]. Therefore, when people are unsure how to act in a new situation, they often imitate and conform to the behavior of other people. "Conformity refers to the act of changing one's behavior to match the responses of others [38]." Thus, humans tend to always respond to the behavior of others.

Here, we propose a robot model that aims to behave adaptively by following group norms. The robot model learns through a framework for understanding a suitable policy without training data such as reinforcement learning [23]. Reinforcement learning is also used in robotics [24, 25]. However, because the robot model does not know the personalities of the group members before the group is established, the robot model needs to adjust itself to the group without prior learning. Humans also adapt to a new group after its formation. In reinforcement learning, the system is unable to revert to a previous state. Furthermore, group members cannot return to the state they were in at the start of the meeting. The robot model needs to adapt to group norms without prior learning by interacting with group members.

Interactive evolutionary computation (IEC) is used to solve problems without prior learning solely through the interactions with a user [26, 27]. However, IEC has a problem associated with the size of a search space because users' fatigue arising from the interactions with the IEC system has to be considered. Because human group members build their group norms in only a few encounters, this experiment is challenging given the size of a search area and the restriction on the number of interactions, which are quite limited.

Therefore, we propose a model that can enable robots to learn the value of each action the robot can select in a group by observing the behavior of the group members. Learning group norms in real-time requires both learning the value of actions, as in reinforcement learning, and finding the optimal solution (the robot's action), as in IEC.

2.3.3 Group Norms for Human–Robot Experiments

This study was focused on unspoken and unwritten implicit rules in human-robot groups. In everyday life, people behave according to various regulations, ranging from stated explicit restrictions (such as laws) to unspoken implicit standards. To follow implicit rules, people imitate the beliefs and ideas of others while making necessary refinements based on others' opinions and ideas in situations when there is no apparent acceptable way to conduct. Each participant in a group triggers an observation loop by monitoring their interactions with other group members. Unspoken and unwritten group norms emerge gradually on an ad hoc basis when each group member follows the loop without direct contact.

Therefore, in human society, group norms emerge according to a given situation and context, even though there is no direct communication or instruction. The group members are then expected to behave according to the group norms. The expected behavior is implicitly shared among the group, community, or people in the situation, and it is often not explicitly stated. However, humans can infer group norms by observing others without direct interaction with them. By behaving appropriately, a group of people with such abilities can maintain a group as a unified entity.

In a future society where humans and robots would interact symbiotically, people may expect robots to behave according to group norms as members of the group, just as humans instinctively behave according to their implicit norms. In addition, humans may feel disinterested in robots that cannot interact in a human-like manner, preventing the long-term interaction necessary to establish such a symbiotic society. The ability to adapt to implicit group norms can lead to the realization of a human–robot symbiotic association. Therefore, a given robot behaves in a group considering group norms, it is expected that human members will feel intimacy and trust in the robot as a group member, which will lead to more interaction and communication between humans and robots. In other words, it can be expected that robots that behave by conforming to implicit group norms can contribute to the realization of a human–robot symbiotic society.

The group norms considered here are rules of action. Such rules encompass different dimensions of norms, ranging from action-level norms to belief-level norms within a group. Here, we consider an example of people walking in a public space, such as a train station. In such spaces, people need to move to avoid collisions with others. Thus, people may flow naturally in their directions of travel, such as passing on the right or left side of their pathways, without verbal interaction with each other. The norm of the action level in such a situation is that a robot should move in the direction that others are walking. The belief-level norm in such a situation is to move in a way that avoids collisions with others.

When a robot follows behavior-level norms, it is more likely to avoid collisions with others trying to move in the opposite direction. Humans have belief-level norms, and these norms imply that humans should move in a way that avoids collisions with others. However, when a robot follows action-level norms, it does not necessarily mean that the robot learns that the norms are for avoiding collisions with others. The belief-level norms are more advanced than the behavior-level norms.

Here, we propose robots that infer and adapt to implicit norms in human groups without any direct communication with other group members. To achieve this goal, we investigated whether the robot can learn norms at the action level where it shares with other members by observing their actions and whether group norms between humans and robots can be generated. Note that norms at the belief level are out of the scope of this study and would be considered in future studies.

2.3.4 Research Questions

In many studies on communication robots, the basic premise is that robots communicate directly with humans in various predefined scenarios. In such direct human–robot interactions, sociability is required. There is extensive ongoing research on robots that can communicate verbally and nonverbally with humans, including emotional expressions and gestures. Herein, we focus on how robots can cope with group norms and behave toward their human counterparts.

In human society, social behavior is not required only in situations where there is direct communication. In a situation where there are several people in the same space, even if there is no direct communication, they are still subject to interactions. People can perceive what kind of behavior is being expressed by others. That is, even without direct communications, people implicitly form norms of behavior, such as group norms, that should be followed in each situation. These norms also emerge from the social nature of humans and contribute to the formation and preservation of human society.

In this study, we focus on implementing the sociability in robots, especially in situations where there is no direct human–robot communication and interactions. For humans and robots to coexist in a single society, robots need to form and follow implicitly shared group norms, just as humans do. However, when adapting to group norms that appear ad hoc or differ from group to group, it is paramount for robots to observe the group's behavior on an ad hoc basis and infer those group norms.

Herein, we propose a robotic model for decision-making based on group norms in human–robot groups. The proposed model enables a robot to observe the actions of its group members and estimate implicit group norms to adapt to and behave in a socially acceptable fashion following the group norms.

Previous studies on sociality in human–robot groups focused on the social pressure of robots to human(s). In those studies, robots did not make sociable decisions in an adaptive way; they only behaved as preprogrammed by the experiment organizers. Contrarily, herein, robots attempt to make decisions socially by following group norms in human–robot groups.

We considerd the following research questions to investigate group norms created by humans and robots, as shown in Fig. 2.1.

- Is the proposed model for robots that learn group norms valid?
- Is the proposed model for robots effective in estimating group norms in human–robot groups?
- Do human–robot group norms have a social influence on humans?

2.4 Summary

In this chapter, we present an overview of the core concepts and theories related to this study. First, we introduced communication robots in various scenarios, highlighting that such robots need to act acceptably to people. In human–robot interactions, robots need to adjust to humans' communication styles. Second, we gave an overview of human sociability and the norms established as a result of it.

Humans are social animals that can establish laws to sustain their communities. These guidelines might be stated explicitly or implicitly. For example, when a human wants to be a part of a group, he or she needs to follow the norms that are exclusive to that group; yet, the group's behavioral style and regulations are frequently shared implicitly. As a result, a newbie needs to infer the implicit norms by studying the group's behavior. Group norms are such unspoken regulations that emerge from human social traits. It is required to follow such

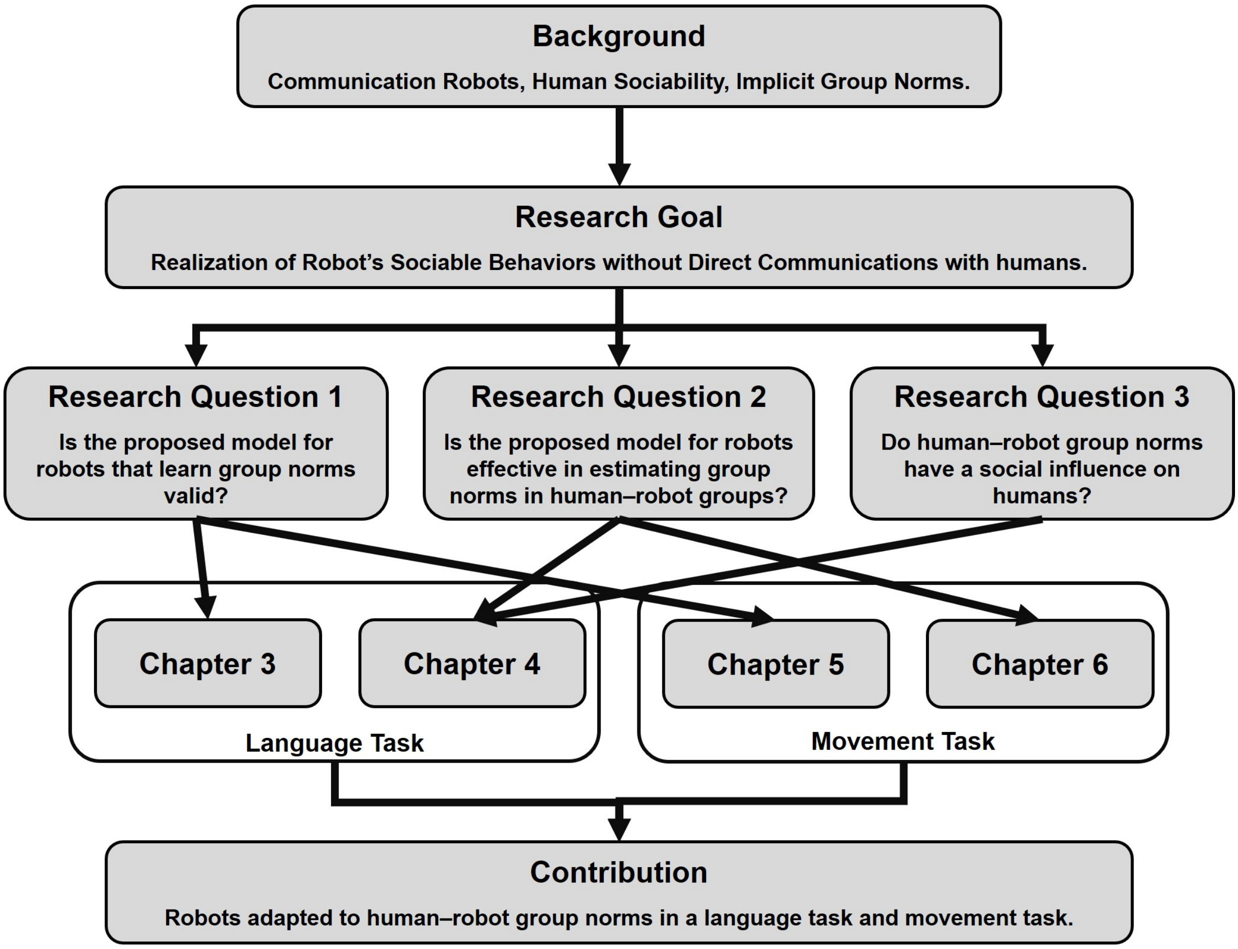

Figure 2.1: Overview of the background, goals and contributions of this thesis.

guidelines to be accepted as a member of a social group. Third, we present prior research on human–robot group experiments and learning methodologies.

This study was mainly motivated by two issues: first, few prior studies on human–robot group experiments have thoroughly investigated into whether robots can develop group norms through subjective decision-making and the social implications of doing so. Second, there are few approaches for inferring ad hoc group norms that are adequate for learning. This thesis offers a robotic model that can estimate implicit group norms in a human group by tackling the above two challenges.

Chapter 3

A Robot Model that Obeys a Norm of a Human Group by Participating in the Group and Interacting with Its Members

3.1 Introduction

In this chapter, we propose a model to allow a robot to create a suitable criterion for decision-making according to a group norm in a multiparty quiz scenario in groups composed of only humans.

Recently, efforts to develop communication robots that can please people through emotional expressions and communicate with people naturally by behaving like living creatures have increased. However, to date, these robots did not have the ability to join a multiparty group or conversation. Moreover, to communicate more humanly in multiparty situations, such robots will need to learn sociality [1]. The aim of designing social robots is to enable them to interact with people or other robots in a human-like manner [2, 3, 4].

Robot models that consider sociality have been proposed previously [5, 6, 7, 8, 9]. These models enable robots to behave cooperatively. Carlucci et al. proposed a robotic system design that considers social behavior by implementing already-known social norms shared in a human society. Within their model, the robots were able to behave cooperatively with humans. However, sociality is an endeavor to form a group and live with the group members. In every human society, people cooperate with many unrelated individuals [10].

To exhibit sociality in a human society, robots need to adapt to group norms that are formed by the members of the group. People conform to expectations and common group behaviors in human groups. Therefore, robots must also learn to behave as a member of a group by observing other members. However, all humans have unique personalities. This reflects the dynamic integration of a person's subjective experiences and behavioral patterns [12]. Because of the unique personalities, people have different criteria for making decisions and can respond differently from one another when facing the same situation [13]. Although people have different personalities and decision-making criteria, the criteria converge into one common criterion when a group is formed.

We therefore proposed a model for a robot that creates decision-making criteria by interacting with people in its group. A robot system using this model learns the criteria suitable for the group. We investigated whether the system can adjust its own behavior according to a suitable criterion in a group including humans, i.e., we investigated whether the group members and system's answers converge on their own to a suitable criterion when they answer easy quizzes that can have vague answers. We proposed two conditions for the experiments. First, one of the participants in a group only obeys the system, while the other participants are unaware of the system to avoid bias toward the system's answers. Based on this condition, we investigated whether the answers of the system exhibit appropriate behaviors based on a normative criterion in a group, which is similar to how humans answer. Second, the participants should not be familiar with the social science concept of group norms, because it is assumed that this concept would influence the participants' quiz answers.

3.2 Group Norm Model

The proposed model enables a robot to create a suitable criterion, i.e., the group norm, for decision making by interacting with the people in a group through reinforcement learning. Fig. 3.1 shows an overview of the group norm model. In this study, we aimed to investigate a robot system's decision-making ability on the basis of group norms and determined whether this decisions-making approach resembles that of a human. For a robot to adjust its behaviors according to a group that includes human members, it needs to infer a specific way to behave in the group with regard to the other group members' behaviors while a group norm is being formed. Before a robot behaves in a group on the basis of the robot system, we investigated whether the robot system, considering a group norm can make decisions.

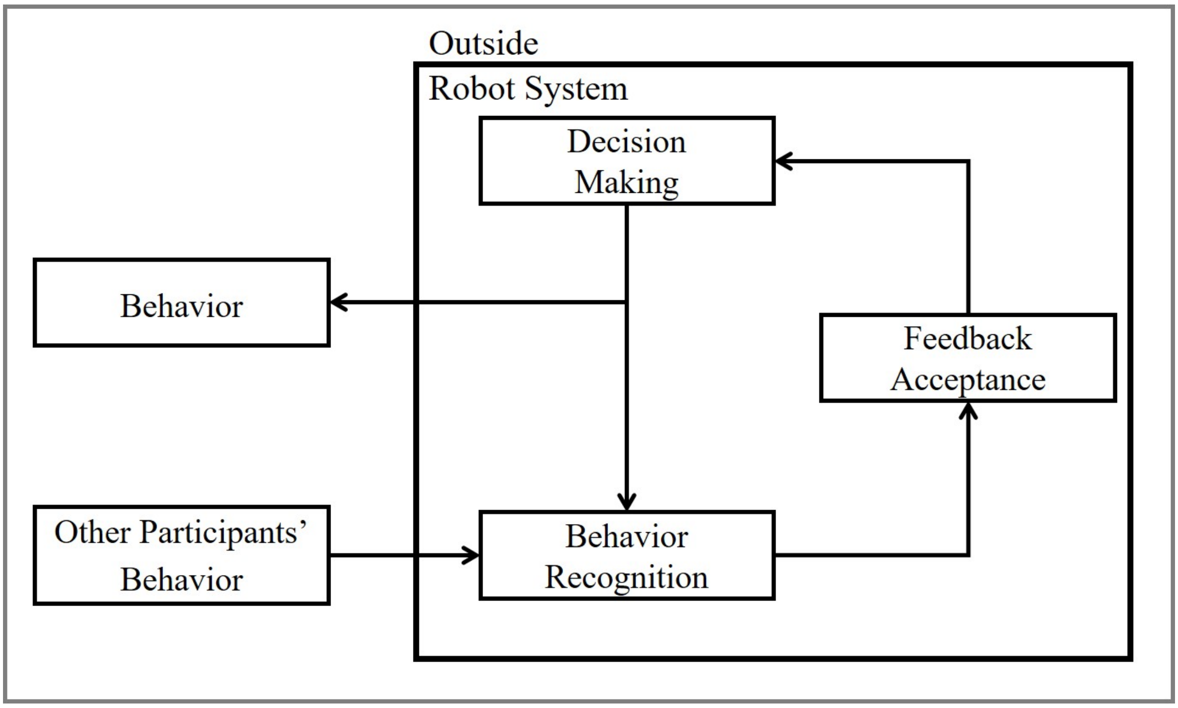

Figure 3.1: Diagram of group norm model.

3.2.1 Decision-making

We proposed a model, as shown in Fig. 3.1, that a robot uses to follow a group norm. The robot's behaviors within the group are determined by this model. The robot recognizes the behaviors of the other group members and compares its own behavior with these behaviors. Thus, it behaves cooperatively and creates a suitable group criterion by learning from other members' behaviors.

The model uses three stages to learn a suitable behavior: decision making, behavior recognition, and feedback acceptance. The inputs pass through these stages. Inputs to the model comprise the group members' behaviors, and the output is the model's behavior. Moreover, the decision-making module learns the group norm via reinforcement learning.

The decision-making component determines the robot's behavior. The robot then inputs its own behavior into its behavior recognition component. Here, the robot learns a suitable behavior using the hypothesis that people also converge to a suitable behavior in a group.

The behavior recognition component receives both the system's behavior and those of the other members. These behaviors are first input to the system's behavior recognition component

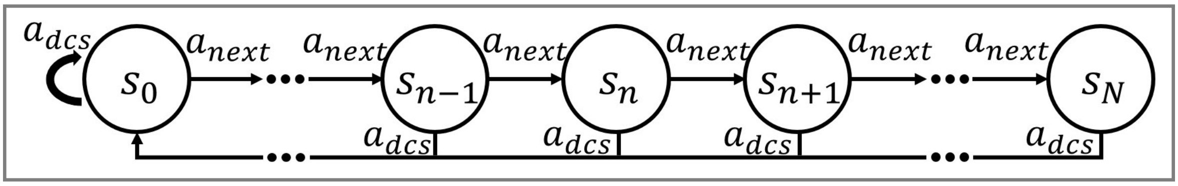

Figure 3.2: State transition.

and are fed to the feedback acceptance component.

Based on a combination of the group members' answers, the feedback acceptance component gives a feedback to the decision-making component. The feedback acceptance component judges whether the system's behavior suits the group to which it belongs, resulting in the system receiving a positive or negative feedback. When the system's behavior corresponds to that of one of the members, the system receives a positive feedback. However, when the system's behavior does not correspond to those of the other members, it receives a negative feedback. The feedback is then input to the decision-making component, which uses the feedback to learn how to select suitable behaviors.

The system prioritizes the different behaviors that it can execute through the repetition of this process. The priority is based on whether the participants' behaviors correspond to the system's behavior. As the system's behavior and other participants' behaviors correspond to each other, the behaviors within the group become unified.

The decision-making component creates a suitable criterion for group participation by learning the group members' behaviors through reinforcement learning. An agent in the decision-making component is used to make the decisions and has a role in learning suitable behaviors. The agent adjusts the value parameters of the different behaviors, which are the values of each behavior that the system can execute. After the agent selects a certain behavior based on the value parameters of different behaviors, it receives a feedback.

3.2.2 Reinforcement Learning Parameters

Reinforcement learning in this study involves actions, states, a value function, Q values, and rewards. The proposed model also employs a reinforcement learning environment in the decision-making component (Fig. 3.2). The robot system using the proposed model has a set of behaviors that the system can execute. When such a system operates in a real-world scenario, an agent in the decision-making component relies on the reinforcement learning environment and decides which behavior the system should select. In a group, each behavior is assigned a value that can be selected by the system.

There are $N+1$ states and two actions, which constitute the reinforcement learning environment shown in Fig. 3.2. The nth state s_n represents a criterion that the robot comes up with at nth time in order to behave socially. N represents the maximum number of states. The actions are a_{dcs} and a_{next}. a_{dcs} denotes that the agent decides when the robot exhibits its behavior based on a present state: a certain criterion. a_{next} shows that the agent moves from the present state to the next state.

There also are Q values, rewards, and a value function. The mechanism of the group norm model assigns a high value to the robot's adjustment to the group that includes human members. A value function, $V(s_n)$, shows the value of s_n as a criterion in a group. The Q value $Q(s,a)$ denotes the value of a combination of a certain state and action. When a robot adjusts its behavior according to the group, the robot selects an appropriate way of behaving with the group by searching the space of states. The values of these ways are derived from the value function. In addition, rewards are used to renew the value function. Until the robot using the proposed model makes a decision in the group, the robot system executes a_{next} several times and a_{dcs} once while moving from the present state to the next state in the environment, as shown in Fig. 3.2. The a_{dcs} denotes that the agent decides that the robot carries out a behavior based on a present state: a certain criterion, that is may be suitable for a group. The a_{next} indicates that the agent moves from a present state to a next state. When a_{dcs} is executed, the agent judges the present state is not suitable criterion.

Each time the agent in the robot system moves to the next state, it has to make a small decision, i.e., to select either a_{next} or a_{dcs} in a certain state. The value of the small decisions indicates a Q value, which is derived from the value function. In this case, the equation for renewing the value function at the tth step is given in Eq. 3.1, where γ is a discount factor, α is the learning rate, S is a set comprising states, and r is the reward at the tth step. Moreover, the equation for deriving rewards r at the ith step is given in Eq. 3.2, where s_k is a criterion that each group member has in the group. Additionally, the initial Q values of each action are random numbers.

$$V^{t+1}(s_n) \leftarrow V^t(s_n) + \alpha\left(r + \gamma \max_{s' \in S} V(s') - V(s_n)\right) \tag{3.1}$$

$$r = \begin{cases} +1 & (\text{if } s_n = \text{a certain } s_k) \\ -1 & (\text{the others}) \end{cases} \tag{3.2}$$

Moreover, the equation for deriving Q values is given in Eqs. 3.3 and 3.4. The conditions of the variables in Eqs. 3.3 and 3.4 are $m \in \{0, 1, 2, \cdots, N-1\}$, $n \in \{0, 1, 2, \cdots, N\}$, and $l \in \{0, 1, 2, \cdots, N\}$. The agent selects an action that has higher value than its present state.

$$Q(s_m, a_{next}) = V(s_{m+1}) \tag{3.3}$$

$$Q(s_l, a_{dcs}) = \frac{1}{V(s_l) - \max_n V(s_n)} \tag{3.4}$$

Eq. 3.4 has two cases corresponding to the value of $V(s_l)$. When $V(s_l) = \max_n V(s_n)$, Eq. 3.5 indicates the following scenario: the robot feels that s_l is appropriate as a group norm.

$$Q(s_l, a_{dcs}) = \begin{cases} Q(s_l, a_{dcs}) \to \infty & (\text{if } V(s_l) = \max_n V(s_n)) \\ Q(s_l, a_{dcs}) < 0 & (\text{the others}) \end{cases} \tag{3.5}$$

In other words, the agent moves in the environment by executing a_{next} or a_{dcs} on the basis of the Q value of executing an action in a certain state. However, it is difficult for robots to come up with a certain criterion at the beginning of the experiment. Therefore, based on a limited scenario of experiments, a set of states is provided to the robot in this study.

3.3 Experiments

We carried out three experiments with 30, 15, and 4 participants in an investigation about descriptive terms, group experiments, and another investigation for the Mann–Whitney U test, respectively. The 30 participants in the investigation do not include the 15 participants in the group experiments. Moreover, the four participants are different from the 30 and 15 participants.

We did not use a real robot in our experiments, because we aimed to investigate whether group norms occur or not even if one of the group members make decisions in accordance with making-decisions of the robot system. We developed a system based on the proposed model for robots to socially make decisions in a group. Therefore, we use the word "robot" in this study, although a real robot does not participant in these experiments.

3.3.1 Quiz Environment

In this study, we prepared quizzes about the descriptive terms of a quantity of dots for participants in an experimental group. Each participant answering this quiz can describe his or her degree of the amount of some descriptive terms as the number of black dots in a white box. Each participant answers the same quiz by clicking a button on a laptop. All participants recognize each participants' answers after the participants answer once. This procedure is repeated several times. At first, each participant does not know the correct answer; thus, the participants answer the quiz on the basis of their criteria. However, each participant' answer is affected by other participants' answers and the participants change their criteria because they do not know the right answer and recognize each answer in the group.

Fig. 3.3, 3.4, and 3.5 show an input screen on the laptop and an example of a participant's answer. Fig. 3.3 shows the input screen in its initial state. Fig. 3.4 shows the input screen after a participant has answered. Fig. 3.5 shows the results of the three answers after the participants have finished the quiz.

Figs. 3.3 and 3.4 have two buttons beneath the white box: BUTTON and FINISH. If the participant clicks on BUTTON once, a black dot appears on the input screen. The number of BUTTON pushes represents the number of dots that equals the descriptive term. Each time the participant clicks on BUTTON once, a black dot appears at a random location in the white box. The number of dots indicates the answers of a participant in a quiz for the application. Each black dot appears in according with a same pattern. However, the pattern makes it difficult for participants to expect where a next black dot appears in the white box. Additionally, the quiz allows participants to click to a maximum of 100 times. Although the participants are unaware of this limit, they can determine the number of dots in their own answer.

Answers in this study are white images with black dots, like Fig. 3.4. In this study, good answers do not exist because the quiz does not have a clear answer. However, the meaning of the answers depends on the human's or robot system's perspective. When a participant pushes BUTTON X times, a white image including X black dots is created. If he or she is satisfied with the image as an answer of a quiz, he or she pushes FINISH and the image becomes his or her answer. However, the robot system regards answers as the numbers of dots in the white images regardless of the location of these black dots.

Table 3.1 provides a list of the descriptive terms that the three quizzes use. The participants

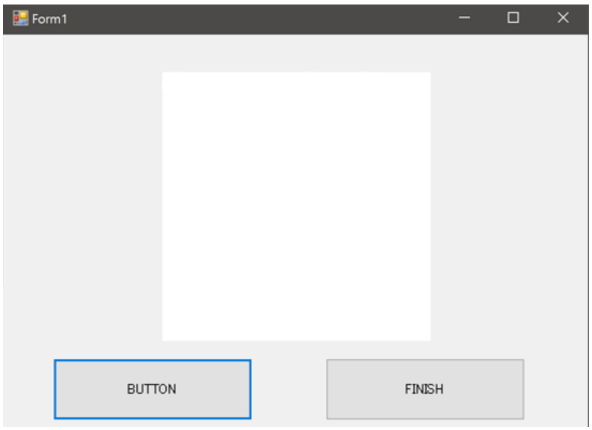

Figure 3.3: Initial quiz input screen.

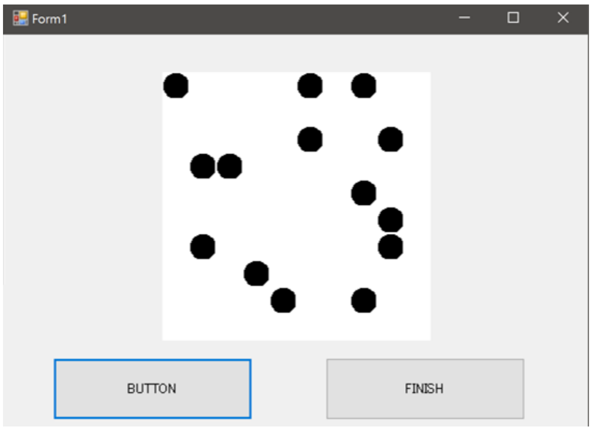

Figure 3.4: Input screen with the answer.

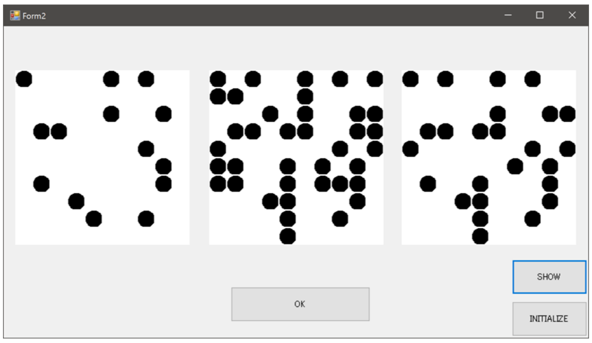

Figure 3.5: Result at end of a step.

Table 3.1: Six descriptive scale.

	Japanese	English
A	Hodoyoku	You see a moderately large number of dots
B	Sokosoko	You see a somewhat large number of dots
C	Dochirakato-ieba	If you had to choose, you would say that you could see a large number of dots
D	Warito	You see a comparatively large number of dots
E	Kekko	You see quite a lot of dots
F	Kanari	You see a considerably large number of dots

answered a quiz that required them to follow this instruction: "continue pushing BUTTON until, in your opinion, you see X." The label X is replaced by a descriptive term that is selected in an experiment. It is substituted with one of the English translations of the descriptive terms (A, B, C, D, E, or F) listed in Table 3.1. In addition, we informed the participants of the existence of the six descriptive terms in the quizzes before the test. We also informed them that they could make their own criteria for each descriptive term. For example, the quiz asks participants to continue clicking BUTTON until, in their own opinion, they see a considerably large number of dots.

We investigated 30 university students' answers to six quizzes before experiments were performed for the system in order to use the results as a dataset for clustering. These participants indicated their descriptive scales by entering an answer on our laptop. In these experiments, the number of dots represented the participants' descriptive scales.

3.3.2 Flow of Experiment in Group

Fig. 3.6 shows an environment wherein the experiments were performed. A laptop was placed on a table, and a chair was placed near the table. In addition, three participants and a quiz host sat on the table. Therefore, in this study, a group comprised three human participants. A place surrounded by a dotted line where the participants sat was referred to as the "waiting area," whereas the other place surrounded by a dotted line next to the quiz host was referred to as the "answering area," as shown in Fig. 3.6. Additionally, the people in the waiting area

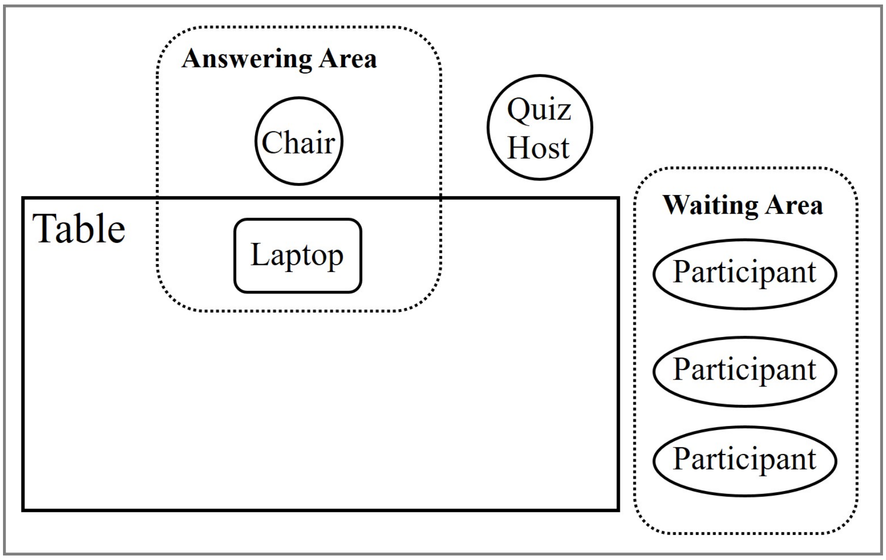

Figure 3.6: Environment of experiments.

were not able to see the display of the laptop in the answering area. This was done to prevent them from being aware of the other participant's opinion because the people in the waiting area can use this information to seek advice to answer the quiz.

Fig. 3.7 shows a flowchart that defines the experiment controlled by the quiz host. At first, all participants who intended to join our group experiments answered the six quizzes without any advice in order to enable a comparison between individual answers and answers in a group before performing the experiment. Next, a quiz host taught the participants how to use the laptop before the experiment was performed. Then, the quiz host selected only three participants as group members in a single experiment, of which two answered differently in the same descriptive term quiz, i.e., the individual difference between each of them is large.

Here, one out of the three participants in a group, who is referred to as "Participant" and is our collaborator, knows the aim of these experiments. At this point, the "Participant" only obeyed the system on the laptop, answered based on the proposed model, and pretending that he was answering by himself while the other participants answered the quiz on our laptop. In this experiment, a robot system was included in the application (Figs. 3.3, 3.4, and 3.5). When the third participant attemtped to answer, the application automatically displayed the robot system's answer as the third participant's answer. This was the phase of forming a group, i.e., at this point, each participant considered the other participants as group members.

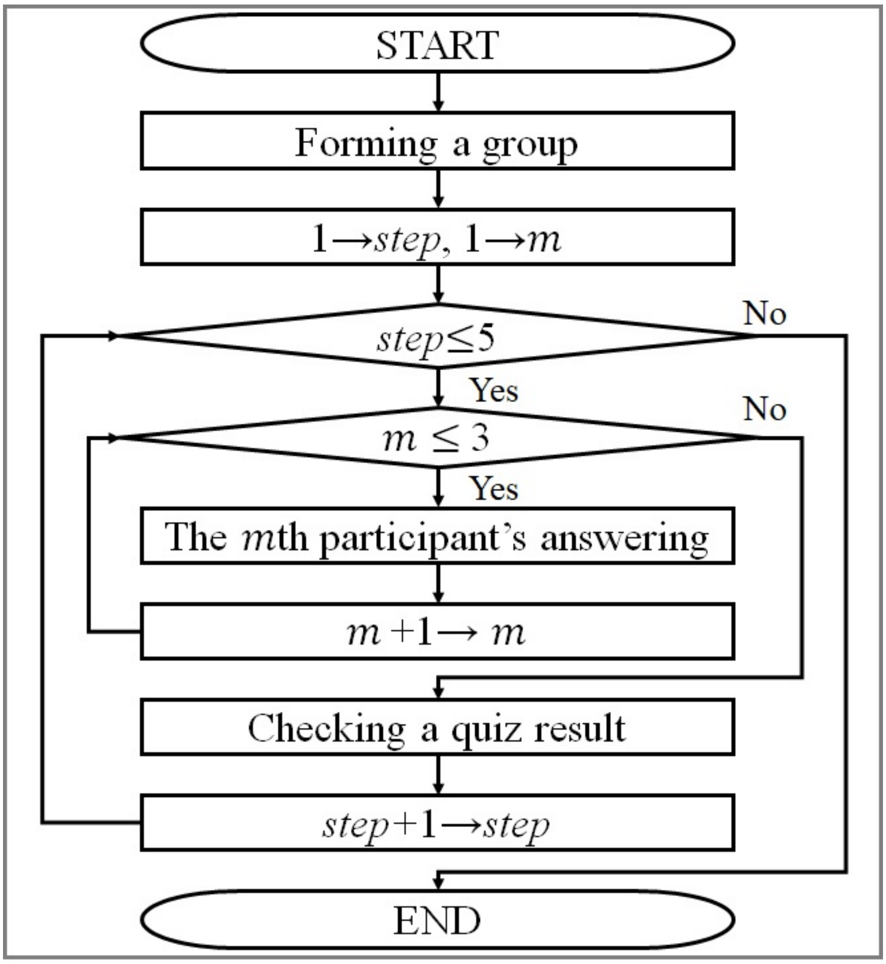

Figure 3.7: Flowchart of experiments.

Next, the quiz host decided who answered the quiz at first such that the first and second participants were human members, whereas the third participant was "Participant." When it one of the participants turn to answer a quiz, he or she sits on the chair. The quiz host ensures that there is no discussion about this experiment while someone is answering a quiz on the laptop. Then, the three participants see each other's answers. At the same time, the robot system on the laptop checked the human participants' answers and registered this information for learning the participants' behaviors. When the numbers of dots of human participants' answers were k_1 and k_2, the robot system recognized their answers as s_{k_1} and s_{k_2}, respectively, and renewed the values using Eqs. 3.1-3.4. The participants repeated this procedure five times. At the beginning of each step, they did not know the each others' answers. However, at the end of a step, they had this information. We thought if the participants had already known all of the information in Table 3.2, they would be affected by one another's answers and change their own answers.

Table 3.2: Results of investigating descriptive scale.

Descriptive Scale	Average	Standard Deviation
A	18.70	11.35
B	20.03	11.51
C	24.87	11.92
D	27.80	12.34
E	34.73	19.53
F	50.73	20.85

3.3.3 Individual Differences and Clustering Dataset

We investigated 30 university students' answers to six quizzes before the experiments were performed. Table 3.2 shows the averages and standard deviations of the number of dots generated from each university student's answers. These results revealed that there were individual differences among participants' quiz answers. The standard deviations indicated the existence of individual differences in the quizzes when the participants answered without any advice. As the average increased, the standard deviation increased (Table 3.2).

In reinforcement learning, the agent in the robot system selected the actions in a given state from a set of 100 states. Then, the system selected some states as representative states using the k-means++ clustering algorithm [28] in order to reduce the search space. The states corresponded to answers concerning the number of dots. The number of states was 100 because the system pushed BUTTON from 1 to 100 times when the participants answered a quiz. Therefore, we set the number of clusters to four. Consequently, $N = 4$, which is the maximum value of the number of states. The system used the results of the experiments to investigate the individual differences among quizzes (Table 3.2).

The system separated the resulting dataset into four clusters and considered the four centers of the clusters to be representative answers. Thus, the agent in the system selected a certain action in a given state from the four representative states. We presumed that clustering diminished the choices of states and accelerated the system's convergence to a group norm. In

Table 3.3: Parameters of reinforcement learning.

Learning Rate	0.1
Discount Factor	0.9
Reward	± 1

addition, the system considered the other members' answers as a certain representative state that was closest to the four representative states.

3.3.4 Test of Convergences in Experiments

We ran the Mann-Whitney U test to investigate whether the answers in Figs. 3.8-3.12 converged or not [29]. The three participants' answers in a group affect each other's opinions, so that their answers converge. In other words, mutual influences cause convergence of their answers in a group. We investigated whether such influence exists by using the Mann–Whitney U test.

We prepared two samples to use the Mann–Whitney U test. These samples are depended on whether the participants in a group recognize the other participants' answers. One sample is a set of variances of each group answers (Figs. 3.8-3.13). We must investigate whether change of answers in a group would depend on if participants in the group recognize one another's answers or not. If the change exists, mutual influences and convergences in groups also exist. Therefore, we investigated answers of human groups where the participants do not recognize the others' answers.

To observe change of answers in case participants in a group do not recognize one another's answers, we also investigated four extra participants' answers without advice on their own in four descriptive terms (A, B, C, and D). The four participants answer each quiz five times, that is, a total of 20 times. In the experiments (Figs. 3.8-3.12), we did not use descriptive terms E and F, so the participant does not answer the quizzes about the term E and F.

If we pick three participants from the four participants, we can regard the three participants as a group. Moreover, the group including the three participants answers four kind of descriptive term quizzes. Therefore, ${}_4C_3 \times 4 (= 16)$ groups can exist. We define the group as pseudo-group.

We used the Mann–Whitney U test on between five experiment groups (Figs. 3.8-3.12) and

16 pseudo-groups. Then, the observation in each sample is a difference between the value of a variance of answers in a group at steps 5 and 1. These values mean changes of participants' answers in each group.

3.3.5 Results

Figs. 3.8-3.12 show the results of the five experiments wherein two participants and the system in each group answered five questions per experiment. We selected two participants who had large individual differences for a certain descriptive scale in each experiment. The descriptive terms used in the experiments 1, 2, 3, 4, and 5 are D, A, D, B, and C, respectively. Table 3.3 lists the parameters of reinforcement learning in each experiment. The horizontal axis shows the step number, whereas the vertical axis shows the number of dots that each participant answered (Figs. 3.8-3.12). In addition, Fig. 3.13 shows standard deviations of the five experiments that indicate the degree of their individual differences in each step. Sherif et al. reported similar results using only human participants [13].

Table 3.4 shows two samples of experiment groups and pseudo-groups in the Mann–Whitney U test. Each value is a difference between the value of a variance of answers in a group at steps 5 and 1. These samples do not include results of quizzes about descriptive terms E and F because we did not use these terms in the group experiments. Additionally, a box plot of data from the two samples in Fig. 3.14 indicates each statistical distribution and the two-sided p-value. The result revealed a statistical significance ($p = 0.0019$, two-tailed test). Therefore, we can see that when participants recognize the others' answers, they will be affected by the others' answers.

These results showed that each participants' answer in all groups converged to a criterion of the number of dots at the fifth step. This confirmed that their answers converged to become the group's norm in all experiments. However, the standard deviations decreased as the number of steps increased. These findings revealed that groups with a high value of individual differences at the first step tended to converge more strongly.

3.3.6 Discussions

As a result of learning, we observed that if the standard deviation was comparatively lower at the first step, the participants did not feel the need to change their answers at the next step. However, it appeared that if the participants changed their answer at the next step, they felt the need to find a more suitable answer by considering the answers of the other group

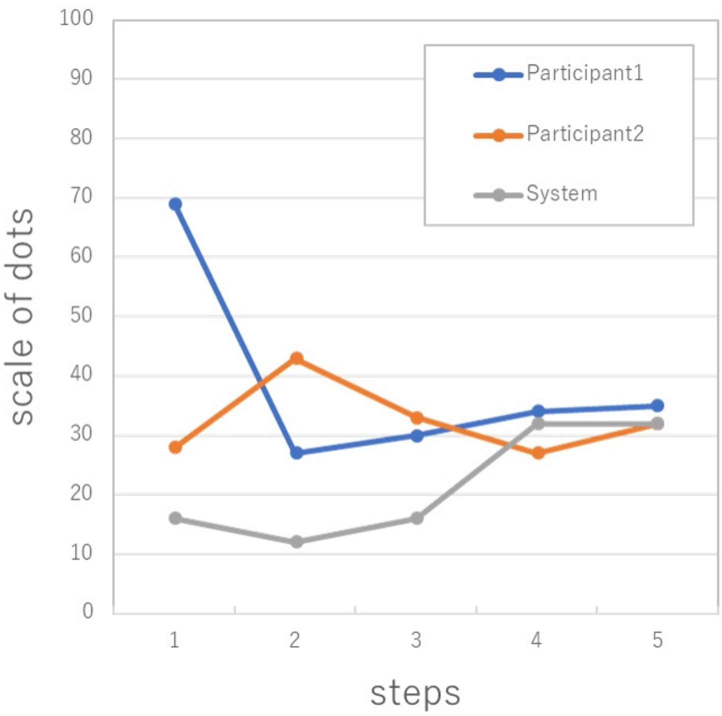

Figure 3.8: Result of Experiment 1 (The descriptive term is D).

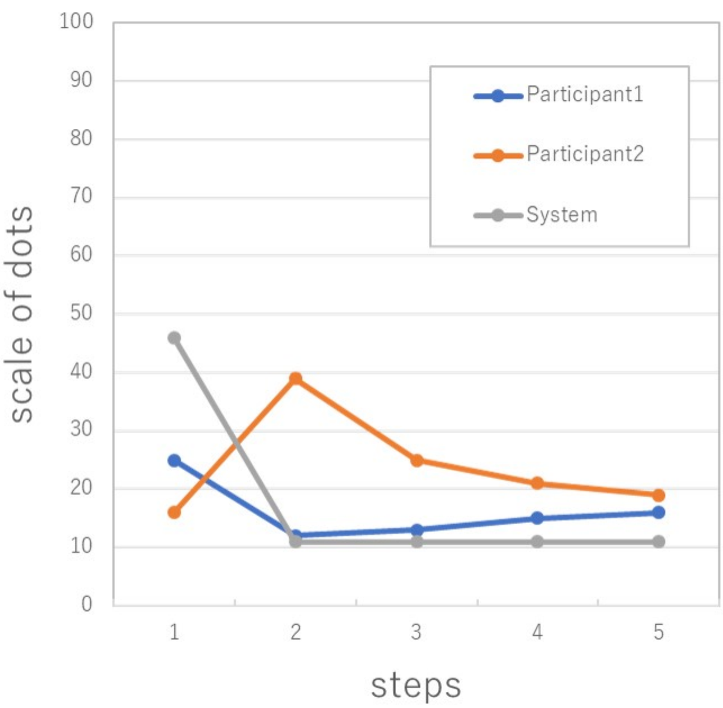

Figure 3.9: Result of Experiment 2 (The descriptive term is A).

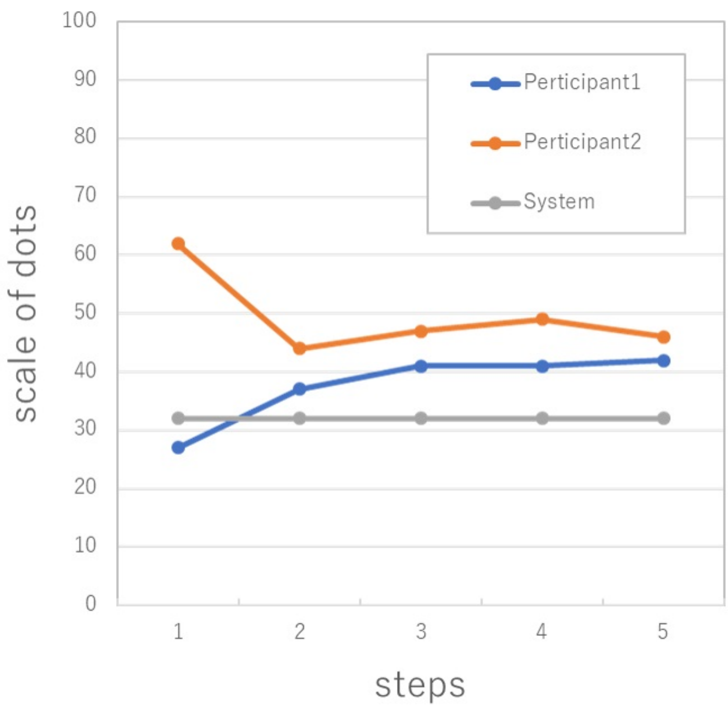

Figure 3.10: Result of Experiment 3 (The descriptive term is D).

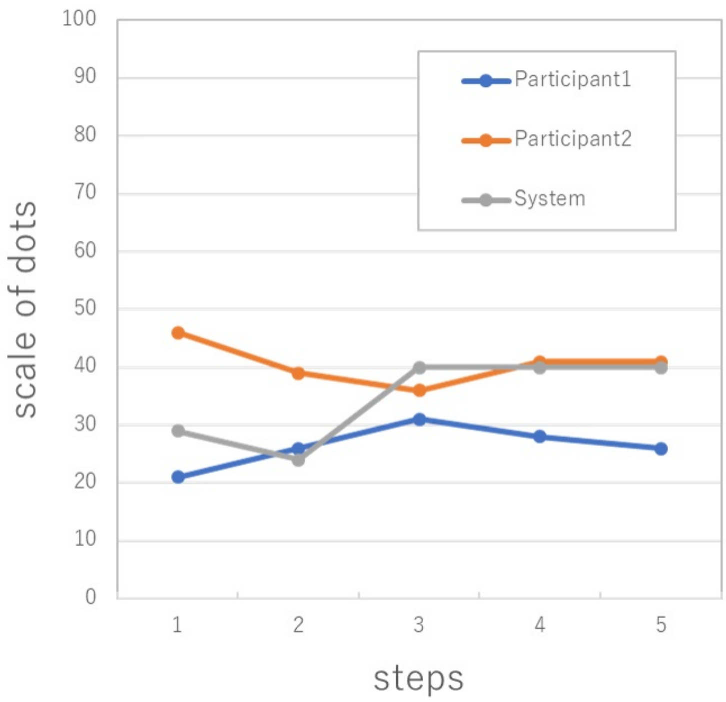

Figure 3.11: Result of Experiment 4 (The descriptive term is B).

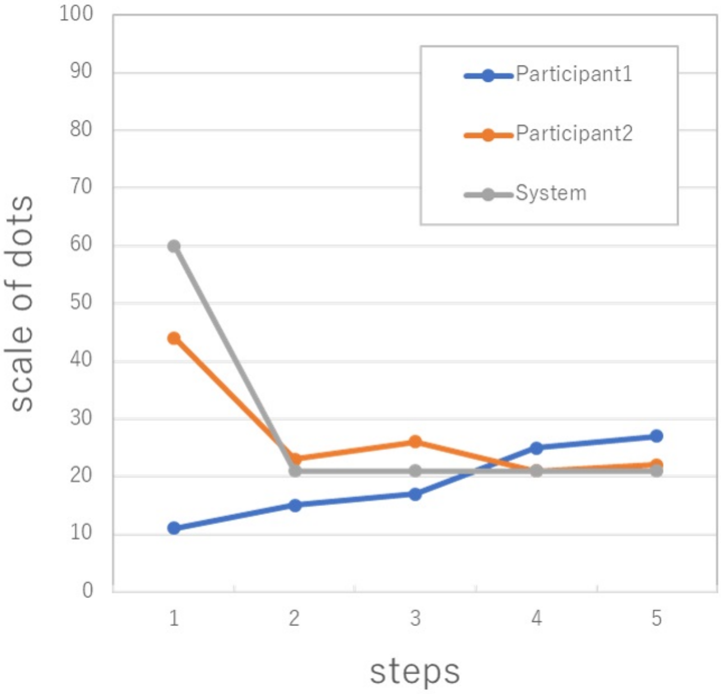

Figure 3.12: Result of Experiment 5 (The descriptive term is C).

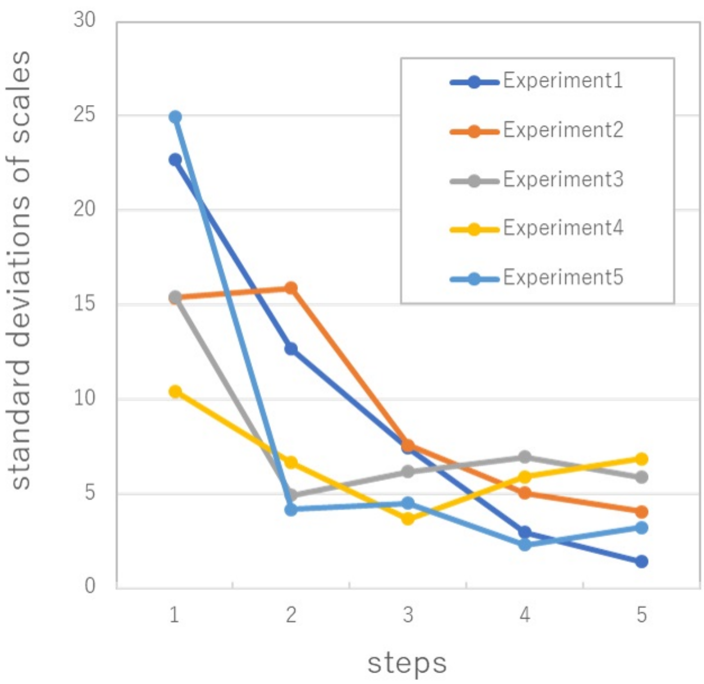

Figure 3.13: Standard deviations of Experiments.

Table 3.4: Differences of variances between steps 5 and 1.

Group	Variance at step 1	Variance at step 5	Difference between variance at step 5 and step 1
Experiment group			
group 1	514.9	2.0	512.9
group 2	237.0	16.3	220.7
group 3	238.9	34.7	204.2
group 4	108.7	46.9	61.8
group 5	624.3	10.3	614.0
Pseudo-group			
group 1	90.9	174.2	-83.3
group 2	12.7	26.0	-13.3
group 3	84.2	146.9	-62.7
group 4	112.7	208.2	-95.6
group 5	4.2	38.0	-33.8
group 6	16.7	16.9	-0.2
group 7	18.7	60.2	-41.6
group 8	10.9	66.9	-56.0
group 9	89.6	180.7	-91.1
group 10	11.6	6.9	4.7
group 11	74.9	156.2	-81.3
group 12	62.9	148.7	-85.8
group 13	348.7	210.9	137.8
group 14	12.7	4.7	8.0
group 15	280.2	234.9	45.3
group 16	354.9	202.7	152.2

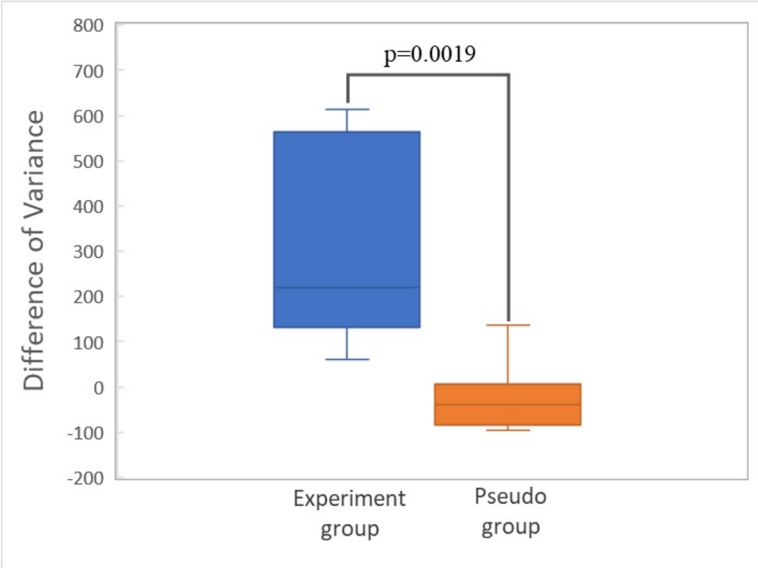

Figure 3.14: Statistical distribution of two experiments samples and two-sided p-value.

members. We also observed that the system's answer affected the participants' answers. For instance, compared to the answers at the first step, it appeared that the answers of Participant 2 were closer to those of the system at in second and third steps (Fig. 3.8). We assumed that the participant felt that the system's answer was as natural as a human's answer because the participants in the group formed group norms considering the system's answers. However, we cannot completely conclude that the system's answers were as natural as a human's when considering the fact that the third participant only obeyed the system because the system gave the same answers unnaturally in a row (Fig. 3.10). Moreover, the third participant only obeyed the system and pretended to answer in a way similar to how humans answer. The other participants were unaware of this information. We cannot conclude that the system's answer was as natural as a human's answer solely by considering that the first and second participants knew that the third participant only obeyed the system.

From the results of these experiments, we concluded that the robot system made decisions in groups involving human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system's behaviors. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

Further studies are required to investigate whether using the proposed model, a real robot can adjust its behavior to be in line with human participants' behaviors and whether participants could create a suitable criterion considering the robot's answer even in a situation wherein the participants can recognize that they are interacting in a group that includes a robot. Herein, two out of three participants in a group did not know that the other participant only obeyed the system's decisions and pretended to answer questions.

Moreover, we only confirmed that the framework of reinforcement learning worked well in our experiments. Therefore, it also is necessary to verify whether other ways of learning can learn group norms more efficiently than reinforcement learning. Additionally, the application in this study had only two buttons, BUTTON and FINISH, so that a participant could not decrease the number of black dots. This fault could cause observe answers based on his or her descriptive terms. Thus, to observe participants' descriptive term precisely, we need to make a new button to decrease the number of black dots on our quiz application. Additionally, when participants answer the descriptive term quizzes, nothing motivates them in this study. Therefore, we should investigate whether group norms are formed when a participant's conformity to a group norm results in his or her disadvantage.

3.4 Summary

In this study, we proposed a model to allow a robot to create a suitable criterion for decision-making by interacting with humans in a group in a multiparty quiz scenario wherein a system that obeys the model finds a suitable criterion based on the observation of the behaviors of other participants in a group.

Robots need to behave socially in multiparty scenarios to adapt themselves to a human society. All humans have unique personalities and use their choices to form criteria to govern their behavior. When people form a group, they influence each other's decisions, resulting in the generation of a group norm. This norm is a thought or a behavioral pattern that we expect a robot in a group to obey. We investigated whether a robot system that uses our proposed model behaves socially in a group that includes humans.

Our results revealed that a system that adjusts itself to each group can generate group norms with human participants. The experimental results demonstrated that using the proposed model, the robot system adjusted own answers according to participants' answers. Moreover, each member of the group adjusted their answers according to other members' answers. Sherif et al. reported similar results using groups involving only humans. We assumed that the results indicated the system's answer to be as natural as a human's answer because the human participants formed group norms considering the system's answers. However, we observed the system's unnatural behaviors in experiments when considering that only the third participant obeyed the system. The proposed model enables robots to make decisions socially in order to adjust its behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities. From the results of these experiments, we concluded that the robot system made decisions in groups that include human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system's behavior.

This research aimed to investigate (1) whether using the proposed model, a real robot can adjust its own answers according to human participants' answers and (2) whether the participants were affected by the real robot's answers. In the next chapter, we will reveal whether the robots' answers affect people and whether participants create a suitable criterion considering the robot's answer even in a situation wherein the participants recognize that they are interacting in a group that includes a robot.

Chapter 4

Robots in Human–Robot Groups Learn Group Norms That Influence Human Member's Opinions

4.1 Introduction

In this chapter, we evaluate a robot using the proposed model and investigate whether group norms occur in human–robot groups. In addition, we investigate whether gruop nomrs in human–robot groups will affect humans' decision-makings. The experiments for the former verification are described in detail in Section 4.3. The latter experiment is described in detail in Section 4.4. The decision-making model of the robot used in the above two experiments is described in Section 4.2.

For Chapter 3, the goal was to evaluate the proposed model's ability to form group norms in human groups. Chapter 3 shows the results of the experimental scenario in each group composed of only human participants. One of the participants just followed our propsoed model and pretended to behave of his own accord while the other participants behaved on the basis of their decision-making in the experiments. It was not clear whether group norms occurred in human–robot groups in the same experimental scenario as used in Chapter 3. Therefore, we investigate whether group norms occur in human–robot groups that include a robot that uses the proposed model.

In addition, we investigate social influence of human–robot group norms on human decision-making in human–robot groups. Recent studies showed the social influence of robots on humans in human–robot interactions[33, 34]. Moreover, it is important to investigate the influence of robots on humans before robotic interactions are accepted among people. Brandstetter et al. and Salomons et al. conducted human–robot experiments based on Asch conformity experiments[37, 33, 34]. The results of the conducted experiments in groups, which included some robots and single human participant, showed that some participants in the experiment conformed to wrong opinions of robots that were incorrect in the experimental scenario. Although human conformity in human–robot groups has been investigated, few studies have focused on the influence of robots that adjusted their behaviors to group norms in human–robot groups. In these experiments, the robots did not change their opinions and behaviors to put social pressure on humans. Thus, it is unclear whether robots that adjust their behaviors to group norms have social effect on humans. In addition, our previous studies did not show whether social influence on humans happened in groups. Moreover, it was difficult to precisely determine whether the human behavior was influenced by the robot or the other human in the groups.

Therefore, we observed that while the participant and robots responded to quizzes that had unclear and vague answers, the human participant chronologically changed their answers. Thus, the vague quizzes confused participants, and made them give respond to the quiz without confidence. Although there are different decision-making criteria to answer the quiz, the criteria converge into a common criterion when a group is formed. By comparing answers in human–robot groups with answers without group members, we observed that chronological changes in the answer of the participants. In addition, in the final stage of the experiment, the participants responded to a questionnaire for the quiz to investigate whether the change in their opinions affected by social influence. Therefore, we verified social influence of robots in a human–robot group scenario by observing human behaviors in the quiz scenario and the analyses of the questionnaire results.

4.2 Group Norm Model

In Chapter 3, we proposed a group norm model and a quiz scenario for its evaluation. When answering the quiz, there were 101 possible actions for a robot to choose from. However, the robot did not choose from the 101 possible actions, but instead narrowed down to few actions by using a method of clustering, and then actually executed one action from those. This is a problem in that the robot did not have a wide variety of answers as a possible option. Therefore, in this chapter, to solve the problem, we propose a model with modified learning formulas shown in Eqs. 4.1 and 4.2.

In this study, reinforcement learning involves action, states, a value function, Q values, and rewards as in Chapter 3. The decision-making component of the proposed model uses a reinforcement learning environment, as illustrated in Fig. 3.2. Within the model, a robot has a set of behaviors that it can execute. The agent in the decision-making component explores the reinforcement learning environment and decides which behavior the robot should perform.

If the robot uses Eq. 3.1, it will not be able to make decisions based on a variety of options because clustering will be used to limit the robot's available actions. By using Eq. 4.1, a robot is able to execute a single action selected from all possible actions without using clustering.

$$V^{t+1}(s_n) \leftarrow V^t(s_n) + \alpha \sum_{i=1}^{t} \gamma^{t-i} R^i(s_n) \tag{4.1}$$

The equation for $R^i(s_n)$ at the ith step is given in Eq. 4.2, where M is the number of members in the group joined by the robot (the Mth member is the robot), s_k is the behavior exhibited by each group member at the ith step, and σ^2 is the sharpness of $R^i(s_n)$. In addition, the initial value function of each state is a random number.

$$R^i(s_n) = \sum_{k=1}^{M-1} \exp\left(-\frac{(s_n - s_k)^2}{2\sigma^2}\right) \tag{4.2}$$

In the experiments introduced in this chapter, the robot makes decisions by deriving the Q values shown in Eqs. 3.3, 3.4, and 3.5 using the above value and reward functions shown in Eqs. 4.1 and 4.2.

$$Q(s_m, a_{next}) = V(s_{m+1}) \tag{3.3}$$

$$Q(s_l, a_{dcs}) = \frac{1}{V(s_l) - \max_n V(s_n)} \tag{3.4}$$

$$Q(s_l, a_{dcs}) = \begin{cases} Q(s_l, a_{dcs}) \to \infty & (\text{if } V(s_l) = \max_n V(s_n)) \\ Q(s_l, a_{dcs}) < 0 & (\text{otherwise}) \end{cases} \tag{3.5}$$

4.3 Experiment 1

In the present study, we ran the same experiments as did our previous study in Chapter 3 for the purpose of comparison, and we ran an additional experiment to investigate whether group norms occurred in a human–robot scenario. There were a total of 18 university students as research participants, 14 of whom participated in the experiments that involved a scenario in which group members answered quizzes. Four of them participated in the additional experiment, which was not carried out in Chapter 3. In addition, all the participants were native speakers of Japanese. By using the same experiments, we aimed to compare the behaviors of human groups with the behaviors of human–robot groups.

4.3.1 Experiment Flow in Group

Fig. 4.1 illustrates the experimental environment; there is a laptop on a table, and a robot on chair. Fig. 4.2 displays the laptop and RoBoHoN, the robot group member. RoBoHoN can speak Japanese and interact in a certain planned scenario. The robot is approximately 20 cm tall and can have conversations with people based on the scenario. However, it cannot move or behave autonomously. Two participants and the quiz host sat at a table. Individuals in the waiting area were unable to see the display of the laptop, so they could not see the other participants' answers.

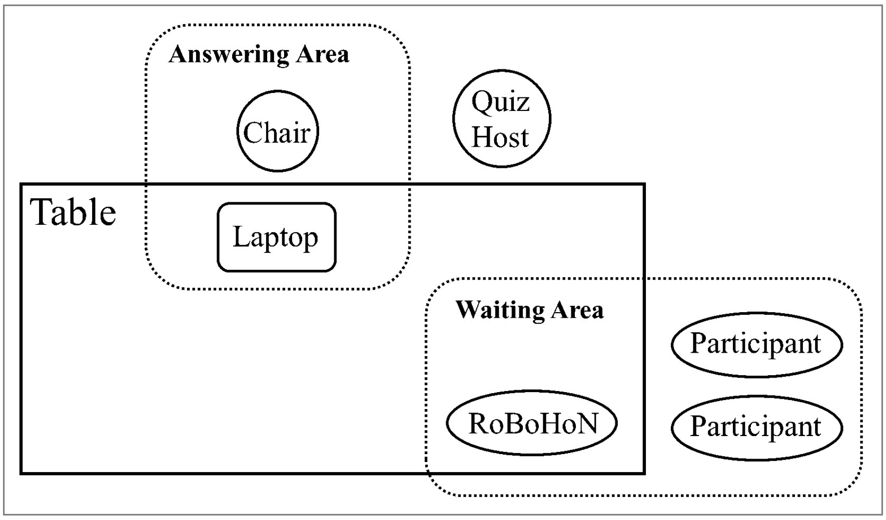

Figure 4.1: Experimental environment.

Fig. 3.6 presents a flowchart for the experiment controlled by the quiz host. First, the participants answered questions about four descriptive terms in the quizzes without any advice. Prior to the group experiments, an experimenter recorded the number of dots provided by each participant. The experimenter then selected pairs of human participants who had very different answers prior to the experiment. The human–robot groups in this experiment were formed by adding a robot to the pair.

Next, the quiz host introduced the flow of the experiment to RoBoHoN and taught it how

Figure 4.2: Laptop and RoBoHoN used in this study.

to use the laptop. After this, RoBoHoN introduced itself to the other two participants and informed them of its intention to join them in the experiment. In this phase of group formation, each participant regarded the other participants, including RoBoHoN, as group members. The quiz host then determined the answering order: the first and second participants were the human group members, and the third participant was RoBoHoN. When the participants took their respective turns to complete the quiz, they sat in the chair in front of the laptop.

After RoBoHoN answered, the three participants were able to see each other's answers. At the same time, RoBoHoN observed the other participants' answers and learned from them. When the number of dots in the human participants' answers were k_1 and k_2, RoBoHoN's system recognized their answers as s_k and s_{k2} and renewed those values using Eqs. 4.1, 4.2, 3.3, and 3.4. The participants repeated this procedure five times. Table 4.1 lists the parameters for reinforcement learning. M represents the number of participants, including RoBoHoN, while N indicates the maximum number of states.

Fig. 4.3 illustrates the flow of interactions between the quiz host (QH) and the robot (R) in the group experiments. Although Fig. 4.3 is presented in English, these interactions were performed in Japanese by RoBoHoN's voice recognition function.

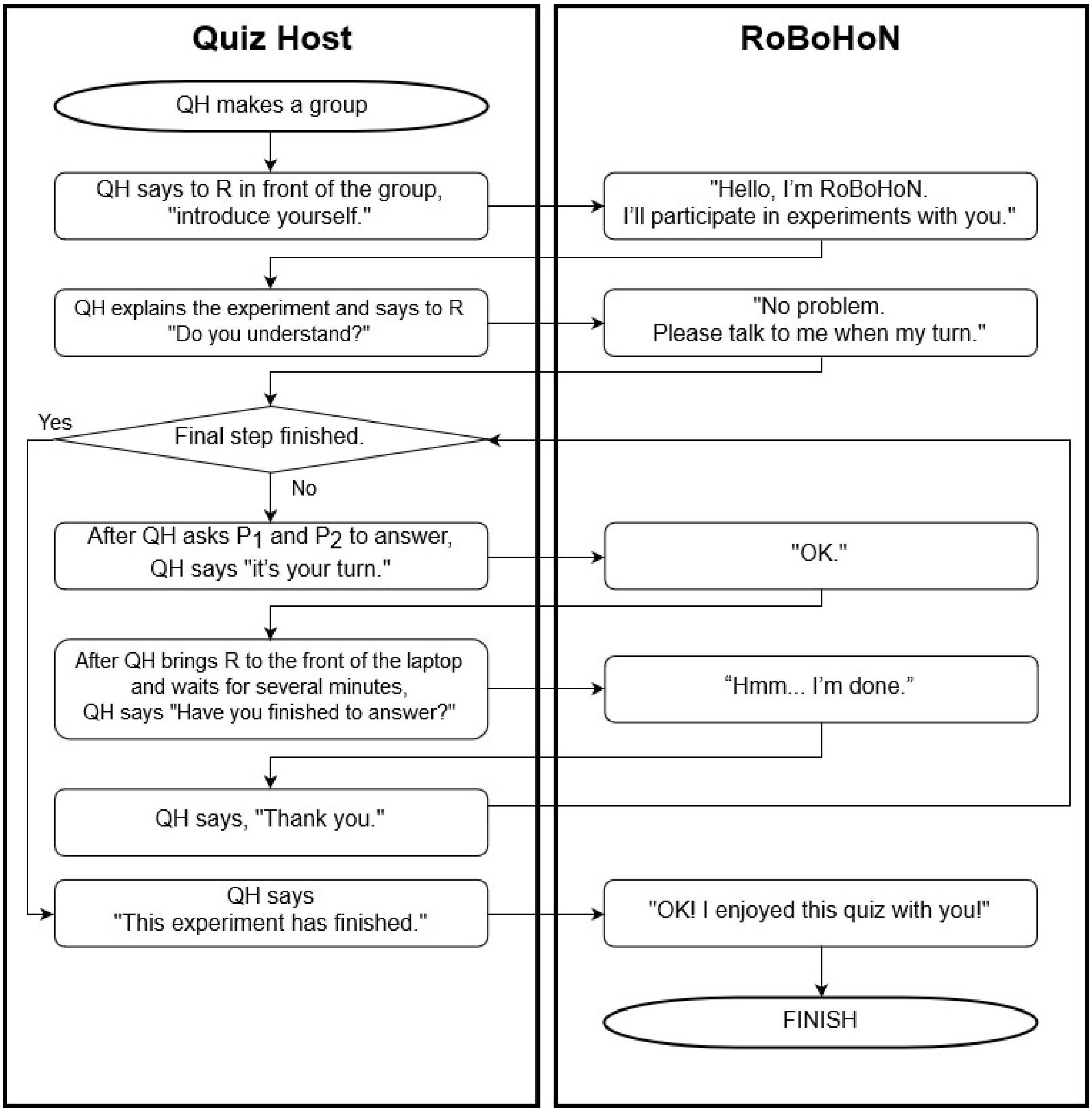

Figure 4.3: Interaction flowchart between the quiz host and the robot. QH, R, P_1, and P_2 respectively mean the quiz host, RoBoHoN, the first participant, and the second participant. In particular, the n of P_n means the order for answering the quiz in the group.

Table 4.1: Experimental conditions.

M: the number of group member	3
the number of group	7
N: the number of state	101
Learning Rate	0.1
Discount Factor	0.9
σ^2	100
initial V function	random number $[1.0, 1.5]$

4.3.2 Test of Convergences and Additional Experiment

We ran the Brunner–Munzel test to compare the results of the experiments with the results of an additional experiment. The Brunner–Munzel test was performed to evaluate whether the answers presented in Figs. 4.4-4.10 converged [35]. It was necessary to investigate whether the change in the answers of the group was dependent on whether the group participants knew each other's answers. The presence of a change implied that mutual influences and convergence were also present. Therefore, the answers of the human–robot groups were investigated for the scenario in which the participants did not know each other's answers.

To achieve this, four additional participants' answers were investigated for four descriptive terms (labeled A, B, C, and D shown in Table 4.2). The four participants answered each quiz five times.

A group was formed by selecting three of the four participants. The three-participant group then answered four descriptive term quizzes. Therefore, ${}_4\mathrm{C}_3 \times 4 (= 16)$ groups were possible. A set of the 16 groups is referred to as a pseudo-group.

The Brunner–Munzel test was used on seven experimental groups (see Figs. 4.4-4.11) and 16 pseudo-groups. The observation for each group was the difference in the variances of the answers between step 5 and step 1. The variance values indicated changes in the participants' answers in each group.

Table 4.2: Four descriptive phrases.

	Japanese	English
A	Kekko	You see quite a lot of dots
B	Kanari	You see a considerably large number of dots
C	Warito	You see a comparatively large number of dots
D	Dochirakato-ieba	If you had to choose, you would say that you could see a large number of dots

4.3.3 Results

Figs. 4.4-4.10 present the results of seven experiments, in which two participants and the robot answered five questions per experiment. Two participants with large individual differences were selected for each group. The horizontal axis indicates the step number, and the vertical axis indicates the number of dots selected by each participant (Figs. 4.4-4.10). Fig. 4.11 presents sample variances for the seven experiments, which indicate the degree of individual differences at each step. The descriptive terms used in Experiments 1-7 are C, B, B, B, A, D, and B shown in Table 4.2, respectively.

All standard deviations decreased by the fifth step for all experiments (see Figs. 4.4-4.10). This result indicates that groups that included the robot tended to converge. This implies that the robot used the proposed model to adjust its answers according to its group. Table 4.3 presents the two samples of the experimental groups and pseudo-groups in the Brunner–Munzel test, and lists the differences in variance for the answers in each group between step 5 and step 1. In addition, Fig. 4.12 presents a box plot of the data from the two samples, which displays the statistical distribution and p-value of each sample. The results show statistical significance ($p = 1.4 \times 10^{-6}$).

These results demonstrate that participants' answers converged at the fifth step, which confirms that their answers converged to a group norm.

4.3.4 Discussion

In the present study, a robot made decisions in a human–robot group by considering group norms in a limited quiz scenario. Our previous study in Chapter 3 used the same quiz exper-

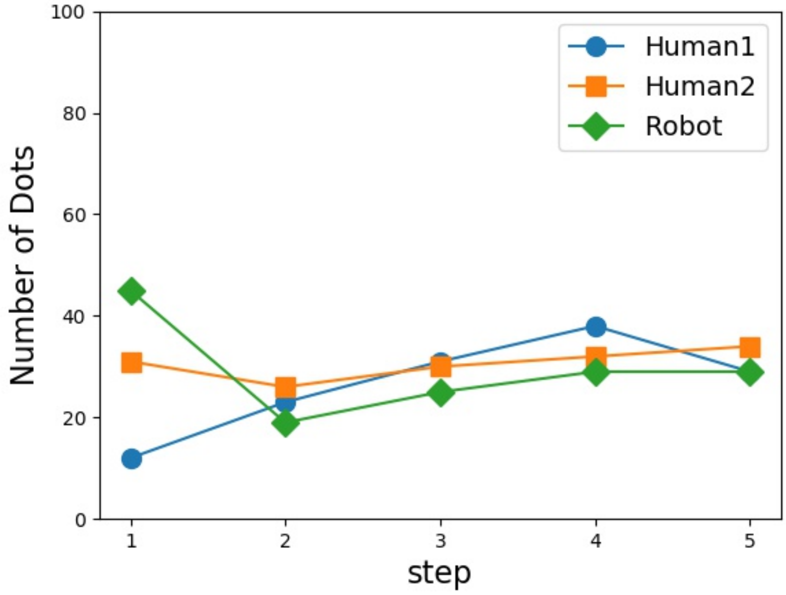

Figure 4.4: Result of Group 1 (the descriptive phrase was C).

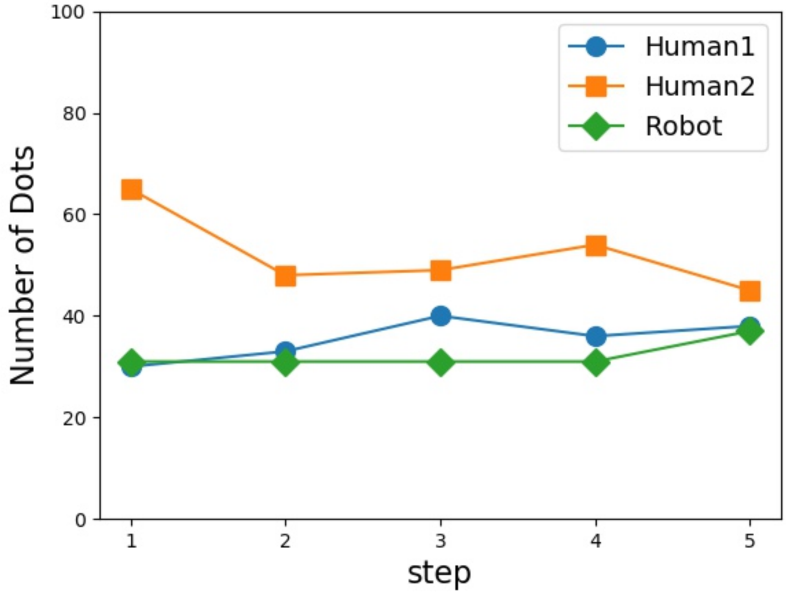

Figure 4.5: Result of Group 2 (the descriptive phrase was B).

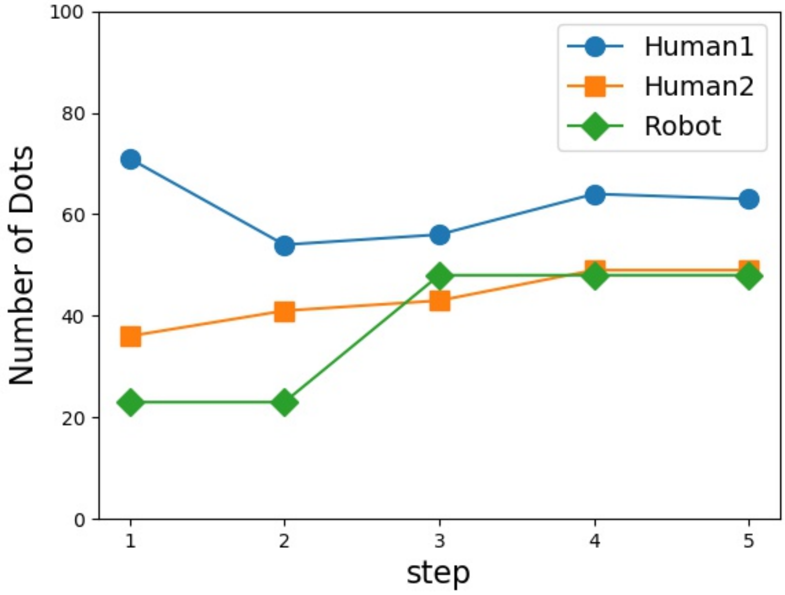

Figure 4.6: Result of Group 3 (the descriptive phrase was B).

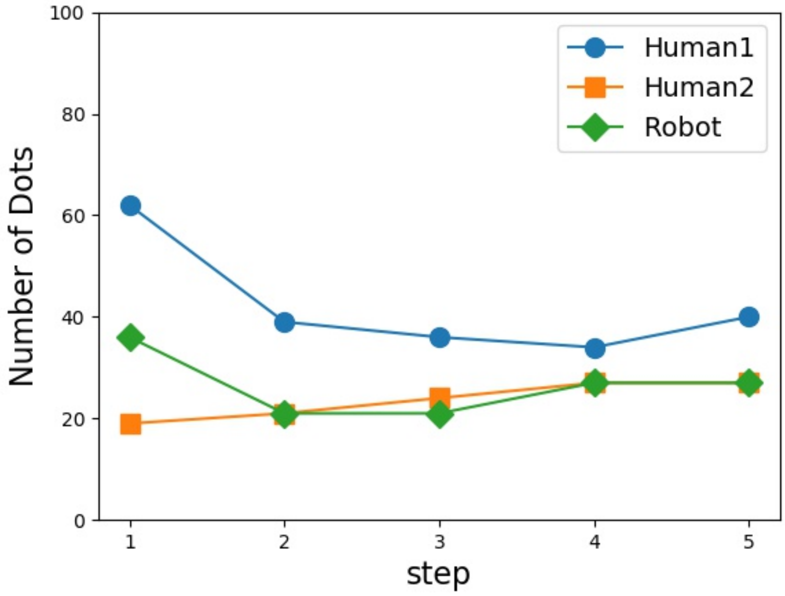

Figure 4.7: Result of Group 4 (the descriptive phrase was B).

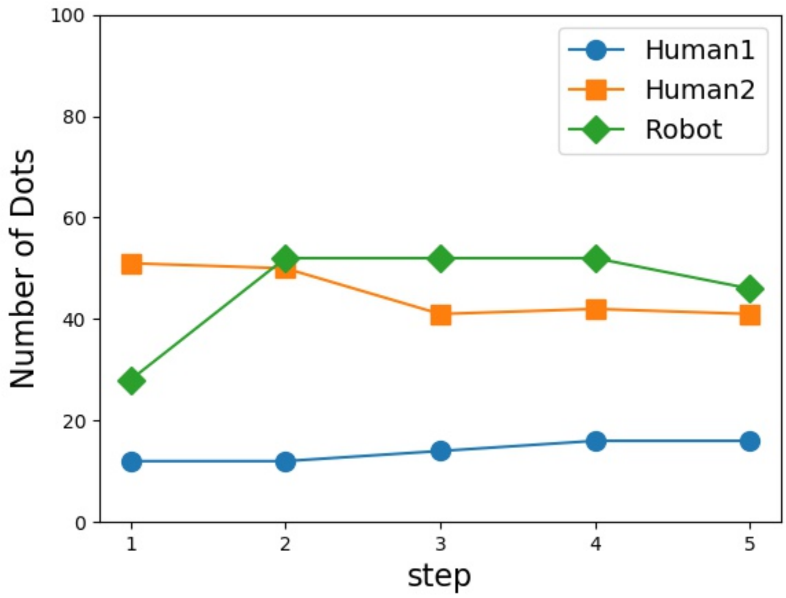

Figure 4.8: Result of Group 5 (the descriptive phrase was A).

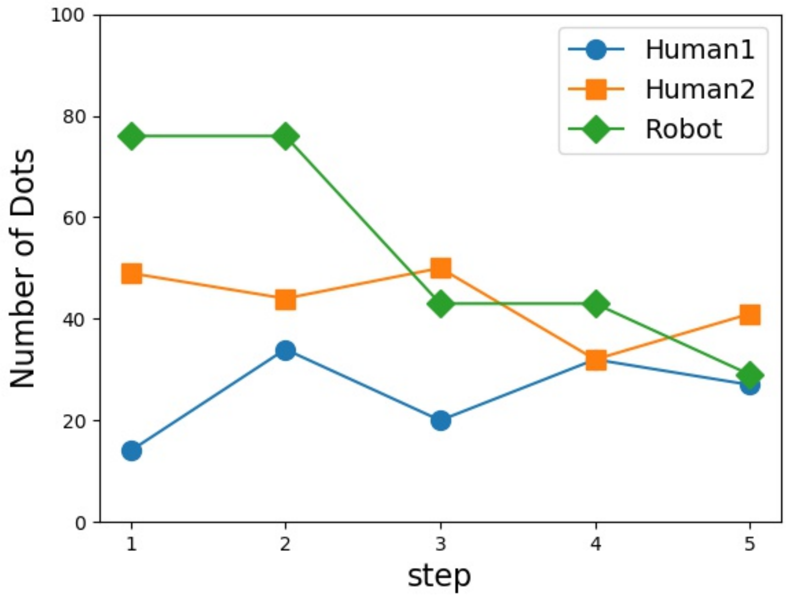

Figure 4.9: Result of Group 6 (the descriptive phrase was D).

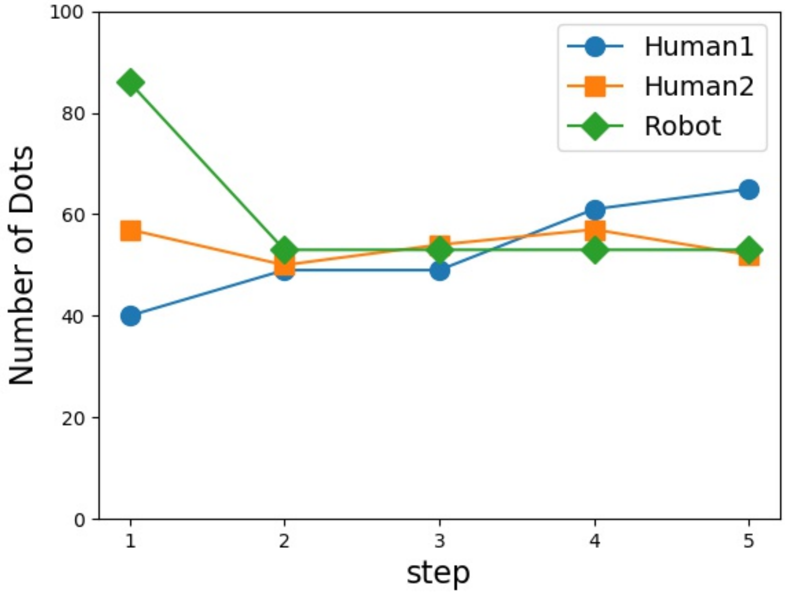

Figure 4.10: Result of Group 7 (the descriptive phrase was B).

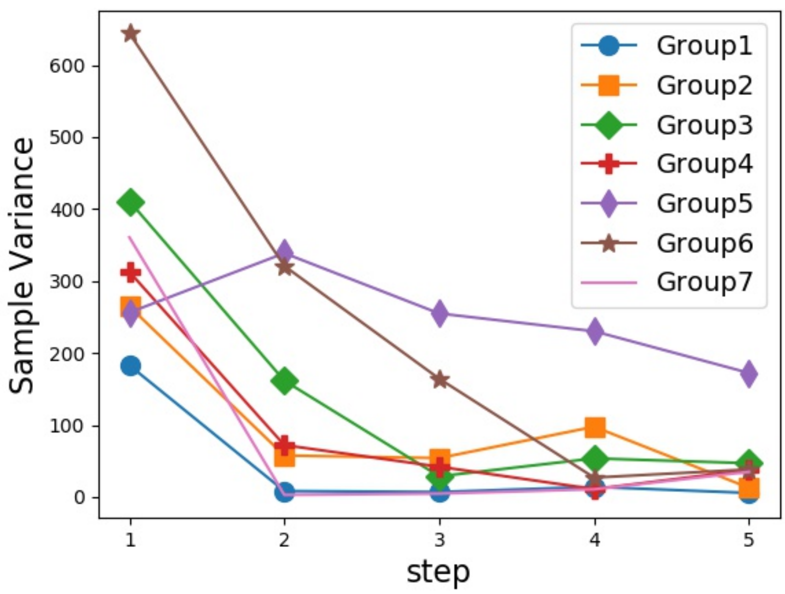

Figure 4.11: Sample variances of the experiments.

Table 4.3: Differences in variance between step 5 and step 1.

Group	Variance at step 1	Variance at step 5	Difference between variance at step 5 and step 1
Experiment group			
group 1	182.889	5.556	177.333
group 2	264.667	12.667	252.000
group 3	410.889	46.889	364.000
group 4	312.667	37.556	275.111
group 5	256.222	172.222	84.000
group 6	644.222	38.222	606.000
group 7	360.667	34.889	325.778
pseudo group			
group 1	4.222	9.556	-5.333
group 2	10.889	14.889	-4.000
group 3	18.667	1.556	17.111
group 4	16.667	14.000	2.667
group 5	139.556	40.667	98.889
group 6	0.667	68.222	-67.556
group 7	133.556	59.556	74.000
group 8	144.667	52.667	92.000
group 9	348.667	210.889	137.778
group 10	12.667	4.667	8.000
group 11	280.222	234.889	45.333
group 12	354.889	202.667	152.222
group 13	89.556	180.667	-91.111
group 14	11.556	6.889	4.667
group 15	74.889	156.222	-81.333
group 16	62.889	148.667	-85.778

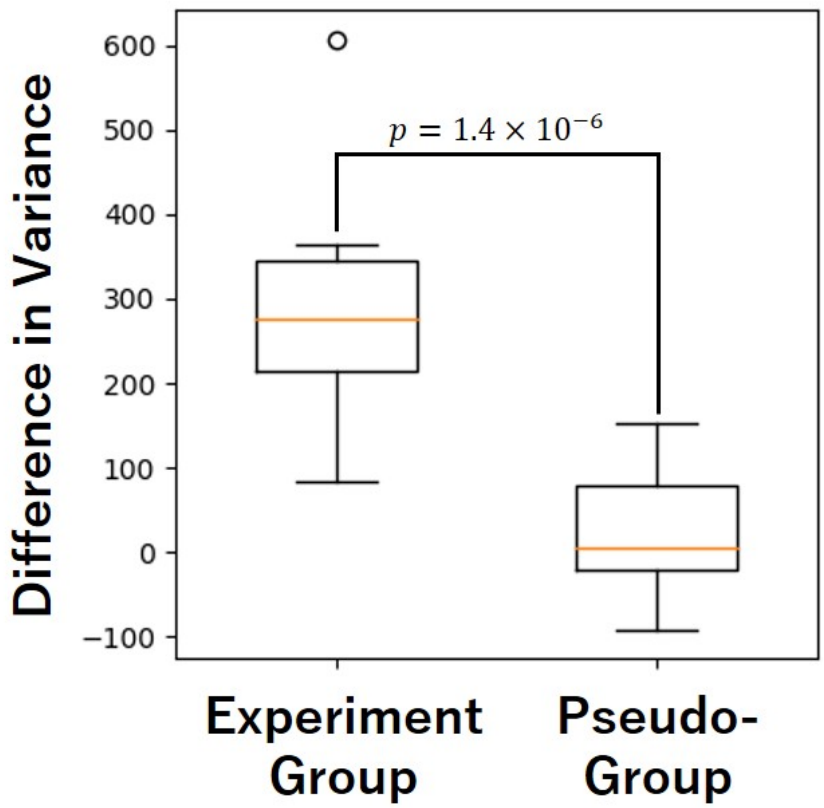

Figure 4.12: Statistical distribution and p-value of two experimental samples.

iment with human groups that included a participant who behaved based on decisions made within the group norm model. The results indicated that group norms were established in each of the human groups. The results of the experiments in this study indicate that, based on the proposed model, not only the behaviors of people but also the behavior of a robot participant adjusted to group norms in the quiz scenario.

Fig. 4.12 demonstrates that the differences in variance between step 5 and step 1 are statistically significant. In Table 4.3, larger differences in the variances of the number of dots can be seen in the experimental groups than in the pseudo-groups. our previous study in Chapter 3 found larger differences between step 5 and step 1 in the experimental groups than those in the pseudo-groups. Thus, in both human groups and human–robot groups, members' answers became similar to each other as the members became aware of each other's answers in the quiz scenario.

As seen in Figs. 4.6, 4.7, 4.9, and 4.10 some human participants may have changed their answers on the basis of the robot's answers. It appears that at a certain step, human participants considered the robot's answer from a previous step because their answers changed to become more like the robot's answers than their own previous answers. Thus, the results indicate that during the quiz, human participants considered not only the other human participants' answers but also the robot's answers.

However, as illustrated in Fig. 4.8, the answers provided by one of the human participants, Human Participant 1, changed only slightly and did not adjust to the group norm. In contrast to this, the results by our previous study in Chapter 3 indicated that human participants generally obeyed group norms. This participant may have been reluctant to adjust to the robot's or the other human participants' answers, or may not have been affected by other participants due to certain personality traits. The results thus suggest that some human participants in this quiz scenario did not adjust to group norms in the human–robot groups. Moreover, although it can be concluded that group norms do occur in human–robot groups, it is not clear whether the robot's behaviors affected the human participants' behaviors. A human participant in a human–robot group may be affected by other human participants but not by the robot. A new method for studying interactions in human–robot groups should be considered in the investigation of the social influence of robots on humans.

4.4 Experiment 2

Based on the method used by Section 4.3, we ran a quiz of dots in this study to observe the social influence of robots on human in human–robot groups. In the experiment, we used two RoBoHoN, which are made by SHARP corporation as shown in Fig. 4.13. Additionally, to investigate the impression of participants on robots in a group. The participants were 14 university students, which were native Japanese speakers.

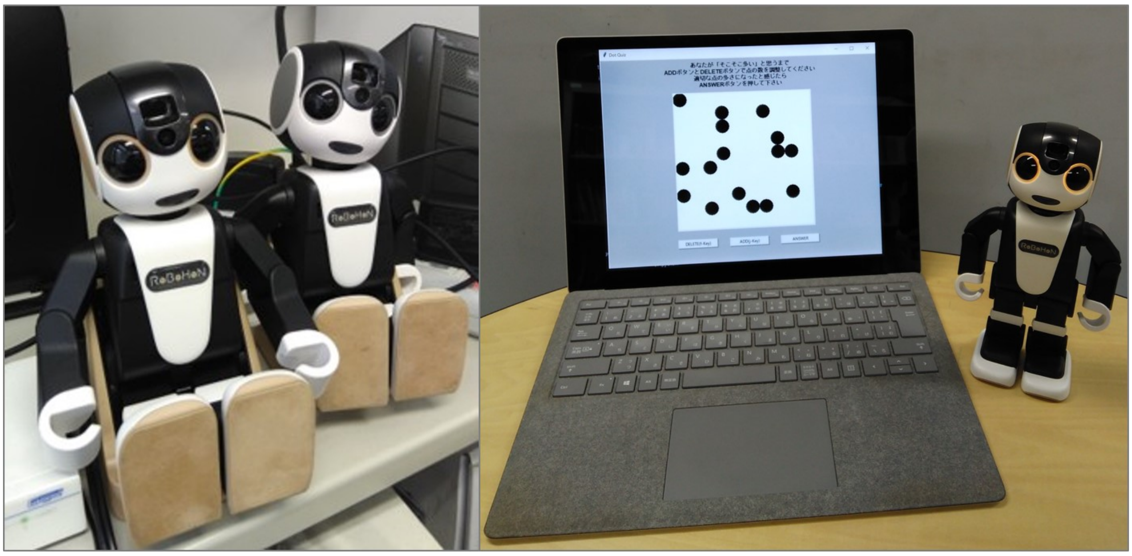

Figure 4.13: Two RoBoHoNs and a laptop used in an experimental scenario.

4.4.1 Quiz of Dots

The participants conducted quizzes about the descriptive terms for dot quantities. An input screen on a laptop and an example of an answer provided by a participant are shown in Figs. 4.14 and 4.15. Thus, the initial input screen is shown in Fig. 4.14, while Fig. 4.15 depicts an input screen after an answer provided by a participant. The English sentence implies the question of the quiz originally written in Japanese. *Kanari*, is a Japanese basic word, which means "considerably" in English as shown in Table 4.4.

The application contained the question and the three buttons labeled "ADD," "DELETE," and "ANSWER," located beneath a white box. A black dot appeared on the input screen when the participant clicked once on ADD. Moreover, the number of the ADD pushes represented the number of dots which is equal to a descriptive term. A black dot appeared at a random location in the white box each time a participant pushed the ADD. The number of dots showed

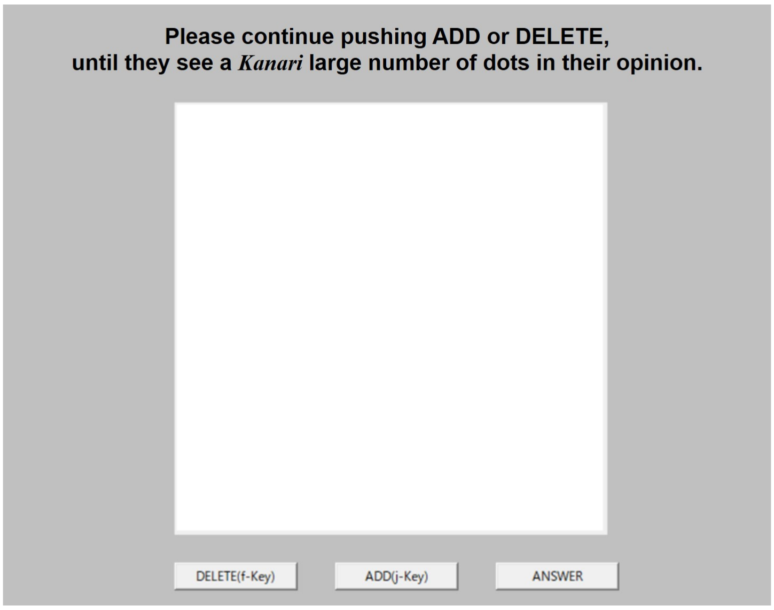

Figure 4.14: Initial quiz input screen of an application input screen to answer a quiz. The English sentence means the question of the quiz that was originally written in Japanese. *Kanari* is a Japanese basic word, which means "considerably" in English.

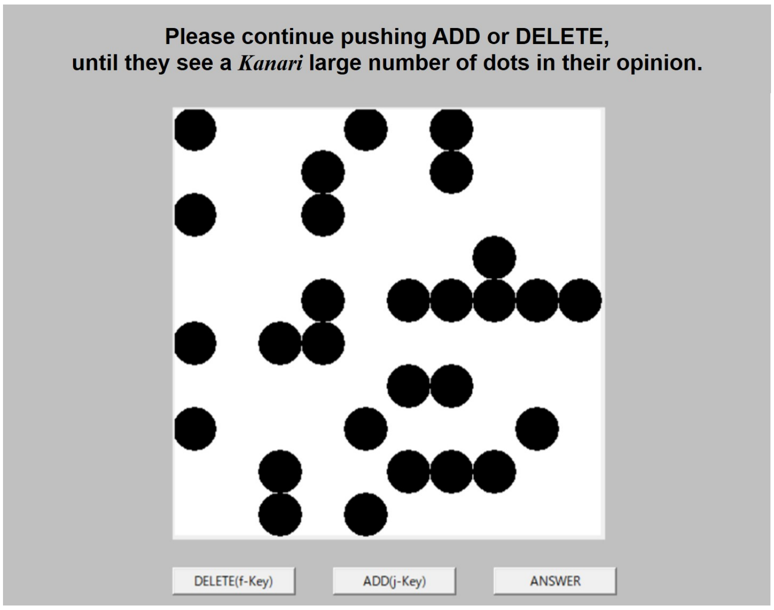

Figure 4.15: Input screen with the answer of an application input screen to answer a quiz. The English sentence means the question of the quiz that was originally written in Japanese. *Kanari*, that is a Japanese basic word, means "considerably" in English.

the answer of the participant to each question. The quiz allowed the participant to click a maximum of 100 times, without being aware of this limit. If the participant clicked once on DELETE, one dot in the white box disappeared. The participants completed the quiz which instructed them to “continue pushing ADD or DELETE until, they see an X large number of dots in their opinion,” where X denotes a descriptive term. Therefore, X was substituted with the English translation of one of the descriptive terms (A or B) listed in Table 4.4.

This quiz made each participant to observe the descriptive terms. The participant clicked on ADD or DELETE severally until he or she was satisfied with the answer and clicked on ANSWER.

Table 4.4: Two descriptive scales in Japanese and English.

	Japanese	English
A	Kanari	considerably
B	Warito	comparatively

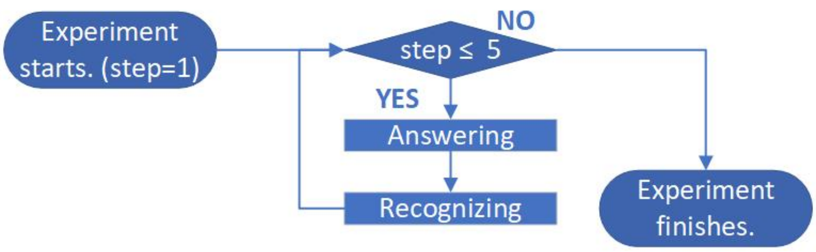

Figure 4.16: The flowchart of the experiment.

4.4.2 Flow of Experiment

We asked one participant to answer the same quiz of dots five times in the experiment. We prepared two experimental sets of participants:

- Those who answered the quiz alone.
- Those who answered the quiz in human–robot groups and a questionnaire.

After we performed the experiments in the two sets, we compared the results to investigate their social influence. Furthermore, we calculated the change in their answers while they

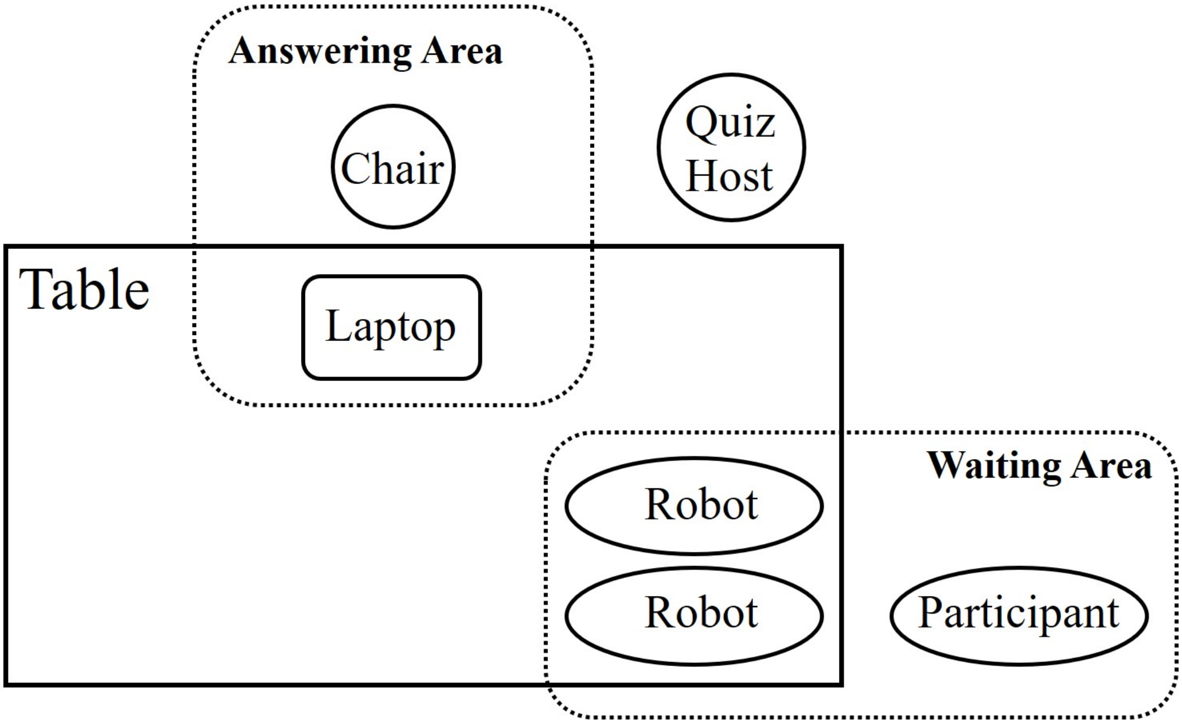

Figure 4.17: Experimental environment in a human–robot group.

answered the same quiz. Moreover, we analyzed the results of the questionnaire on impression on some images with black dots. Based on the questionnaire, we investigated whether the participants valued a group norm that occurred in a human–robot group. Additionally, before the experiment, each participant answered some test quizzes to familiarize himself or herself with the application of the quiz.

The flowchart of the experiment is shown in Fig. 4.16. A single step, which was repeated five times, contained “Answering” and “Recognizing.” When a participant is in the “Answering,” mode he or she answered the quiz in front of a laptop that displays the app as shown in Fig. 4.14. Meanwhile, a participant recognized the answer(s) in Fig. 4.18 or 4.19 when he or she was in “Recognizing,” A participant, who answered the quiz alone, recognized his or her own answer by watching the display as shown in Fig. 4.18, while a participant, who answered the quiz in a human–robot group, recognized each group member’s answer in Fig. 4.19. Therefore, as shown in Fig. 4.19 the quiz host displayed the app in their front. The participants knew each answer of the robot because the two robots were named TARO and JIRO.

The experimental environment in a human–robot group is shown in Fig. 4.17. In the “Answering Area,” the robots and the participant answered the quiz in the following order:

TARO, JIRO, and the participant. The quiz host brought the quiz to the front of the laptop when the robot answered it. In the "Waiting Area," each group member waited for his or her turn to answer. Moreover, the group members recognized each other's answer by watching the display shown in Fig. 4.19.

Each robot answered the quiz with regards to the dots in the white box, ADD, and ANSWER as state s, a_{next}, and a_{dcs}. After each answer by the robot, the three participants saw their answers. Simultaneously, the RoBoHoN observed the answers of the other participants and learned from them. When the number of dots in answers of the human participants were k_1 and k_2, the RoBoHoN's system recognized their answers as s_k and s_{k2} and renewed those values using Eqs. 4.1, 4.2, 3.3, and 3.4. This procedure was repeated five times by the participants.

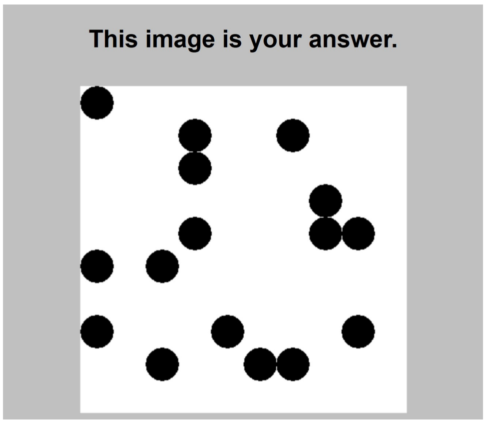

Figure 4.18: The app is to recognize answers alone.

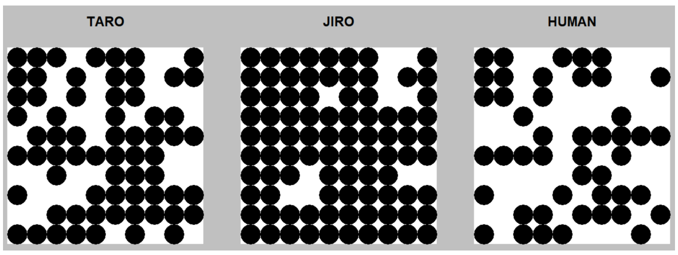

Figure 4.19: The app is to recognize answers in a human–robot group. It shows the images of dots that the two robots(TARO and JIRO) and the human participant provided in the answer phase.

4.4.3 Experimental Condition

The condition of this experiment is presented in Table 4.5. Fourteen participants answered the same quiz five times with no group members and in a human–robot group. In the experiment,

Table 4.5: Experimental Conditions.

M: the number of group members	3
N: the number of state	101
The number of participants	14
α: Learning Rate	0.1
γ: Discount Factor	0.9
$2\sigma^2$: Kurtosis of reward function	100

the descriptive term in the quiz that was answered by the participant alone and in the group was B and A as illustrated in Table 4.4. Eq. 4.3 indicates the initial value functions of the two robots:

$$V(s_n) = rand[0, 0.1] + exp\left(\frac{(s_n - s_P \pm 20)^2}{2\sigma^2}\right) \tag{4.3}$$

The state s_P denotes the number of dots of the participant. To investigate their social influence, the answers of the robots became the number of dots of the participants, ± 20, at step 1. If the answer of a robot is similar to the answer of the participant at step 1, we can not observe how the group members form a group norm. Therefore, to ensure that the participant was in the process to form group norm, we devised a means to initialize the value functions before the experiments.

4.4.4 Questionnaire

Each participant answered a questionnaire between answering and recognizing at step 5 in a human–robot group. Figs. 4.20 and 4.22 show the display of an app to answer the questionnaire. Fig. 4.20 shows six kinds of images of dots as shown in Fig. 4.21. On the other hand, Fig. 4.22 shows slide bars to answer the questionnaire. After answering the quiz of dots, which was an answer at step 5, the participant answered how reluctant he or she was to answer the image shown in ②, ③, ④, ⑤, or ⑥ of Fig. 4.20 at step 5 instead of his or her previous answer shown in ①.

Six images of dots are shown in Fig. 4.20. The images in ①, ②, ③, ④, ⑤, and ⑥ were the answer of the participant at step 5, the answer of the participant at step 1, the answer of robot1 at step 1, the answer of robot1 at step 5, the answer of robot2 at step 1, and the answer

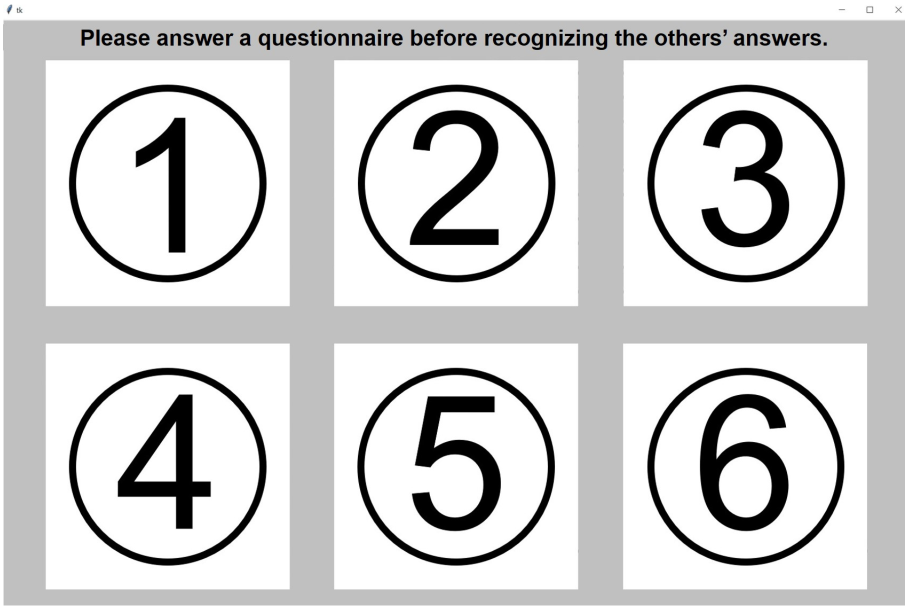

Figure 4.20: Display 1 of app for questionnaire. Each number from 1 to 6 expresses images of dots as shown Fig. 4.21.

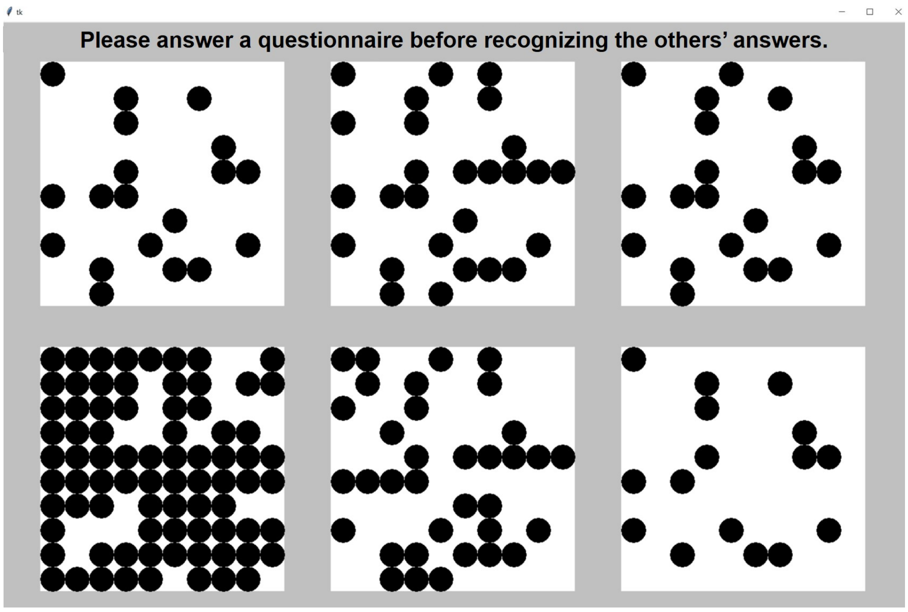

Figure 4.21: Example of the display 1.

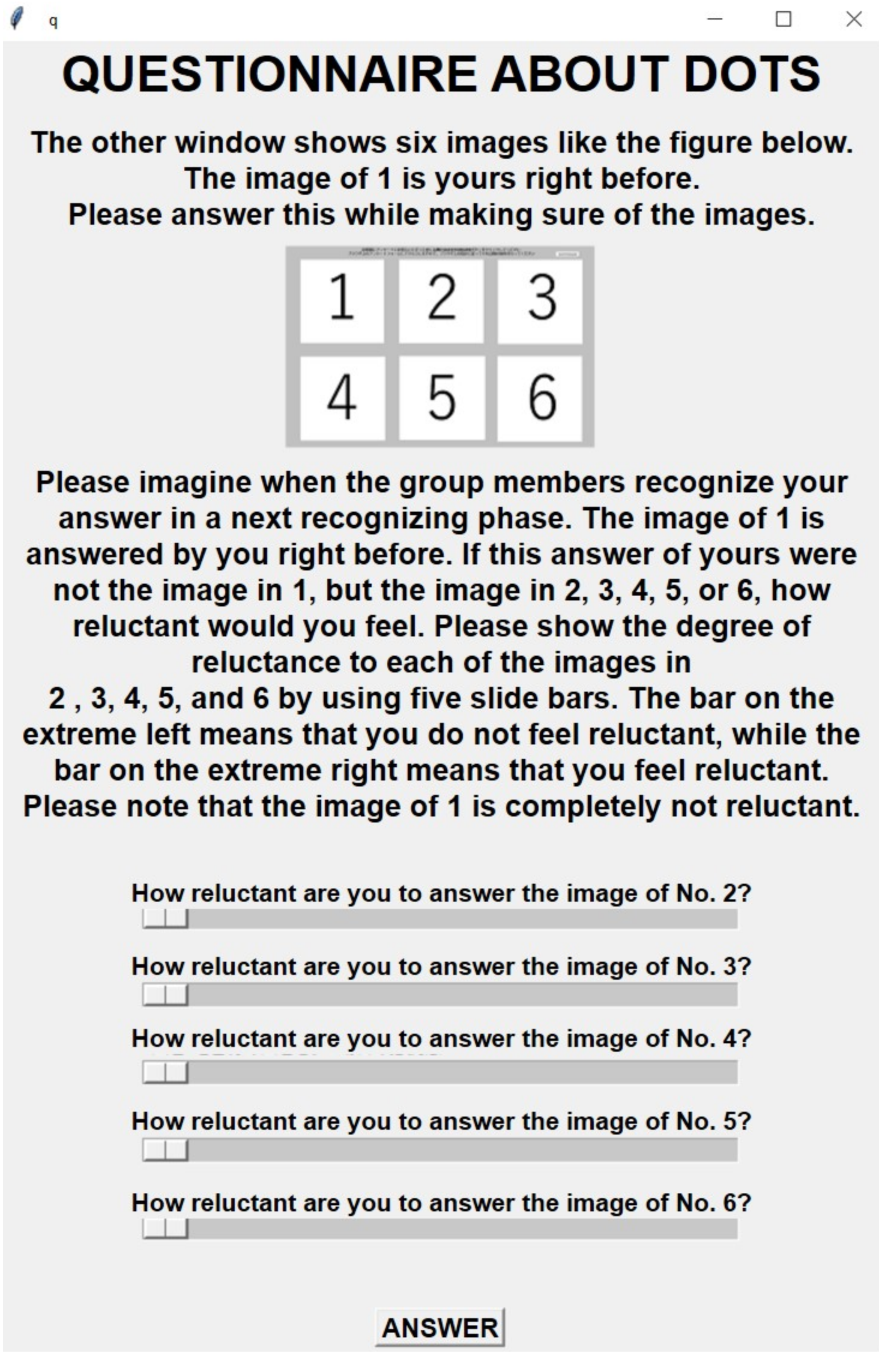

Figure 4.22: Display 2 of the application to fill in a questionnaire while checking the display 1 shown in Fig. 4.20. The English sentence means the questionnaire that was originally written in Japanese.

of robot2 at step 5, respectively. The participant saw an answer that he or she provided at step 5 and five answers. Then, the participant was not informed that ②, ③, ④, ⑤, and ⑥ were provided by him/her or the robots. The participant answered the questionnaire by using display 2 as shown in Fig. 4.22 while comparing ②, ③, ④, ⑤, and ⑥ with ①.

In Fig. 4.22, the location of the slide bar indicated the degree of reluctance from 0 to 100. The participant who answered the questionnaire selected a numerical value by moving a knob along a scale of a range of values. We used the slide bar because the slide bar was more suitable for the participant to finely express their reluctance to five images of dots than radio buttons, which are a typical approach of questionnaires, like Likert scale. The participants answered the questionnaire, and ensured the six images and comparing his or her answer, which is ① at step 5, with the other images. After answering the questionnaire, the participant moved to the waiting area and waited for the two robot to answer the quiz of dots. Finally, the participant and the two robots experienced the phase of recognition and the experiment ended.

4.4.5 Results

In this experiment, we investigated the change in answers of group members and impression of human participants on the opinion of other group members about the quiz. The participants answered the quiz concerning a descriptive scale B or "comparatively" to answer alone, while they answered the quiz concerning a descriptive scale A or "considerably" to answer in a human–robot group, as shown in Table 4.4.

The chronological change in each the answer of member in 14 human–robot groups, which included 14 university students is shown in Fig. 4.23. The vertical axis indicates the number of dots, while the horizontal axis denotes the number of the steps. Each graph has three broken lines, which mean the answers of group members. All of the participants answered the quiz five times concerning *Kanari* or considerably. Generally, although the number of the dots differ in each answer at the first step, Fig. 4.23 shows that each number of dots is similar to the others. However, not all human participants show a similar answer to the answer of the robot. Human participants in Experiment 2, 4, 5, 7, 9, 11, 12, 13, and 14 seem to mimic one of the previous answers of the robot at the second step, other participants in Experiments 1, and 3 clearly did not positively adjust to the answers of the robots. Two robots using the group norm model adjusted their answers, so that the group norm occurred in all of the human–robot groups.

The change of standard deviation of the number of dots at each step in human–robot group is shown in Fig. 4.24. At step 1, standard deviation of each group was similar to each

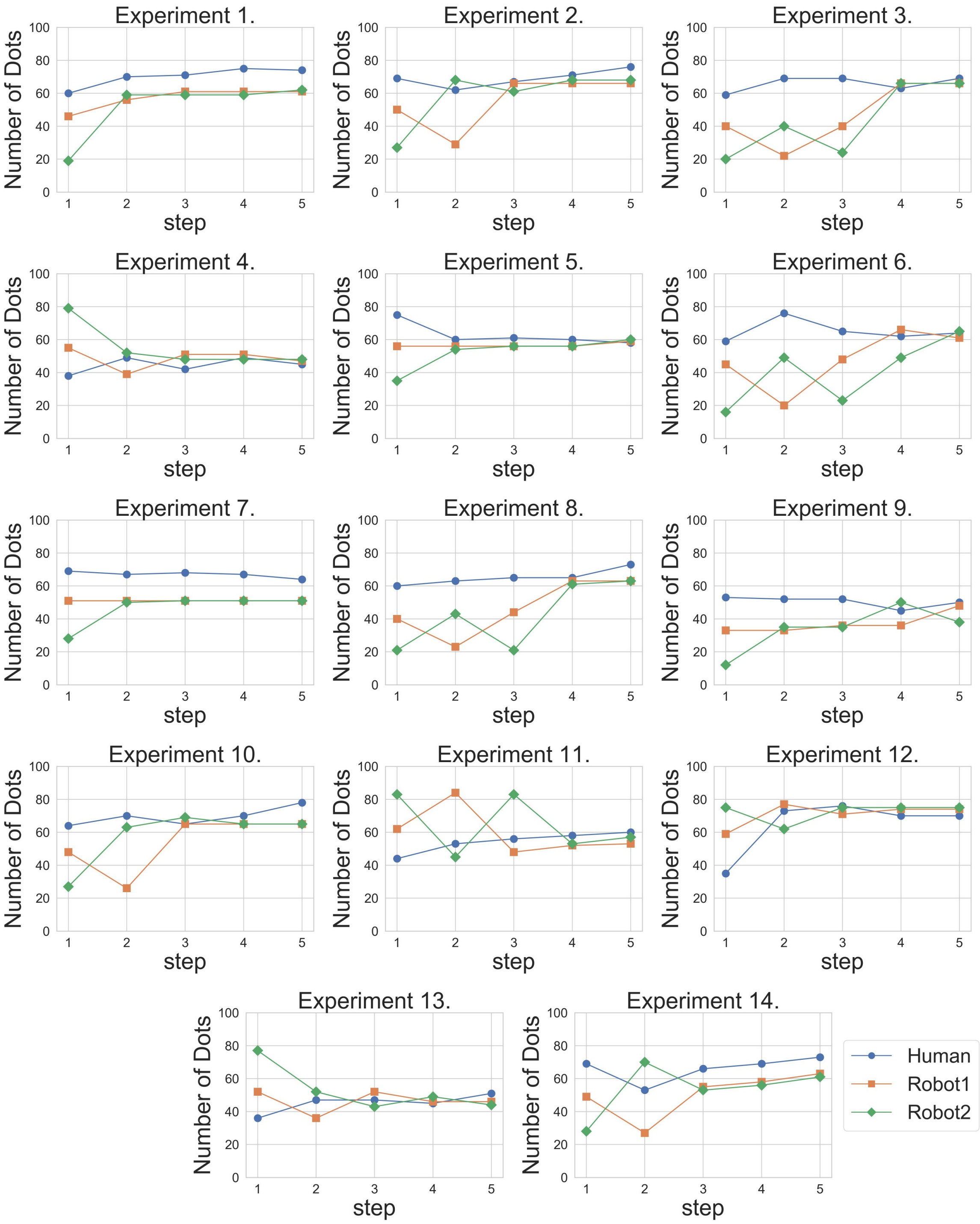

Figure 4.23: Each group member's answers in the 14 human–robot groups. All of the participants answered the quiz concerning "considerably" in the human–robot groups.

other since the initial answers of the robots were adjusted to differ from the initial answer of participant. The standard deviation at steps 4 and 5 was also similar to each other. However, at steps 2 and 3, standard deviation of each group was distributed more widely than at steps 1, 4, and 5. Moreover, the Brunner-Munzel test was performed to evaluate the standard deviation of step 2 and step 5. We intended to compare a set of standard deviations right after we recognized the answers of the other participants (step 2) for the first time with a set of standard deviations after continuously recognizing the others' answers four times (step 5). The p-value was 1.70×10^{-7}. The standard deviation at step 5 decreased. Each group showed a trend of fluctuation while answering the quiz five times and indicated that group norms occurred in human–robot groups.

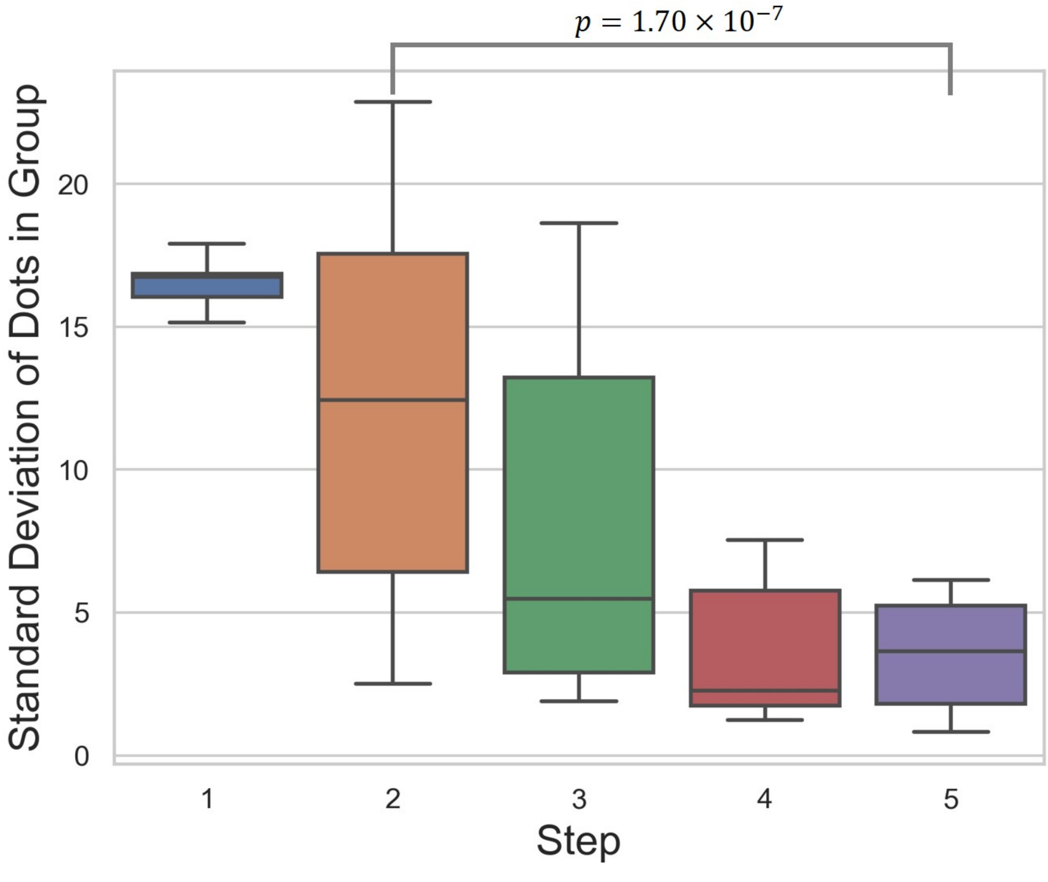

Figure 4.24: Change of standard deviation of the number of dots at each step, in human–robot group. The standard deviations between steps 2 and 5 has a statistical significance due to $p < 0.01$.

The chronological change of each answer of human participant when he or she answered the quiz alone and answered the quiz in a human–robot group is shown in Fig. 4.25. Fig. 4.25 shows that the change of each answer is large and small, respectively. Based on these results, Fig. 4.26 depicts the absolute number of various dots between steps. The *Human* and *Human–robot group* in the legend indicate the variation of dots in the two ways to answer the quiz.

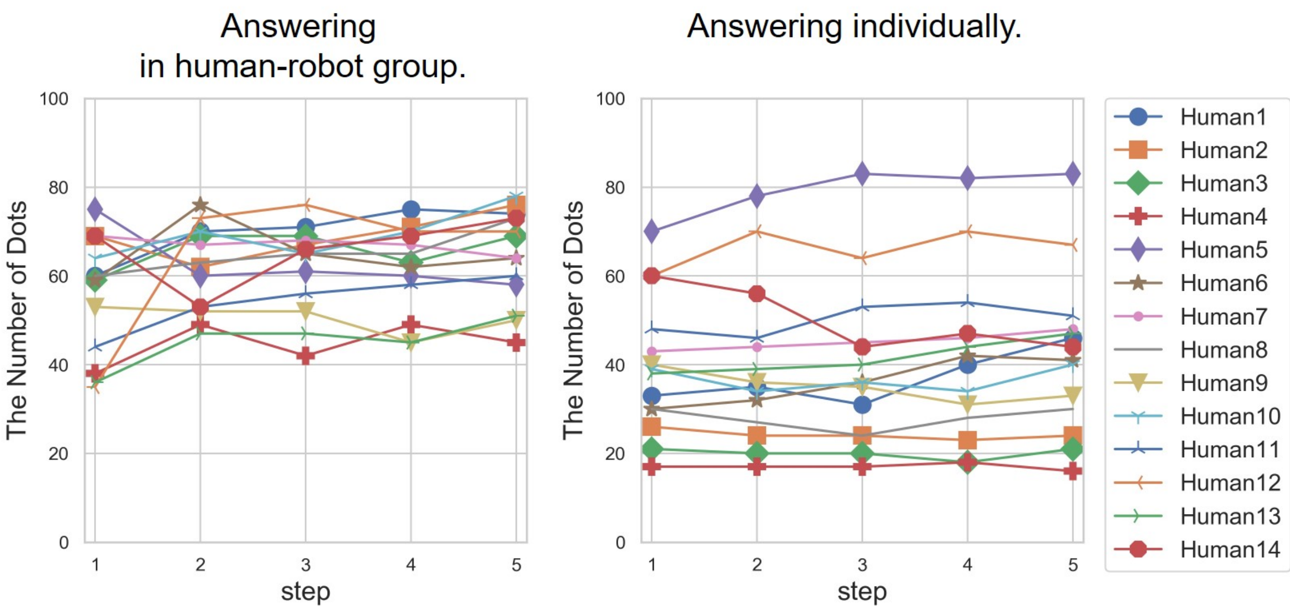

Figure 4.25: Chronological change of the answers of human participants in answering in a group and in answering alone.

Table 4.6 presents the p-value and effect size to evaluate the difference between the results of *Human* and *Human–robot group* as shown in Fig. 4.26. The Brunner-Munzel test was performed to evaluate the various dots in Fig. 4.26. Additionally, we investigated the effect size between the difference in *Human* and *Human–robot group* using Cohen's d [45]. The p-value and Cohen's d demonstrated that *Human–robot group* comparatively has a large difference of various dots at only step 1 to 2. Therefore, in *Human–robot group*, the difference in dots gradually decreased although the variation of dots comparatively maintains the same number of dots to answer alone. However, the value of Cohen's d at step 4 to 5 is larger than at step 2 to 3 and step 3 to 4.

Furthermore, the results of the questionnaire about the reluctance of the participants to answer the quiz based on the other's opinions instead of their own opinions are shown in Fig. 4.27. In addition, Table 4.7 presents the p-value and effect size to evaluate the difference in the reluctance between robot1's, robot2's, and the answers of the participant at steps 1 and 5 as shown in Fig. 4.27. The Brunner-Munzel test was performed to evaluate the various dots

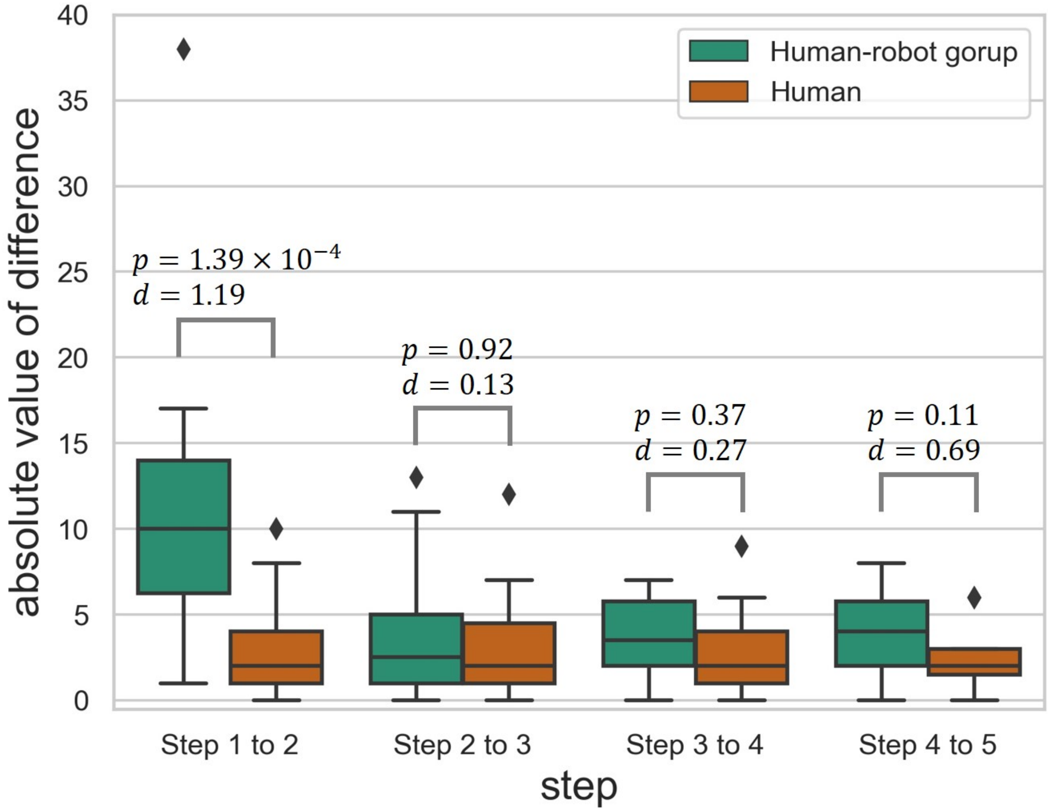

Figure 4.26: Comparison of the absolute variation of dots in *Human–robot group* and *Human*. The absolute value of step 1 to 2 only has a statistical significance due to $p < 0.001$.

Table 4.6: Results of the Brunner–Munzel test and Cohen's d in the various dots. These results show the comparison between the *Human–robot group* and *Human*.

Variety between	step 1 and 2	step 2 and 3	step 3 and 4	step 4 and 5
p-value	1.39×10^{-4}	0.92	0.37	0.11
Cohen's d	1.19	0.13	0.27	0.69

shown in Fig. 4.27. Additionally, we investigated the effect size between the difference of their reluctance at step 1 and 5 using Cohen's d [45]. The p-value and Cohen's d indicated that human–robot group comparatively has a large difference in their reluctance. Therefore, most of the participants felt more reluctant to answer based on the opinions at step 1 than step 5.

As a result, it is obvious that the answer of the human participant and opinion in human–robot groups changed while answering the same quiz five times in a row. Moreover, the results of the questionnaire show that participants generally felt more reluctant to agree to the opinions of others at step 1 than at step 5.

Table 4.7: Results of the Brunner–Munzel test and Cohen's d in the results of the questionnaire about the participants' reluctance.

	Human's answer at step 1 and 5 (No. 1 and 2)	Robot1's answer at step 1 and 5 (No. 3 and 5)	Robot2's answer at step 1 and 5 (No. 4 and 6)
p-value	7.45×10^{-7}	9.44×10^{-3}	7.07×10^{-6}
Cohen's d	1.20	1.26	3.61

4.4.6 Discussion

Human participants were affected by the opinions of the robots about the similarity of answers and generated group norms with the two robots in groups as shown in Fig. 4.23 and 4.24. In the quiz with unclear answers, it was assumed that these participants trusted the answer of

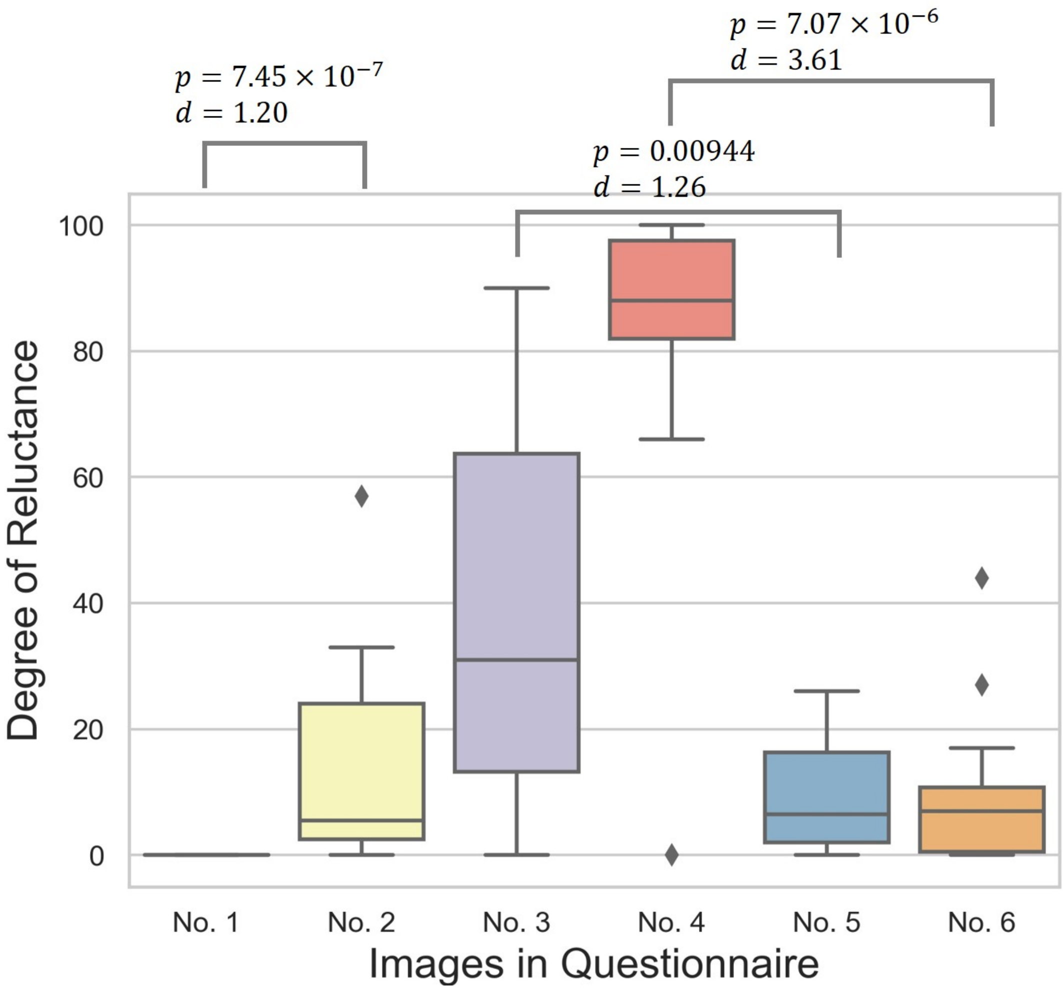

Figure 4.27: Results of the questionnaire about participants' reluctance to answer based on the other's opinions instead of their own opinions. Each group member's answer between step 1 and step 5 has a statistical significant due to $p < 0.01$.

the robot due to lack of their criterion and confidence to answer the quiz. As illustrated in Experiment 1 of Fig. 4.23, the answers in the group did not correspond to the similar answers from the first step to the final step. On the other hand, Experiment 12 in Fig. 4.23 indicates that the human participant sharply changed his or her answer from step 1 to step 2. Therefore, it appeared that the similarity of the answers in a group depends on whether the participant has his or her criterion to answer the quiz or not.

In addition, even though the variation between step 1 and step 2 was large as shown in Fig. 4.26, human participants decreased the variation of dots after step 2. In the quiz with unclear and vague answers, the participants who did not answer with confidence tended to change their answers due to the social influence of the robot in human–robot groups. It was indicated that the participants in the group kept the constant number of dots as an answer to step 2 to 3, step 3 to 4, and step 4 to 5. This was because they were later aware that the robots attempted to maintain group norms. Therefore, it was assumed that the answers of the human participants were affected by those of the robots, who considered group norms in the group, and formed group norms with robots.

However, the numerical value of Cohen's d in step 4 to 5 has a tendency to increase compared with d in step 2 to 3 and step 3 to 4. This might suggest that the human participants tried to show their individuality or personal opinions to answer the quiz after they changed their own answers and accepted the group norm or the criterion of the approach to answer the quiz. The quiz had an unclear answer and no right answers, therefore at first group members had no criteria to answer it. Then, it was difficult for human participants to show their individuality and opinions through the quiz scenario. However, after generating a group norm, they might get a criterion to answer the quiz and get to be able to show their fifth answers as their own opinions. In other words, the human participants might show their individuality by depending on how different their answers were from the group norm. Therefore, their decision–making processes were based on the group norms that were shared with the robots.

Moreover, Fig. 4.27 shows that the group norms changed the opinions of the human participants because they felt answers similar to the group norm more appropriate than answers different from the group norm. In a comparison of answers of human between step 1 and 5 as shown in No. 1 and No. 2 in Fig. 4.27, they preferred the answer at step 5 as an answer in a group, although they decided to answer an image by themselves at step 1. This means that they thought they should answer the quiz while they consider the group norm. Therefore, the group norm gave them a right answer to the quiz that had no correct answers. On the other hand, in a comparison of answers of robots between step 1 and 5 as shown in a pair of No. 3 and No. 5 and a pair of No. 4 and No. 6 in Fig. 4.27, the humans accepted the answers that each of the robots showed while they learn a group norm. This also indicates that the humans gradually accepted the group norms, although they were surprised at a difference of the answers of others and changed their answers. Therefore, although humans generated the group norms with two robots, the norms socially affected the opinions of the participants.

4.5 Summary

In the present study, a model was proposed to enable a robot to create a suitable criterion for decision-making by interacting with humans in a group. The results of the study in the experiment 1 revealed that the robot adjusted itself to each group and was capable of generating group norms with human participants in a limited scenario. In the experiments, group members' answers became increasingly similar to each other when the members became aware of the other members' answers to the quizzes. Therefore, the experimental results suggested that human participants considered not only the other human participants' answers but also the robot's answers when completing the quiz. However, the results also suggested that unlike in human groups, some human participants in this quiz scenario did not adjust to the group norms in the human–robot group. On the one hand, the present study demonstrated that group norms do occur in human–robot groups. On the other hand, it did not reveal differences between the influence of the human participants and the influence of the robot on the human participants.

This study also investigated whether robots affected behaviors of human participants when one human participant joined the group, which included two robots that considered the group norm. In the case of the robots that consider group norms in the group and used for the group experiment, we focused on the change of the behaviors of the humans with robots and an appropriateness of the opinions of the group members in the human–robot group. Two studies showed conformities of humans and social influence on humans from robots that did not change their behaviors [33, 34]. Therefore, it is unclear whether robots that change their behaviors socially affect humans.

Human participants also answered a quiz with unclear answers in the experiment 2. Based on the results of the quiz, we compared answers of human participants in human–robot groups with the answers that they obtained by themselves. The variation between the steps gradually decreased although the answers of these participants largely changed from the first step to the second step. Following the results, it is suggested that the participants kept the constant number of dots as an answer in the group because they were confused about the diversity of the answers and got to be aware that the robots attempted to maintain group norms. Therefore, the human participants also made decisions when they consider group norms like the robots.

In addition, we investigated the kind of answer the human participants accepted as an appropriate answer in the group that they belonged to. The participants determined what kind of answers are appropriate on the basis of the group norm that they shared with the robots. So, the group norm gave them a criterion to answer the quiz that had had originally no correct answers. Thus, we concluded that opinions of the human participants were affected by the robots considering group norms in the human–robot group.

In the next chapter, we investigate social influence in a practical scenario. The quiz scenario prepared for this investigation is not a common situation in human–robot interaction. Therefore, we need to investigate whether group norms in human–robot groups affect humans decision making in a realistic scenario.

Chapter 5

Navigation Model for a Robot as a Human Group Member to Adapt to Changing Conditions of Personal Space

5.1 Introduction

In this chapter, we evaluate a robotic navigation model by considering the changes in the personal spaces in human–robot groups in a virtual space. In addition, this navigation model is based on group norm model shown in Chapter 4.

We have proposed a decision-making model for robots to behave based on group norm in human–robot groups as shown in chapters 3 and 4. An example of a group norm common in human communities is the necessity to maintain the physical distance between people. In human communities, a person usually has a region surrounding him or her called the personal space, which psychologically corresponds to their own private space; if another person intrudes into this space, it may cause discomfort [53, 54]. Although [55] has reported that personal space is dynamic and is dependent on particular situations, people in a group usually tend to maintain an appropriate distance from one another when the group members stand together.

Autonomous mobile robots in a human–robot group also need to move according to the changes in the human personal spaces. However, in the previous related studies, the proposed methods were aimed mainly to avoid colliding with humans and did not prevent from intruding into the human personal space while the robot moved from an initial point to a target one [48, 49, 50, 51, 52]. The previous methods did not consider a situation in which a robot moved in a human–robot group as a group member and had to adapt to the changes in personal space depending on contexts and situations. Therefore, a robot using the previous methods cannot maintain the distance in the group appropriately.

To evaluate the appropriateness of the robot's trajectory in terms of mimicking social behavior patterns as a group member, we prepare a scenario in which robots in a group need to keep an appropriate distance. We conducted a questionnaire to register participnats' impressions on the robot behavior. According to the scenario, each of the three robots was operated by two humans or by a system based on the proposed model, respectively, and then the behavior of robots was evaluated by other experiment's participants, meaning that the scenario outlined changes in the distance kept by group members. To analyze the results of the questionnaire, we assessed how appropriate was the trajectory of the robot using the proposed model. In this way, we investigated whether or not a robot as a member of a human group could determine an appropriate location so as to avoid encroaching on the personal space of another group member and could move in a humanlike way in a simulation in which the human members change their distance that they wanted to keep.

5.2 Related Work

Sociable robots need to perform autonomous navigation in human–robot environments to avoid not only collisions but also human discomfort [46, 47]. Many factors can influence how people use physical spaces during interactions [59]. In the field of human–robot interaction and robot navigation, many studies have considered these factors [46, 47]. Several studies have revealed that humans felt discomfort or reluctance to a space shared by humans and robots depending on where the robots were located [60, 61, 62]. In order to prevent humans from feeling discomfort, several studies aim to navigate a robot on the basis of the human's behaviors [63, 64]. Considering proxemics in human–robot environments, several authors have developed navigation behaviors to enable robots to move in densely crowded areas by learning from human behaviors [65, 66, 67, 68]. In addition, [69, 70, 71, 72] presented navigation systems that enabled a robot to approach interacting humans while avoiding collisions and preventing humans from feeling reluctance.

Personal space has been dynamic and situation-dependent [55]. Therefore, robots should also consider personal space dynamics as well as the distances that people want to maintain to move appropriately in a human–robot environment. Previous studies have investigated the characteristics of an experimental environment with human participants. These characteristics include the brightness of lighting in the environment [73], whether the environment is outdoor or indoor [74], the size of the environment [75, 76], and the crowdedness of the environment [77].

Appropriate position in a given situation is based not only on interpersonal space, but also on spatial and social factors. As these spatial and social factors also influence acceptable positioning in group situations as well as interpersonal space, resultant placement constraints emerge. However, as situations change, the constraints may vanish without conscious acknowledgement from people in a given space. For example, passengers in crowded trains have no choice but to accept usually unacceptable distances between themselves and others. After a large number of passengers have departed from a crowded train, spatial constraints in the environment are eliminated and appropriate distances between passengers are reconstructed. This reconstruction process somehow determines the distance to be maintained by observing the atmosphere of a place. For instance, when several people pose for a picture, they might be asked to move closer together, despite such proximity being unacceptable usually. After the group photo is taken, appropriate distances norms for interaction are reconstructed if those people to form a group again. As described, the situation and implicit behavior rules change under the constraints, while situation changes can prompt participants to reconstruct the rules, and the atmosphere can somehow determine maintainable distances.

Previous studies have considered how robots can navigate and move while avoiding obstacles and maintaining social acceptability for humans [46, 47]. These studies tended to focus on movement between points, investigating ways for robots to reach a goal point while avoiding obstacles in a socially natural (i.e., acceptable to humans) fashion, as shown in Fig. 5.1 (left).

However, previous contributions did not consider the movement of robots within a human–robot group. When humans and a mobile robot belong to a group, it is important for the robot to find an appropriate location to stand. To form and maintain the human–robot group, the robot needs to continuously show the group members, as well as those outside the group, that it belongs to the group. This can be done nonverbally by maintaining a suitable distance from other group members, just as human group members tend to do despite interpersonal space being dynamic and situation-dependent [55].

As humans behaving socially might tolerate unacceptable distances despite feeling discomfort (e.g. humans in group situations occupying their own spaces while sharing a rule governing maintaining personal distance) and as previous methods did not consider said social rules involved in such contexts, it follows that robots using previously proposed methods may not be able to maintain appropriate distances from other group members when interacting in a human–robot group. Robots that assume static destinations cannot cope with environments where such positions may change depending on the situation, as such robots must constantly adjust their positions and adapt to social rules governing how much distance group members should maintain.

Therefore, the novelty of this study is that our mobile robot will be continuously located in an appropriate position based on the unspoken and unwritten rules of proximity in order to belong to a human group. By recognizing the rules that change with changing situations in a space without communicating directly with other group members, our robot will maintain its position by estimating the gradually and naturally established appropriate distance. This will allow the robot to adapt to situations where the relations among group members affect the maintained distance, giving the impression that the robot is socially acceptable. Comparing the previous studies to our proposed model, our robot has to deal with different situations. While the previous study proposed a method to move to a goal point in a human-like way, our proposed model is a method to keep standing in an appropriate position among group members located unconsciously in their own appropriate places. In this study, we shall use questionnaires to evaluate out robot's attempt to obey social rules and move in an experimental scenario.

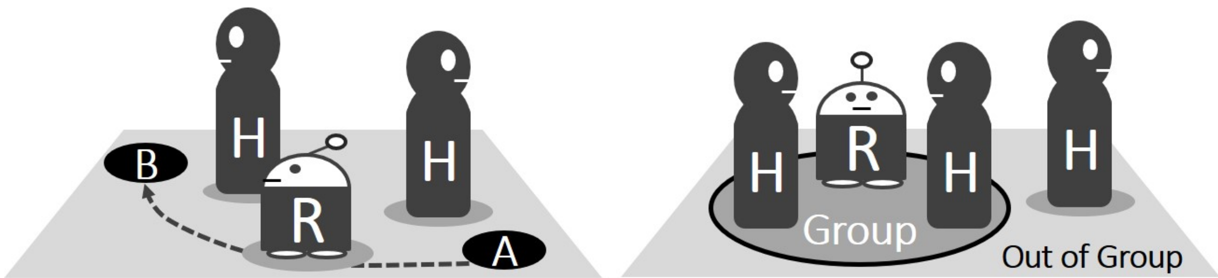

Figure 5.1: Diagrams of the previous method (left) and our proposed model (right). The robot on the left moves from point A to B, whereas the robot on the right is continuously trying to position itself appropriately as a group member.

5.3 Group Norm Model for Distancing

The proposed model is aimed to enable a mobile robot moving in a humanlike way by considering the changes in the personal spaces of other group members.

Fig. 5.2 represents the outline of a mobile robot that uses the proposed model. The mobile robot selects a location appropriate for the estimated physical distance that needs to be maintained within the allowed area of movement. If this is done appropriately, the robot moves in a human group as a group member. Figs. 5.3 and 5.4 represents the locations of certain humans (H) and a robot (R) considering the x-y plane. In Fig. 5.3, the humans and the robot are located at the particular distance from one another. In Fig. 5.4, they are positioned more closely to each another. In these figures, the position of the humans (H) indicate the change of their physical distances according to the distance that humans want to maintain, whereas R corresponds to the robot's ideal location reached by using the proposed navigation model. Therefore, a robot in such a situation must continually identify a location that is not too close or too distant from a human although humans in the group keep moving and changing their physical distances as intended.

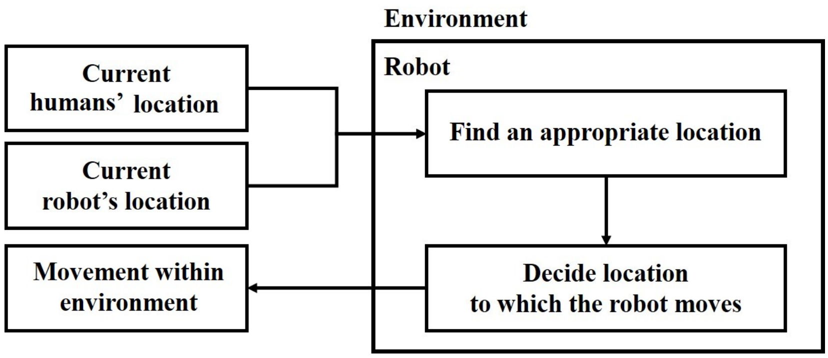

Figure 5.2: Navigation model based on the changes in the group members' personal spaces.

5.3.1 Environment and Robot Action

In the present paper, the robot movement in the human group is observed in the x-y plane, as shown in Figs. 5.3 and 5.4. In this environment, the state of a human or a robot indicates the location at (x, y) at the step t (state s^t). Each group member transits from the state s^t to s^{t+1} by moving from the present location to that in which the group member aims to arrive. The action a_{nm} executed by the robot indicates that it moves from (x, y) to $(x + n, y + m)$. Therefore, to avoid invading the humans' personal space, the robot determines the action that should be executed in the state s at every step.

5.3.2 Learning to Maintain Physical Distance in Group

The proposed navigation model is aimed to enable a robot identifying its own location with respect to a group of humans. To learn the physical distances usually maintained in human groups, the robot estimates the physical distances among the humans considering the location

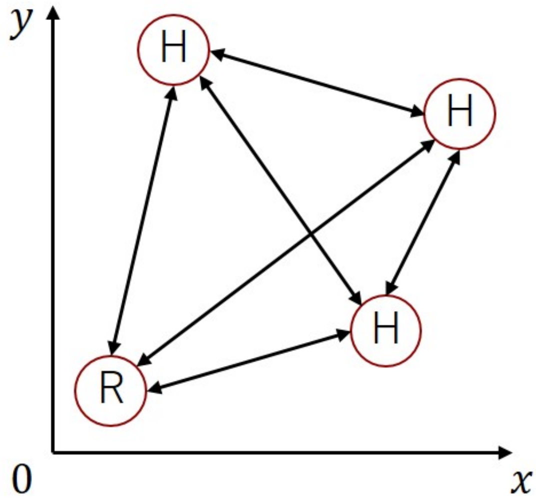

Figure 5.3: Initial state of group members including humans and a robot.

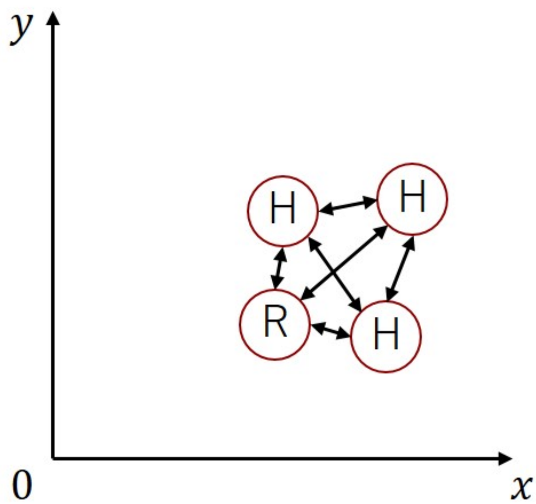

Figure 5.4: State of group members including humans and a robot after moving.

of other group members. The robot then estimates the physical distance maintained in the group. The robot calculates the value function $V(d)$ and the reward function $R(d)$ to estimate the maintained distance in the group. Here, d indicates the physical distance between any two of the group members. The value function $V(d)$ is used to obtain the value corresponding to keeping the distance d in the group, whereas the reward function $R(d)$ indicates the reward for maintaining the distance d. To consider the possible changes in the humans' personal spaces, we rewrite the value function $V(d)$ as per Eqs. 5.1 and 5.2:

$$V(d) \leftarrow (1-\alpha)V(d) + \alpha\left(R(d) + \gamma \max V(d)\right) \tag{5.1}$$

$$R(d) = \sum_{d' \in D} \exp\left(-\frac{(d'-d)^2}{kurtosis}\right) \tag{5.2}$$

$V(d)$ at step t outputs a value of a certain distance that a robot keeps from other group members. In an environment in which group members change their personal space, the distance that should be kept by the group members dynamically change. Therefore, based on the distances that the robot calculated by observing the other group members at every step, the robot needs to learn the appropriate distance that should be kept at a certain step. To this extent, the robot renewed the $V(d)$ at every step by using the Eq. 5.1 which includes $R(d)$. In addition, the calculation of $R(d)$ requires the distances between the other group members as shown in Eq. 5.2. Therefore, by calculating $R(d)$ at every step, the robot could calculate $V(d)$, and make a decision based on Q values obtained using $V(d)$.

Here, α and γ are the parameters in reinforcement learning, and $kurtosis$ stands for the degree of flexibility (deviation) that is taken into account in the robot decision. $kurtosis$ holds a range of appropriate distances that a robot should keep. In addition, when N human group members belong to a group, there are $N(N-1)/2$ values corresponding to the distance between humans. For example, Fig. 5.5 represents the three Hs (H_1, H_2, and H_3) with distances $d_{1,2}$, $d_{1,3}$, and $d_{2,3}$. Therefore, each distance can be represented as follows: $D := \{d_{ij} | i, j = 1, 2, 3, \cdots, N, i < j\}$. In the same vein with the model proposed in Chapter 4, which aimed to learn a group norm in human–robot groups, we adapted it to to a robot that aims to keep an appropriate distance from the other group members in this study.

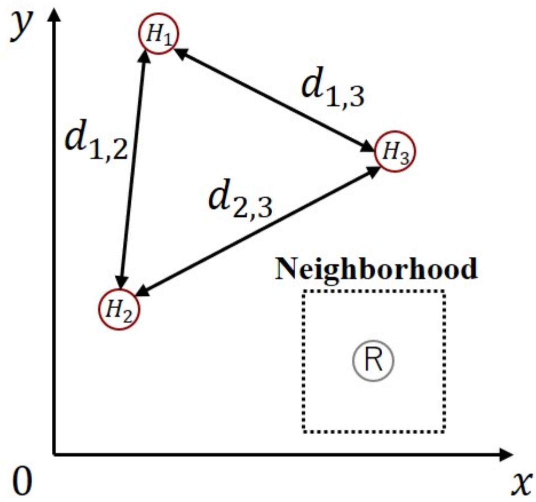

Figure 5.5: Physical distance $d_{i,j}$ maintained by group members(H_1, H_2, and H_3) and the range of the robot's neighborhood.

5.3.3 Criterion for Decision-Making

When the robot in a certain state s is too close to the other group members or too far away from them, the robot needs to adjust its location to maintain a distance suitable for the other group members. The robot uses the proposed model to select an action a on the basis of the value $Q(s, a)$, which means that the robot moves to a certain location in its neighborhood. The Q value indicates the value of executing the action s in the state s as follows:

$$Q(s, a) = \prod_{d' \in D} \exp\left(-\frac{(d' - \operatorname{argmax} V(d))^2}{kurtosis}\right) \tag{5.3}$$

The robot using the proposed model made a decision based on Q values obtained using $V(d)$ which is itself calculated using Eqs. 5.1 and 5.2. In other terms, the Eq. 5.3 is computed using both Eqs. 5.1 and 5.2. Therefore, the robot moves in the environment by executing a_{nm} on the basis of the highest Q value to perform an action in a certain state. In other words, a robot can move in the neighborhood, as shown in Fig. 5.5, by executing an action a_{nm}.

5.4 Experiment and Evaluation

In the present study, we conducted an experiment to investigate impressions about a robot using the proposed model in a 3D space. To evaluate the appropriateness of the robot's trajectory seeking to behave socially as a group member, we prepared a scenario in which robots in a group needed to keep an appropriate distance. We then formulated a questionnaire to ask for participants' impression about robot behavior in the scenario. The scenario was named *Playing Catch Scenario* implying that four robots moved and played catch. In the scenario, each of the three robots was operated by two humans and by a system using the proposed model, respectively, and then the robot behavior was evaluated by other experimental participants. At this time, the other robot did not move in the space. To analyze the results of the questionnaire, we assessed how appropriate was the movement trajectory of the robots using the proposed model.

5.4.1 *Playing Catch Scenario*

To conduct the experiment, we prepared the *Playing Catch Scenario* and a 3D space in which the robots played catch. Fig. 5.6 shows a park in the 3D space, and Fig. 5.7 indicates four robots used in the scenario, which are denoted as red, green, blue, and black. In the scenario, the robots needed to keep an appropriate distance to play catch in the space, so that they spread out and gathered across the park.

The 3D space represented in Fig. 5.6 was decorated with 3D objects typically presented in actual parks. The four robots shown in Fig. 5.7 played catch in a large lawn at the back of the park. The robots moved and played catch in the lawn according to the scenario.

The flow of the *Playing Catch Scenario* was separated into the five parts, as shown in Figs. 5.8-5.12. In the first part, the red, green, and blue robots were grouping around the black robot, as shown in Fig. 5.8. In the second part, to play catch, the robots except the black robot spread out, as shown in Fig. 5.9. In the third part, they played catch with a black ball, as shown in Fig. 5.10. In the fourth part, they stopped playing catch, and the robots started grouping around the black robot, as shown in Fig. 5.11. In the final part, they completely stopped moving, as shown in Fig. 5.12. During these parts, the scenario was aimed to reconstrust the scene of the robots playing catch.

5.4.2 Robots' Movement Controlled by Humans

The three robots moving in the space were controlled by two humans and a system using the proposed model. Figs. 5.13 and 5.14 represent the application screens for the two humans used to control the robots. The screen provides the view on the experimental space from directly

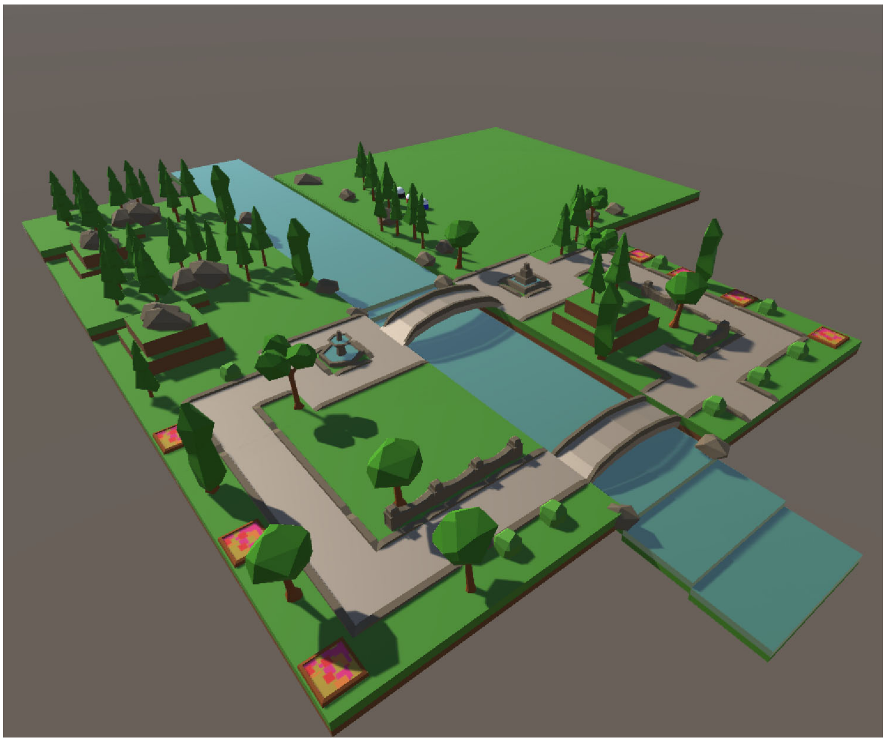

Figure 5.6: Park environment to play catch.

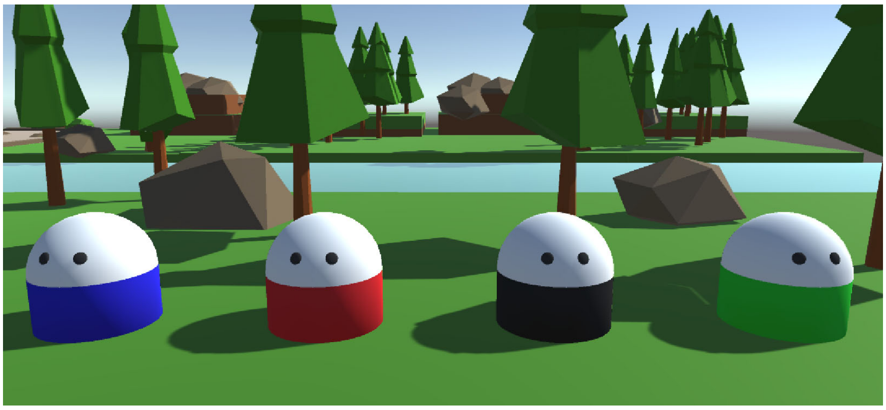

Figure 5.7: Robots in park environment.

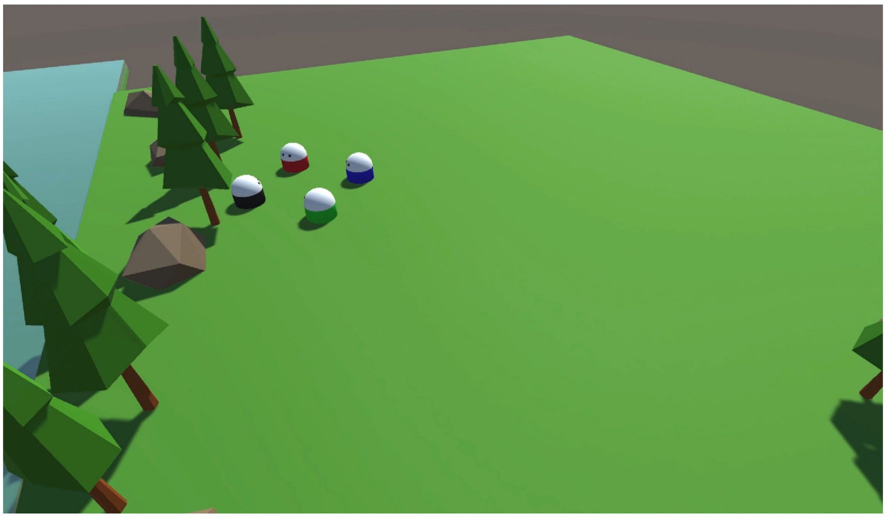

Figure 5.8: Initial state of robots.

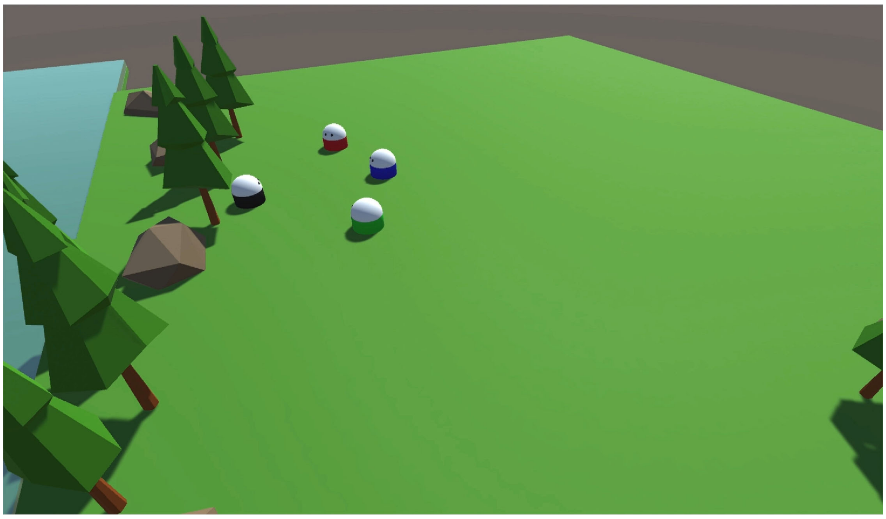

Figure 5.9: Three robots spreading out.

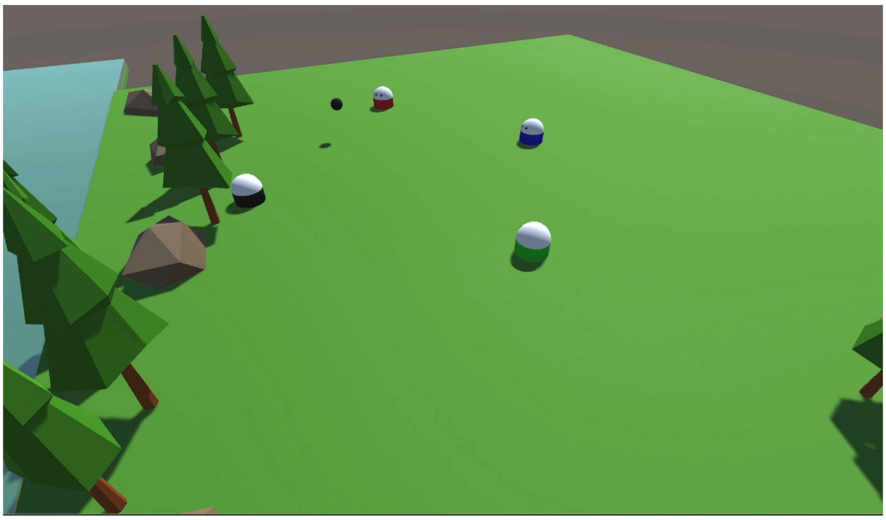

Figure 5.10: Four robots playing catch with the black ball.

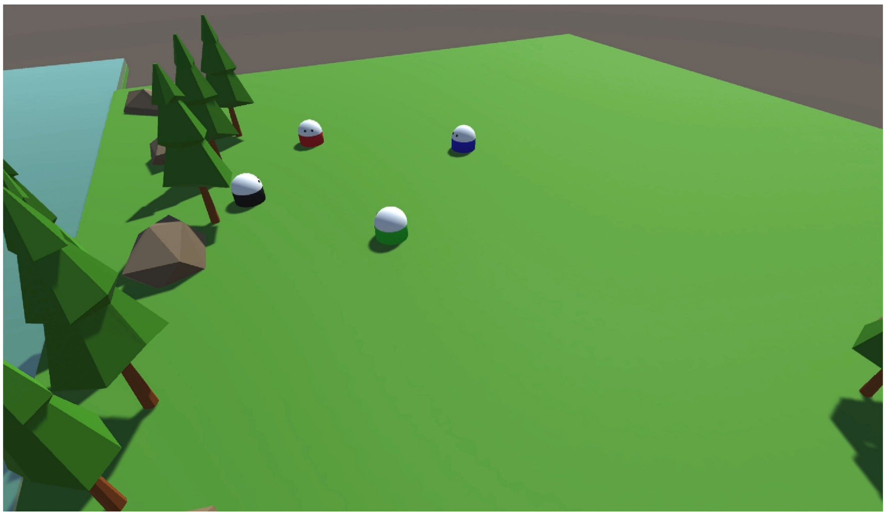

Figure 5.11: Three gathering robots.

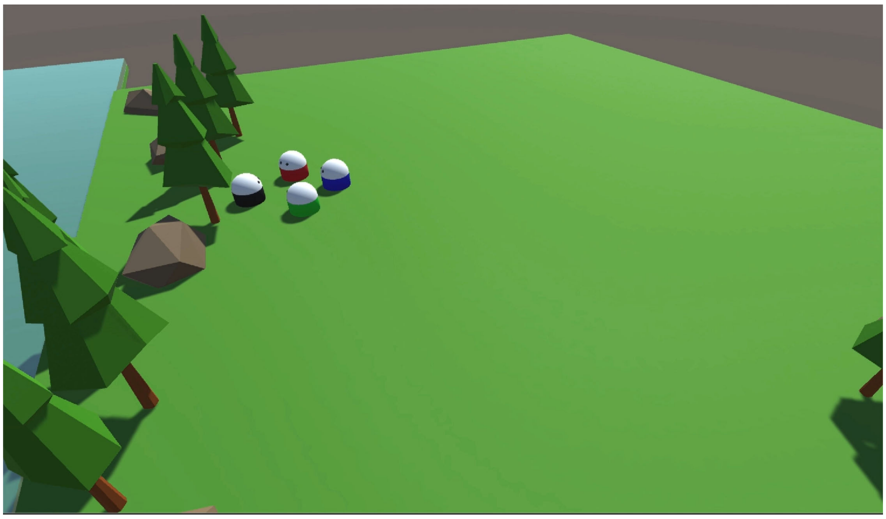

Figure 5.12: Final state of the scenario.

above and on the white heads of the robots. The humans controlled each of the robots while watching the screen from directly above by using a keyboard.

Fig. 5.14 represents a way of operating a robot. The two humans shared a keyboard to control the robots. Similarly as represented in Fig. 5.14, if one of the humans operated the green robot, and the other operated the blue one, then the operator of the green robot controlled it by pushing the keys of "W," "A," "S," or "D" on the laptop's keyboard, and the other operator controlled the blue one by pushing the keys of "8," "4," "6," or "5" on a numeric keypad. As shown in Fig. fig:key, each robot considered a direction of the black robot as its front. For example, a robot continuously moved to the black robot while a human continuously pushed the "W" key. Therefore, the humans controlled the robots on the basis of the direction of the black robot by using the keyboard.

In addition, the red, green, and blue robots watched the black robot or the center between the four robots while moving in the park environment. This is because the robots that do not look around do not seem natural as people usually observe the surrounding when walking backward. The robots randomly switched their direction with respect to the robot not moving and the center of the group. The Eq. 5.4 indicates the center of the four robots. Here, l_c is the center of a group, whereas l_i represents the locations of each group member. Moreover, N is the number of the group members. Therefore, the robots naturally switched their direction at a different time.

$$l_c = \sum_{i=1}^{N} l_i/N \tag{5.4}$$

5.4.3 Alternative Robotic Model for Comparison

To evaluate the proposed model, we set up another robotic system to compare with a robot using the proposed model. The proposed model was aimed to facilitate a robot keeping an appropriate distance by learning a group norm in real time. In addition, we introduced a robot using the previous method that did not imply maintaining the distance in the group. Therefore, we prepared such robot for the purpose of comparison, which moved without considering an appropriate distance.

The model implemented for comparison allowed a robot only moving from a start to a goal while maintaining a constant speed. The start point was located at an initial location in Fig. 5.8. The goal was the place where the robot controlled by a human as a leader started

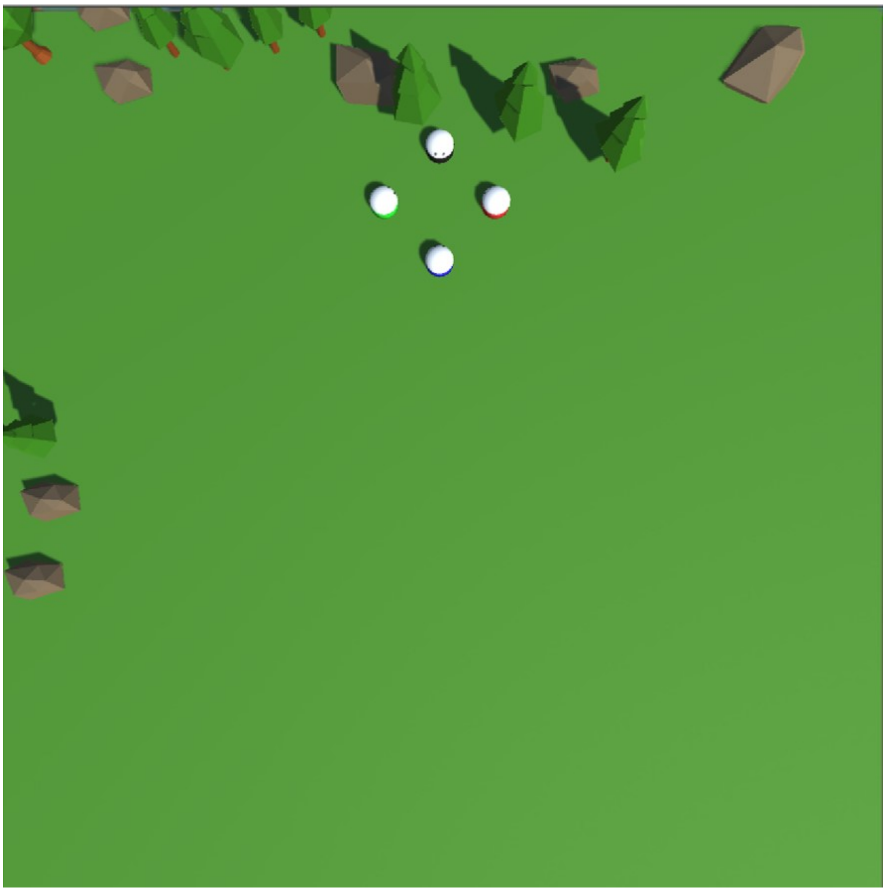

Figure 5.13: Display for controlling a robot. A human operator of a robot watches the environment from directly above.

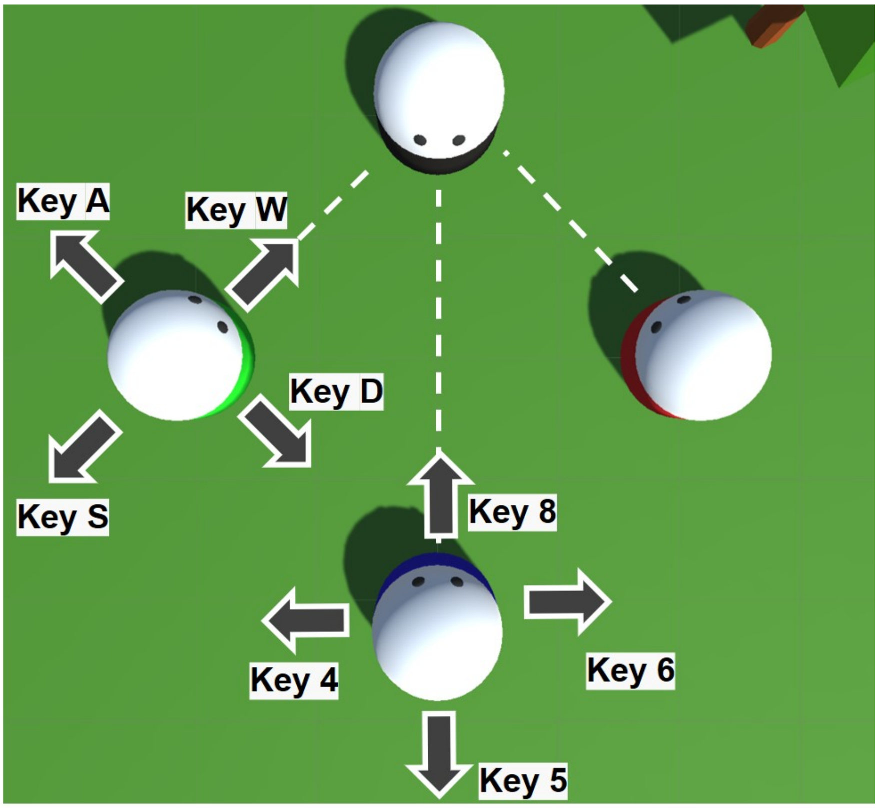

Figure 5.14: Way of controlling a robot.

to play catch after spreading out as shown in Fig. 5.9. As a result, the robot moved from an initial place to a location to play catch.

5.4.4 Way of Controlling Robots

In the experimental scenario, two humans and a system using the proposed model played two kinds of roles: a leader and followers. In general, to keep an appropriate distance, group members needed to move while considering the other members' locations and should not have moved freely. Therefore, one of the humans needed to consider how far they could spread out or group while moving, whereas the other human and the system needed to move following the leader.

We asked the two humans to be a leader and a follower in the scenario. The robot using the proposed model was a follower as the model was aimed to make a robot keep distance. Therefore, the group members including the humans and system were able to keep an appropriate distance in the scenario.

In a group including the two humans and a robot using the model for comparison, the robot moved as a leader, and the humans were followers. As the robot did not consider the dynamic distance shared in a group, it could not move as a follower. In the present study, we evaluated the robot using the proposed model as a follower, whereas the robot for comparison only moved as a leader, as shown in Table 5.1.

Table 5.1: Two groups and their members.

Group	Group member
1.	A human follower, a human leader, and the proposed model as a follower.
2.	Two human followers and the model as a leader for comparison.

5.4.5 Questionnaire and Records

To evaluate participants' impression on the trajectory of robots, we prepared an application to perform a questionnaire and uploaded the records in YouTube in which the robots were displayed during the *Playing Catch Scenario*, as shown in Fig. 5.17. The records represented the records of *Playing Catch Scenario* in group 1 and group 2, as shown in Figs. 5.8-5.12. In addition, Figs. 5.15 and 5.16 represent the app developed to perform the questionnaire. The experiment participants answered the questionnaire about each robot group. The first question allowed them indicating whether they perceived each robot as a leader or a follower; the second question was stated to specify a color robot of which color was controlled by the computer.

The participants were told that a computer system operated one of the robots only after completing the first question, so they answered the question about *leader–follower* without bias. Moreover, the app facilitated answering the questions instinctively. In this way, they provided answers about their impressions about these robots controlled by humans and robotic models.

5.4.6 Results

Table 5.2 represents the experimental conditions. We run the Brunner-Munzel test to investigate whether or not the results had statistical significance. In addition, we used *Cohen's d* to investigate the effect size between samples.

Fig. 5.18 represents the results of corresponding to the first question aimed to investigate the impression of a robot operated by a human in group 1 and gruop 2, corresponding to the proposed model and the previous model, respectively. The participants answered whether each robot in a group seemed a follower or a leader. The vertical axis means a degree of whether a robot was regarded as a leader or a follower, whereas the horizontal axis denotes four types of robots. The robots operated by the proposed and previous models, as well as by the humans, yielded different impressions and were confirmed to be statistically significant as both of the *p-value*s were less than 0.01. The values of *Cohen's d* have the large effect size. In addition, impressions on a robot operated by the humans resembled those of the robot operated by the proposed model.

Fig. 5.19 represents the results of the second question that implied answering the robot of which color was controlled by a computer system (based on the proposed model or previous model). The vertical axis corresponds to the correct answer rate, and the horizontal axis denotes the two groups including a robot controlled by the proposed model or the previous

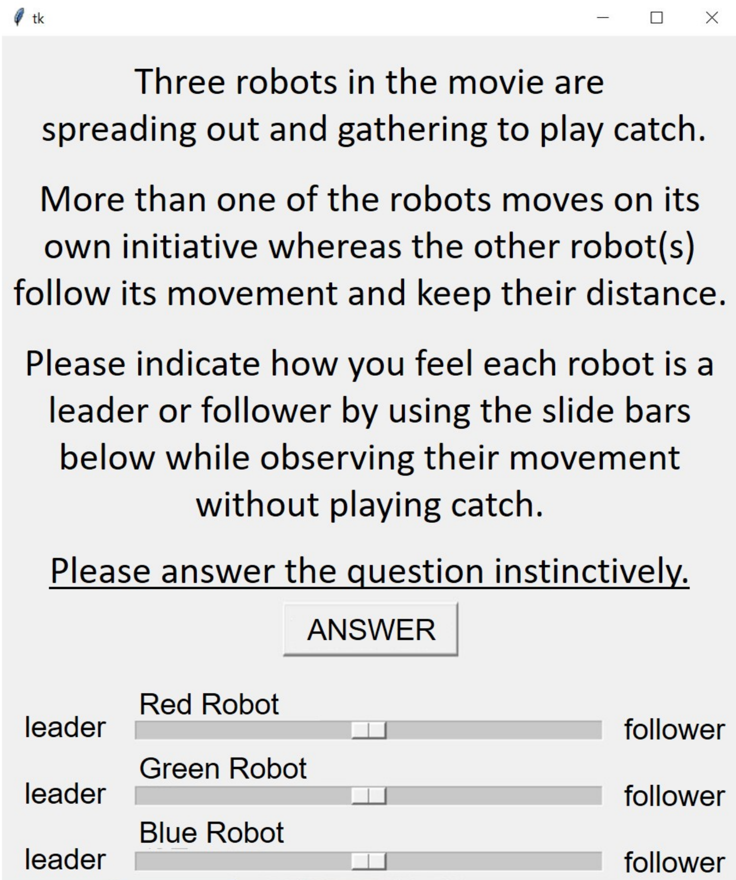

Figure 5.15: Display of the first question.

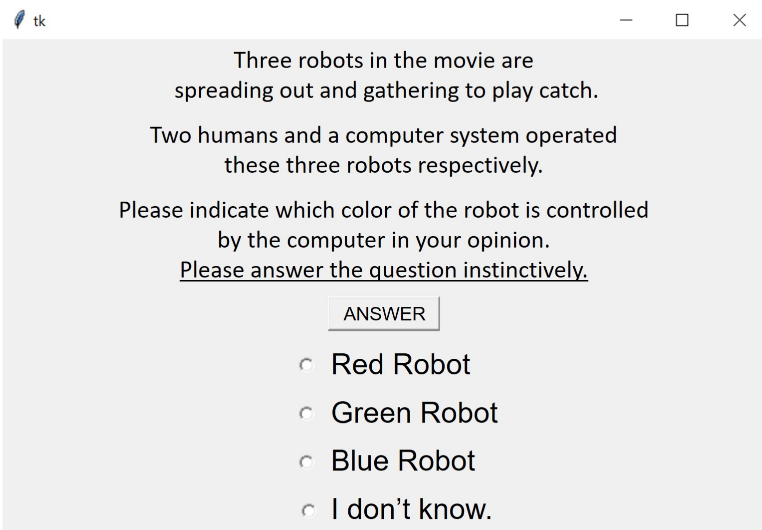

Figure 5.16: Display of the second question.

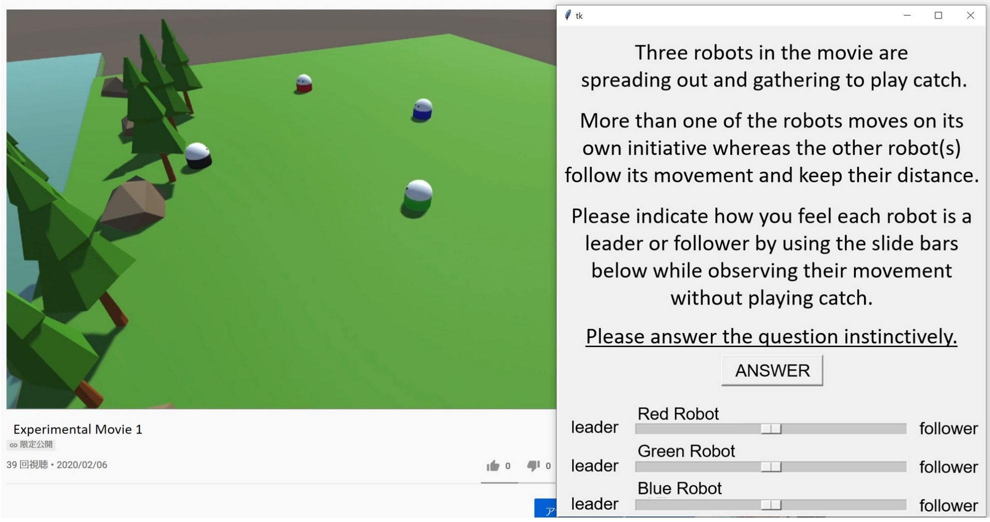

Figure 5.17: Environment for the questionnaire.

method. As a result, the participants had to distinguish between the two types of robots. In addition, the result was statistically significant as the p-value was less than 0.005.

Fig. 5.20 demonstrates whether a robot considered by the participants as a robot controlled by a computer system was a leader or follower according to the second question. The vertical axis represents the rate of answers, and the horizontal axis denotes a robot that a participant indicated in the questionnaire. Most of the participants selected a robot actually following the other group members as an answer, as the result was statistically significant and had the large effect size.

Table 5.2: Exprimental conditions.

Operator of robots	Two humans, the proposed model, and the previous model
Number of groups	Three groups including two humans and the proposed model and three groups including two humans and the previous model
Participants of the questionnaire	Ten (average age: 34.40, standard deviation: 8.66)
step	about 0.1 second
Neighborhood	$0.5m \times 0.5m$
kurtosis	10000
α	0.1
γ	0.9

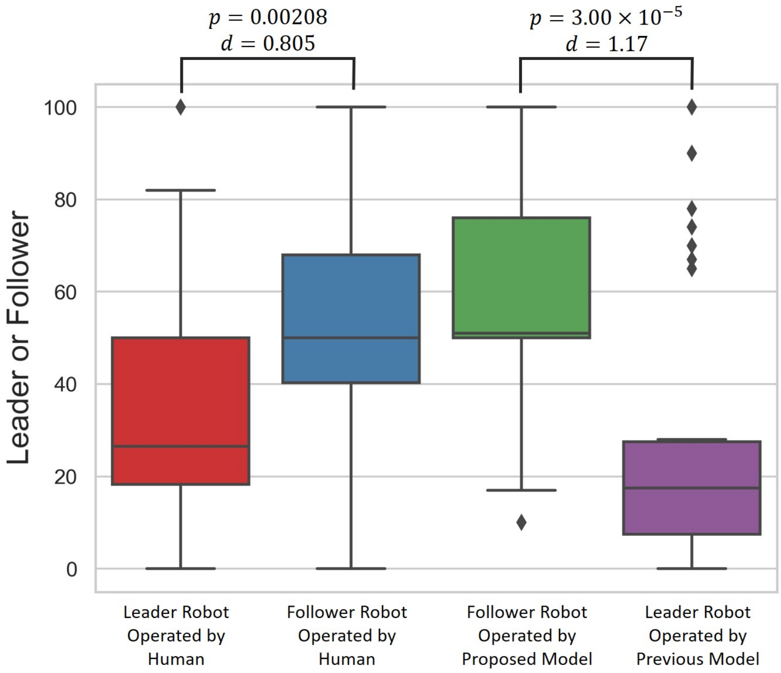

Figure 5.18: Results of the first question. 0 means that a robot seems to be a leader, whereas 100 denotes that a robot seems to be a follower.

5.4.7 Discussion

In the conducted experiment, we investigated the impression about the robot using the proposed model by asking two questions. We then evaluated the proposed model by comparing the robots controlled by a human or a previous method.

The results of the first question provided in Fig. 5.18 indicate that the robot using the proposed model was moving while following the other group members, unlike in the previous method. Considering that the results had the statistical significance and large effect size, they also indicated that the participants could distinguish between a follower and leader regardless of whether a human or computer system controlled a robot.

Fig. 5.20 outlines that the participants clearly answered the second question about recognizing a robot operated by a computer system as a follower. As it can be seen in Fig. 5.18, they were able to distinguish between followers and a leader before being informed the fact that the robot group included a robot operated by a system. Therefore, the participants thought the computer system was a follower in order to answer the second question.

Fig. 5.19 demonstrates that the participants distinguished between a robot operated by a

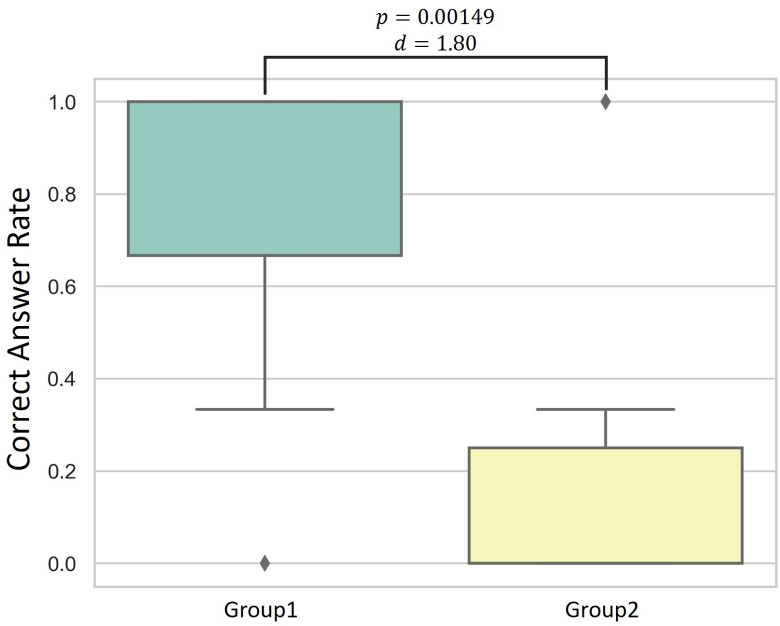

Figure 5.19: Results of the second question. The participants answered which color robot seemed to be controlled by a computer system.

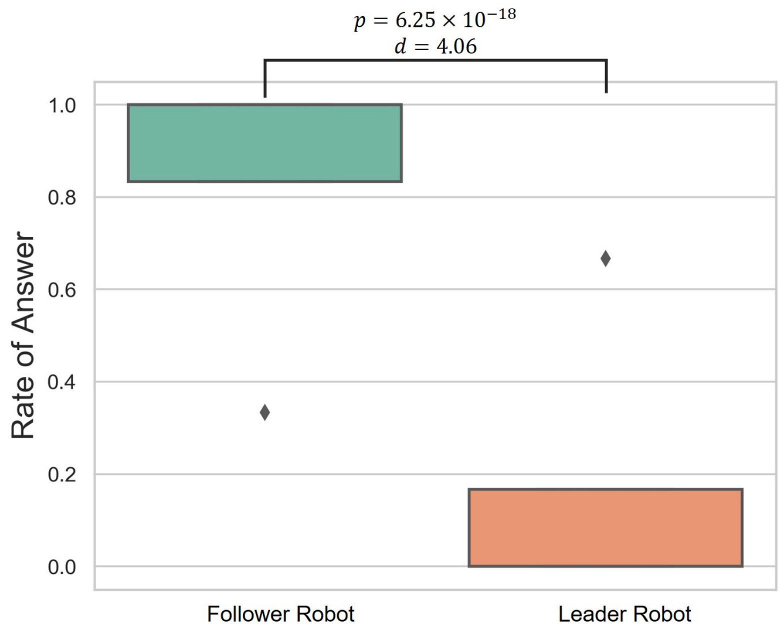

Figure 5.20: Tendency of participnats' answers. It is shown whether a robot considered by the participants as a robot controlled by a computer system was a leader or follower according to the second question.

computer system and the other robots in only group 1 although they did not distinguish in group 2. This is because the participants thought the computer system was a follower. The computer system in group 2 was based on the previous method, so that the robot controlled by the system in group 2 moved as a leader. Then, the participants provided answers considering the premise that a computer system was a follower. Therefore, the participants recognized the robot operated by the proposed model as a follower, so that the correct answer rate was higher in group 1 than in group 2.

In addition, when they answered the second question after watching the records corresponding to group 2, it is possible that they tended to confuse a human-controlled robots versus computer-controlled robots. The results provided in Fig. 5.19 indicate that the robot controlled by a computer system seemed to be controlled by a human, as the correct answer rate was low. This means that one of the robots controlled by two humans was recognized as the robot controlled by the computer system. Bearing the premise that the participants thought the computer system was a follower as shown in Fig. 5.20, some of the participants could regard the robot controlled by a human as the robot controlled by the proposed model, which was aimed to be a follower. Therefore, the participants could consider that the robot using the model moved in an appropriate way like robots controlled by humans.

5.5 Summary

In the present study, we proposed a model to enable a robot as a group member moving in a human group without encroaching on the changing personal spaces of humans. In general, the humans in a group maintain physical distances from one another in accordance with their closeness or particular context. Therefore, to identify an appropriate location, personal robots in human communities need to learn the physical distances that humans maintain in groups.

In the conducted experiment, we evaluated the proposed model by applying it to a robot moving in a group including robots operated by two humans with the purpose of avoiding interruptions of the human personal spaces. The robot attempted to move as a group member while the distance between the group members was constantly changing. We revealed that robots controlled by the proposed model tended to behave as followers and moved in the robot group while adapting to the changes in the distance kept by the group members. Moreover, we observed that the participants confused whether the trajectories were generated by the model or other human participants. Therefore, we concluded that the robot as a group member selected its pathway while keeping an appropriate distance with respect to the robots controlled by humans in an appropriate way for the human participants.

In the next chapter, we will improve the proposed model and conduct an experiment using a real robot and a human person to investigate whether the physical distance will be maintained in a human–robot group.

Chapter 6

Group Norm-Aware Robot Continuously Maintains Suitable Interpersonal Distance in Human–Robot Group

6.1 Introduction

In our previous works, we proposed a method that enables a robot to obey the unspoken and unwritten social rules in a human–robot group and also developed a robot navigation model considering changes in personal space, which was successfully implemented and evaluated in a virtual environment in Chapter 5. A robot equipped with the proposed model moves by constantly estimating its ideal position with respect to its distance to other group members. In other words, the proposed navigation model enables a mobile robot belonging to a human–robot group to maintain a socially acceptable distance from other group members while moving. However, we did not investigate the effectiveness of the model in a real human–robot environment. Therefore, the present study aims to tackle this aspect.

We designed an experimental scenario where human members of a human–robot group were asked to move and adjust their position according to what they believed to be suitable in a given situation. Here, the distances between group members are regarded as an unspoken and unwritten rule, and our intent was to evaluate the extent to which the robot could move and adapt its own position according to this rule in order to maintain a suitable distance from the other group members. We also asked for participants' opinions on the robot' behavior by collecting their impressions via questionnaires that were administrated at the end of each turn of interactions. In the rest of this paper, we provide greater detail on the proposed method and the experimental settings as well as our key findings.

6.2 Group Norm Model for Distancing

The proposed model aims to enable a robot to move in a humanlike manner by considering the changes in the interpersonal distances of other group members. This model estimates group norms for distance in a similar way to the methods presented in Chapter 5 as shown in Eqs. 5.1, 6.1, and 6.2.

$$V(d) \leftarrow (1-\alpha)V(d) + \alpha\left(R(d) + \gamma \max V(d)\right) \tag{5.1}$$

$$R(d) = \sum_{d' \in D} \exp\left(-\frac{(d'-d)^2}{kurtosis_V}\right) \tag{6.1}$$

$$Q(s,a) = \prod_{d' \in D} \exp\left(-\frac{\left(d' - \arg\max V(d)\right)^2}{kurtosis_Q}\right) \tag{6.2}$$

In addition, the robot using the proposed model faced the center of the group which is calculated using Eq. 6.3. Here, l_c is the center of the group, whereas l_i represents the location of group member i. N is the number of group members. Therefore, the robot moved while looking at the center.

$$l_c = \sum_{i=1}^{N} l_i / N \tag{6.3}$$

6.3 Experiment

6.3.1 Overview

In our experiment, we verified whether a robot embedding the proposed model could continuously situate itself appropriately in human groups while shrinking the interpersonal distances of the group members. To develop sociably acceptable robots, in our previous works in the previous chapters, we focused on proposing models that enable mobile robots to learn implicit group norms and make natural decisions while moving within such groups. In the current study, as a practical application and to serve as a proof of concept, we targeted a scenario where a group of few humans and a robot had to move together while keeping an implicit amount of interpersonal distance. We then investigated whether it was possible to give humans the impression that a robot embedded with the proposed model was moving in a socially acceptable way (i.e., able to learn and move according to the group's interpersonal distance norm). It followed that our research hypothesis could be stated as follows: "A robot embedded with the proposed model (i.e., moving following the group distance norm) can convey a higher degree of adaptability to the group than a comparison robot." An experiment evaluation was subsequently conducted to test this hypothesis.

Each human–robot group was composed of four members, a robot and three humans who stood in front, on the left, and on the right of the robot to form a circular space. The group members initially gathered around a certain location as specified in the experimental scenario, which was designed to require participants to move within the experimental environment. Then, as they moved around, the distance that group members should maintain from one another changed dynamically over time. In such a dynamically changing situation, we investigated whether the robot could adjust its own position to adapt to the group changes.

Throughout the experimental task, at the end of each interaction, the human participants were asked to evaluate, by questionnaire, the robot's ability to move adaptively as a group member.

During the experiment, each participant was equipped with an *HTC Vive Tracker*, so that the robot system was able to track their locations. In addition, we also recorded the locations of each group members every 0.5s using the *HTC Vive Trackers*.

6.3.1.1 Experimental Environment

Fig. 6.1 is a top-down view of the experimental environment, where a group of humans and the robot performed the experimental task in a rectangular experimental environment of size 6.4m $\times$ 3.7m. Table 6.1 provides an overview of the composition of each group with respective locations of participants and their behavior during the experimental task. Note that among the three humans, two were experimental collaborators (i.e., Hosts, as shown in Table 6.1); thus, their opinions were not collected during the system evaluation surveys. At the beginning of the experimental task, the humans and robot were positioned at the locations indicated by the circled 1, 2, 3, or E in Fig. 6.1. For instance, the hosts of the experiment were positioned at 3 and E, whereas the participants and the robot were positioned at either 1 or 2.

As the group engaged in the experimental task in this environment, the group members standing at positions 1, 2, and 3 gathered progressively around the human standing at position E. Throughout the process, we verified whether the robot could adapt to the other group members.

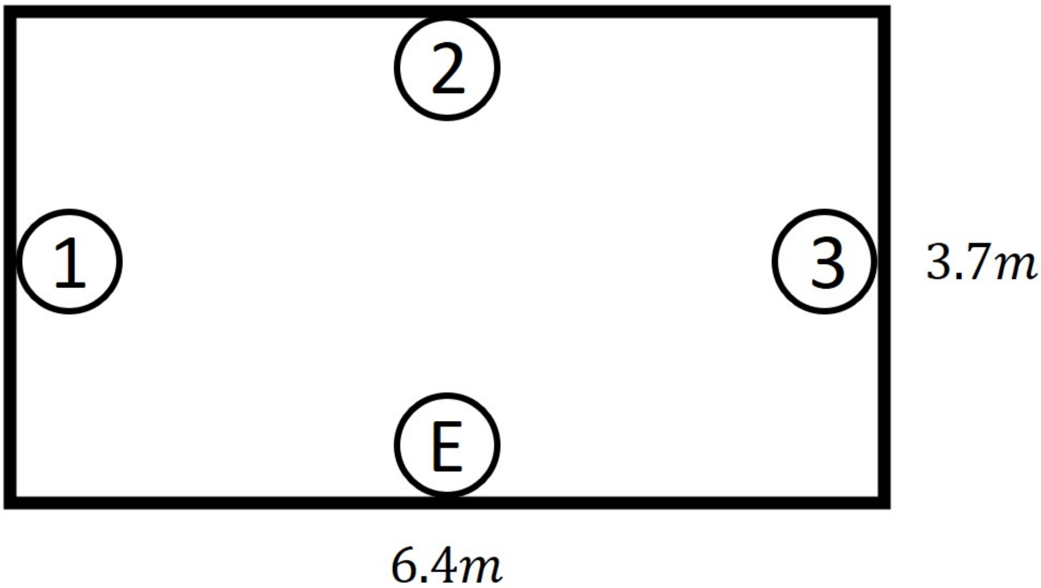

Figure 6.1: Top-down view of the experimental environment. The experimental group members, including a robot, moved in the environment while performing the experimental task. As shown in table 6.1, the robot was initially located at position 1 or 2 in our experiment where three humans and a robot participated.

Table 6.1: Experimental group members' location and mobility.

location	member	mobility
1	participant or robot	Yes
2	participant or robot	Yes
3	Host (leader)	Yes
E	Host (organizer)	No

6.3.1.2 Robot Design

Fig. 6.2 shows a photo of the robot used in our experiment. The robot was a cart-type robot with a cylindrical body. Its height was approximately 1.3 m and its width at the base was approximately 0.4 m. We believe that these dimensions were ideal to enable the robot to be large enough to interact with humans while standing up, as is the case in the current experiment. This was also expected to increase participants' impression of the robot's membership. The robot could move in all directions, owing to its omni-wheel. The eyes and mouth of the robot, which were painted on its body and did not move, allowed the humans in the group to be aware of the direction the robot was facing. In our experiments, the appearance of both a robot using the proposed model and a comparison robot was the design shown in Fig. 6.2.

6.3.1.3 Participants

The participants were 12 undergraduate or graduate students (male : female = 9 : 3), all majoring in engineering, with an average age of 21.25 years. All of them participated in the experiment without any prior knowledge of this study.

6.3.2 Experiment Flow

Fig. 6.3 shows the experiment flow. To begin, participants were given a brief overview of the robot' mobility aptitude. To make the participants aware of the mobility, we prepared a short demonstration scenario, where participants were able to observe the robot following the experiment organizer as he walked around the experimental environment. This was necessary not only to familiarize the participants with the robot, but also to attenuate the possible effects of the novelty factor on the participants' impressions. After this, the participants were provided an explanation regarding the experimental task before carrying out the experiment itself.

Before performing the experimental task, the four group members, including the robot, moved to positions 1, 2, 3, and E shown in Fig. 6.1, which were the group members' initial positions for the experimental task. The humans and robot at positions 1, 2, and 3 started moving based on the experimental scenario, whereas the experiment organizer standing at E did not move. Based on the organizer's instructions, the participants and robot moved and gathered around the organizer standing at E. After that, the participants responded to

Figure 6.2: Robot used in our experiment.

questionnaires about their impression of the robot that moved with them as a member of the group during the experiment.

The above process, from standing at the initial position to answering the questionnaires was equivalent to one trial of the experimental task. Four trials were conducted per participant. The robot embedding the proposed model was used in two of the four trials, whereas the robot embedding the comparison model participated in the other two trials.

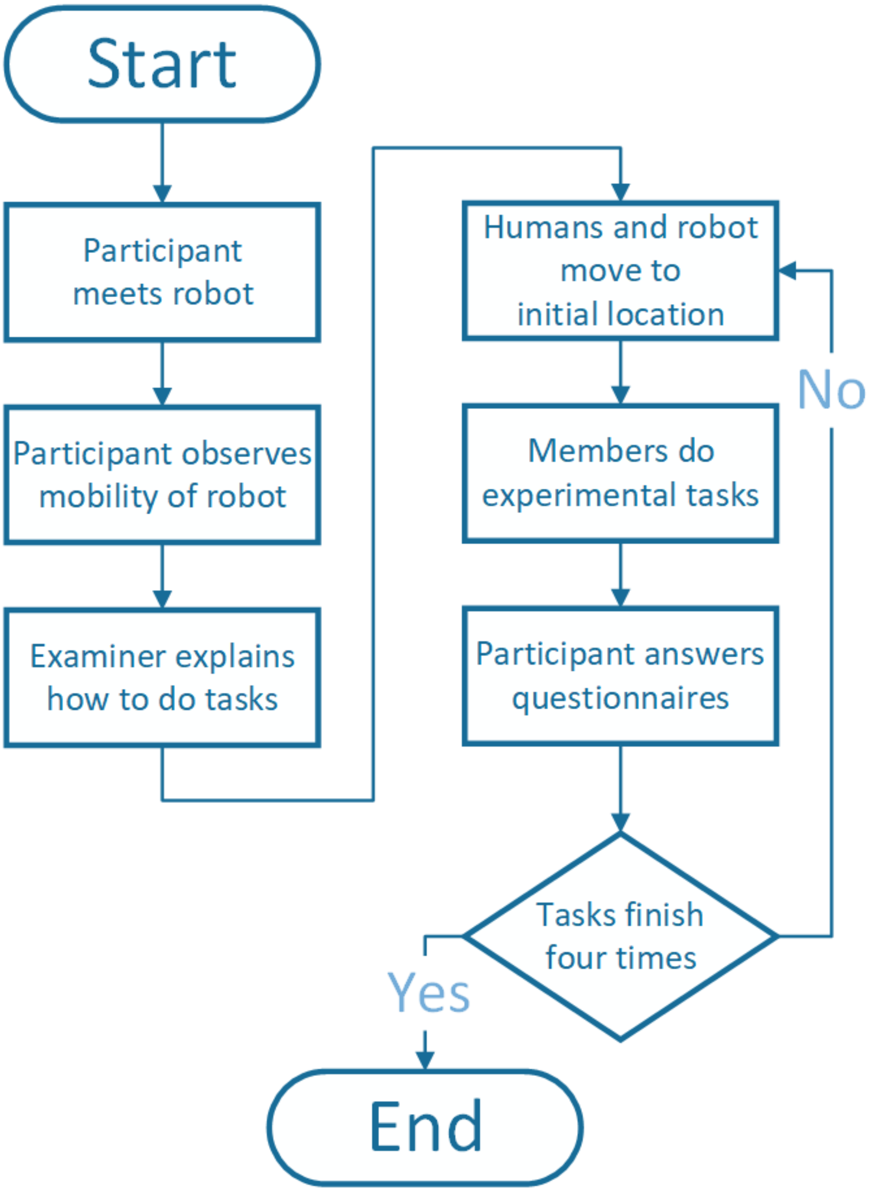

Figure 6.3: Flowchart of the experiment.

6.3.2.1 Experimental Task

As described above (Table 6.1), each group during the experimental task consisted of four members: the experimental participant, the robot, and two other people who we will call the organizer and the leader. In each trial, the participant and the robot stood at the initial position 1 or 2, as shown in Fig. 6.1 and Table 6.1. The organizer stood at position E, and the leader stood at position 3 (see Fig. 6.1 and Table 6.1).

In the experimental task, the organizer gave instructions to the group members standing at positions 1, 2, and 3 in Fig. 6.1, which they followed and moved accordingly. The instruction was to "gather around the organizer according to the movement of the leader." Note that the role of leader was played by the experimental collaborator standing at position 3. The leader was responsible for actively moving toward the experimental organizer regardless of the others. Once the instruction was given, the other group members also started gathering around the organizer according to the movement of the leader.

In addition, let us also mention that in the experimental task, the collaborator did not linearly approach the experiment organizer, but paused for a while once. In other words, the leader started moving, paused for a while, started moving again, and stopped near the leader. After the participants moved from their initial positions to locations near the organizer, they were asked to answer a questionnaire about their impressions regarding the robot movement.

6.3.2.2 Comparison Robot

We prepared a comparison robot for comparison with the robot using our proposed model. This comparison robot had the same design as the robot in Fig. 6.2, but only moved along a pre-specified path. Thus, the comparison robot differed from the robot with the proposed model only in the way that it moved when interacting with humans.

To design a natural motion path for the comparison robot, we performed the experimental task in advance with a group of only humans and recorded their motions as they moved from their initial position to the goal position. Specifically, we recorded the standing positions of each group member at the beginning and end of the experimental task. Hence, two paths, each corresponding to members standing initially at positions 1 and 2 in Fig. 6.1, were obtained. Therefore, during the experimental task with a group of humans and the comparison robot, the robot followed one of these pre-obtained motion paths depending on its initial position (i.e., 1 or 2). In addition, the robot's direction corresponded to the movement direction.

That being said, the comparison robot did not consider the actual positions of the other group members. Nonetheless, we designed the comparison robot in such a way because previous models were not suitable for our experimental scenario. Most previous studies aimed to avoid obstacles or to approach humans, enabling a robot to move only from a point A to B (Fig. 5.1 (left)). Our experimental scenario did not provide an a priori goal point (a "point B"), because the final location of the robot was determined by its position in relation to locations of the other human group members. The previous methods assume the existence of a final position already known, which is not the case in our study. Therefore, we could not employ previous methods for comparison to our proposed model.

As could not find prior methods for comparison, we needed to determine the movement trajectories of our comparison robots in advance. In this experimental scenario, the comparison robot only moved from point A to a point B and did not consider the positions of the other group members. However, if were to set point A and B following the approach taken in previous methods, the issue would be determining the "point B" location in the experimental environment (i.e., the target point of the comparison robot). To overcome this issue and prepare a comparison robot suitable for the context of our study, it was necessary to provide a reasonable pseudo point B. Therefore, we proposed to conduct the experimental scenario in a human-only group setting and move the comparison robot based on the records of average human trajectories. In this way, we could record a reasonable point B position. We thought that this would be the best way to achieve believable trajectories for the comparison robot while avoiding arbitrary decisions.

For these reasons, we prepared the comparison robot following the methodology described above, and we investigated whether a robot with the proposed model could convey better impressions to the group members than the comparison robot. We examined whether the proposed model had differences in the questionnaires results compared to the comparison robot. If it was found that there was a difference, it could be statistically claimed that the mobile robot using the proposed model possessed adaptability.

6.3.2.3 Group Design

To avoid possible order effects, as shown in Table 6.2, we used the counterbalance method to set up four groups (A, B, C, and D), each with different orders for participants' interaction with both robots. The twelve participants were subsequently split into these four groups, and took part into the experiment according to the sequence specified for their group.

Table 6.2: Four kinds of groups to avoid the order effect.

group	first trial		second trial		third trial		fourth trial	
	initial location	model	initial location	model	initial location	model	initial location	model
A	1	proposed	1	comparison	2	proposed	2	comparison
B	1	comparison	1	proposed	2	comparison	2	proposed
C	2	proposed	2	comparison	1	proposed	1	comparison
D	2	comparison	2	proposed	1	comparison	1	proposed

6.3.3 Questionnaires

At the end of each trial, participants were asked to evaluate their impression of the robot that participated in that trial. They were presented with a 6-point Likert scale questionnaire offering the answer options {0: Disagree a lot, 1: Disagree, 2: Disagree a little, 3: Agree a little, 4: Agree, 5: Agree a lot} to the question "Do you have the impression that the robot is *X*?" The label *X* is replaced by an adjective listed in Table 6.3. The questionnaire items in Table 6.2 were used to investigate the participants' feelings about the robot's adaptability (questions 1-6) and collect their impressions of the robot's behavior in the group while carrying out the experimental task (questions 7-11). Note that because all participants interacted with and provided their impressions of both robots, as shown in Table 6.1, the results of this questionnaire allowed us examine the differences between the proposed robot and the one used for comparison.

Table 6.3: Eleven items in the questionnaire.

num	adjective
1	adaptable
2	selfless
3	subordinate
4	rigid
5	improper
6	selfish
7	mechanical
8	intelligent
9	conscious
10	responsive
11	friendly

6.3.4 Results

Through the experiments, we were able to confirm that the robots behaved as expected. The experiment conditions are highlighted in Table 6.4. Fig. 6.4 shows three photographs from the actual experiment, depicting the environment as well as the procedure used for the experiments.

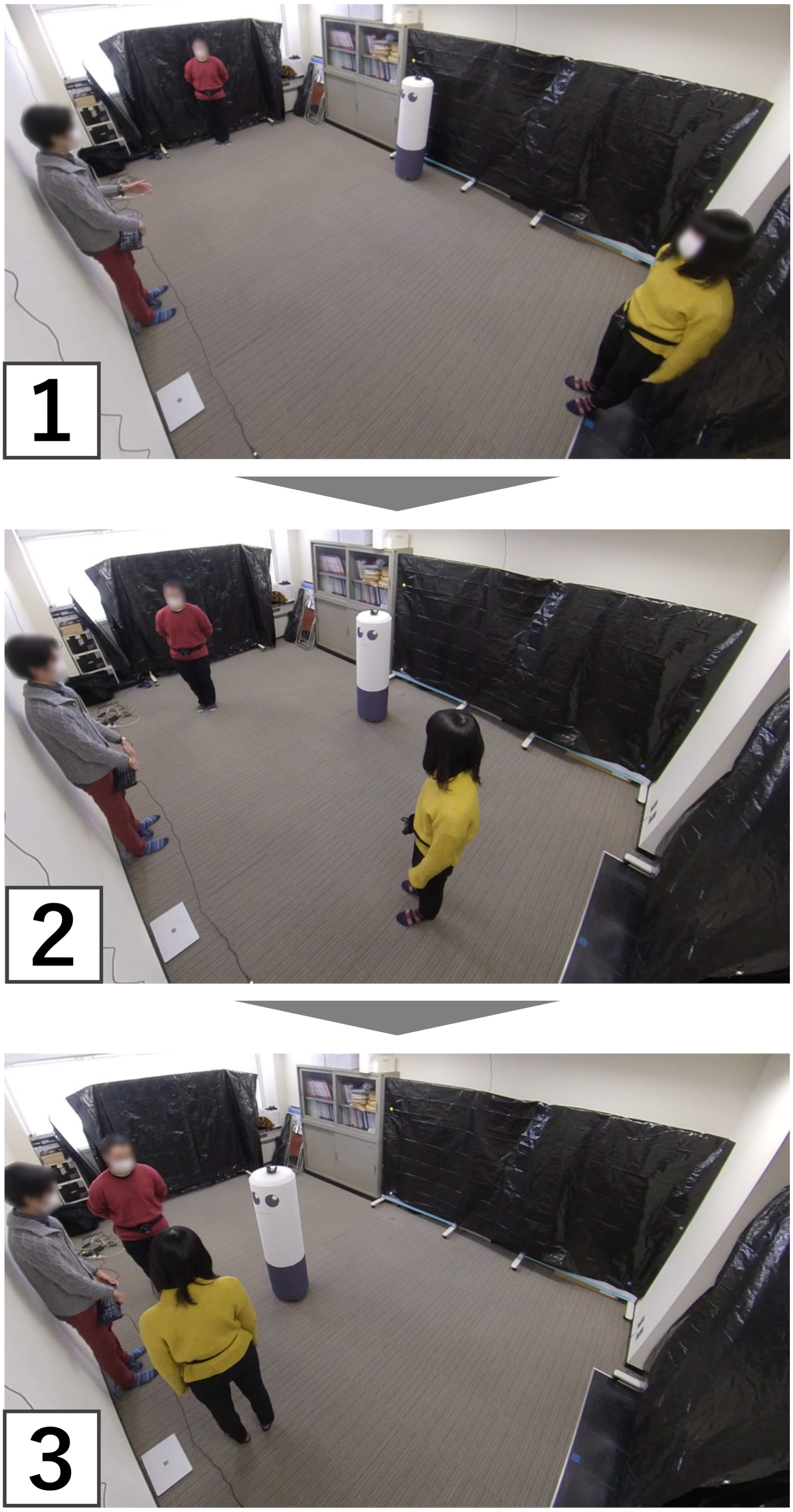

Figure 6.4: Actual experimental environment. The three pictures show that the group members including the robot gathered around the experimental organizer not moving.

Table 6.4: Experimental conditions.

Participants	
number	12
average age	21.25
standard deviation	1.23
male-to-female ratio	9:3
proposed model	
step	0.5 s
M: number of group members	4
N: number of states	100
neighborhood	within a 0.5 m radius
$kurtosis_V$	1
α: Learning Rate	0.6
γ: Discount Factor	0.4
$kurtosis_Q$	10000

The photograph at the top shows the participants standing at their initial locations. The middle picture shows the participants gathering around the experimental organizer. In this scene, the participants stopped moving to maintain a suitable distance from the leader, who stopped moving as well. In this situation, the robot embedding the proposed model was prompted to adapt to the change in the interpersonal distance by finding its own appropriate location. In the bottom picture, the participants stopped near each other, as they felt that they could not move closer to one another. Once this situation occurred, the experimental task was ended.

Table 6.5 shows the detailed results of the questionnaire. Based on Table 6.5, we provide two boxplot figures (i.e., Figs. 6.5 and 6.6) showing the questionnaire results regarding the adaptability of the robot and the overall impression of the robot in each of the experimental tasks, respectively. The two legends, "proposed model" and "model for comparison," refer to the robot embedding the proposed model and the comparison robot, respectively. The score from 0 to 5 corresponds to the questionnaire answers.

Table 6.5: *Mean* and *S.D.* of the results of the questionnaires "Do you have the impression that the robot is *X*?"

	label *X*		*Mean*		*SD*	
num	adjective	investigation objects	proposed model	comparison	proposed model	comparison
1	adaptable	adaptability	3.458	1.625	1.079	0.949
2	selfless	adaptability	3.375	1.292	1.285	1.172
3	subordinate	adaptability	3.750	1.417	1.090	1.256
4	rigid	adaptability	2.208	3.458	0.999	1.190
5	improper	adaptability	1.792	3.292	1.258	1.136
6	selfish	adaptability	1.417	3.708	1.187	1.338
7	mechanical	overall impression	3.250	3.833	0.878	0.986
8	intelligent	overall impression	3.167	1.833	1.106	0.898
9	conscious	overall impression	2.500	1.458	1.041	0.957
10	responsive	overall impression	3.833	1.708	1.312	1.306
11	friendly	overall impression	3.000	1.667	1.041	1.067

Table 6.6 shows the results of a statistical test and the effect size driven from Cohen's d[45]. The statistical hypothesis testing method used was the Brunner-Munzel test [35], which is recommended for small sample sizes. Note that because each of the twelve participants answered the questionnaire four times, the sample size for the current experiment is 24. We found that there was a significant difference between the robot embedding our proposed model and that for comparison.

Table 6.6: Results of the Brunner–Munzel test (two-sided p-value), the Brunner-Munzel test statistic (W_N^{BF}), and Cohen's d in the results of the questionnaire about impressions of the robots. The question was "Do you have the impression that the robot is X?" The label X is replaced by one of the listed adjectives.

num	adjective	two-sided p-value	W_N^{BF}	Cohen's d
1	adaptable	4.78×10^{-9}	-7.84	1.80
2	selfless	2.56×10^{-8}	-6.71	1.69
3	subordinate	3.35×10^{-11}	-8.92	1.98
4	rigid	5.25×10^{-5}	4.48	1.14
5	improper	4.22×10^{-5}	4.54	1.25
6	selfish	2.61×10^{-8}	6.75	1.81
7	mechanical	2.64×10^{-2}	2.30	0.62
8	intelligent	5.78×10^{-6}	-5.31	1.32
9	conscious	4.37×10^{-4}	-3.79	1.04
10	responsive	6.99×10^{-8}	-6.62	1.62
11	friendly	2.51×10^{-5}	-4.69	1.26

Fig. 6.7 shows four typical motion paths of the experimental group members. The x-y plane indicates the experimental environment, whereas a vertical axis indicates the time step. The 3D graphs indicate the position of each group member at each time step of 0.5 s. In each motion path, we can see that other group members moved toward the experimental organizer, who was stationary. The top two graphs show the group in which the robot embedding the proposed model participated, whereas the bottom two graphs show the group in which the comparison robot was used. The top two graphs show that the robot using the proposed model stopped in the way of moving in order to adapt to the leader. On the other hand, the bottom ones show that the robot for comparison just kept moving toward the organizer

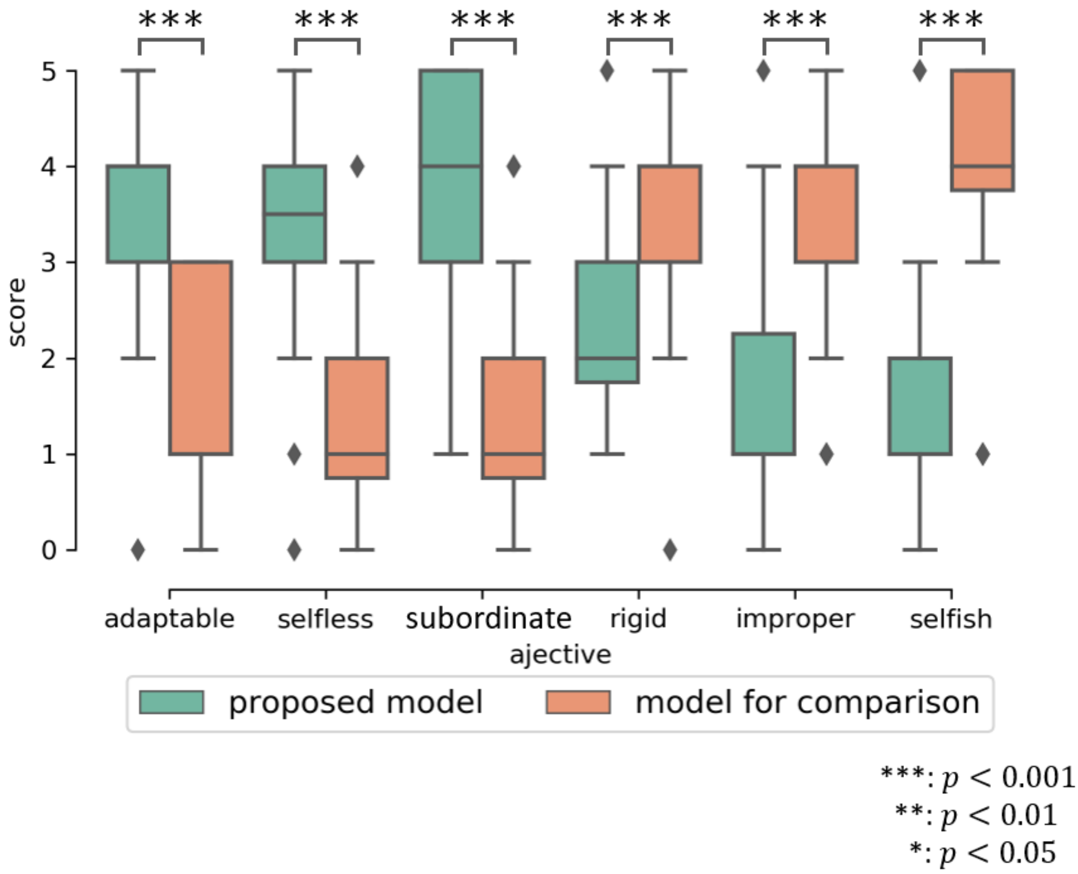

Figure 6.5: Results of questionnaire regarding the adaptability of the two robots in each of the experimental tasks. The diamond points in this figure are outliers.

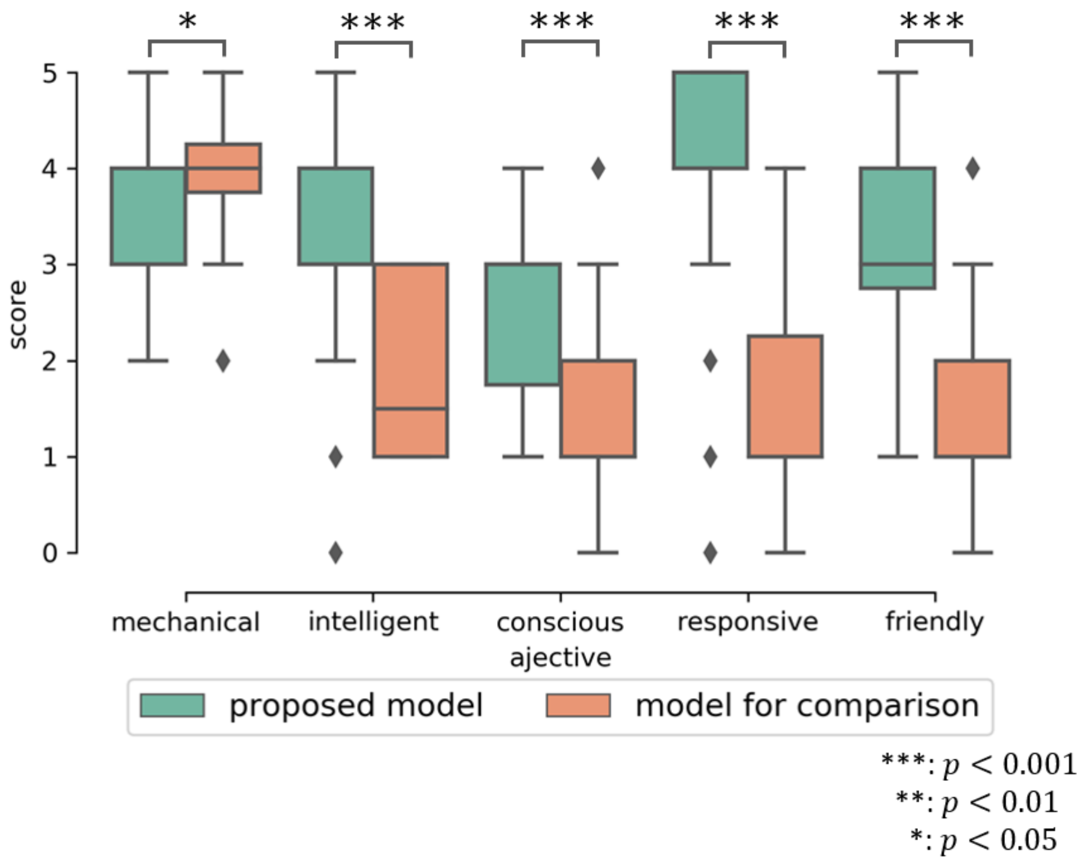

Figure 6.6: Results of questionnaire regarding the overall impression of the two robots in each of the experimental tasks. The diamond points in this figure are outliers.

without stopping.

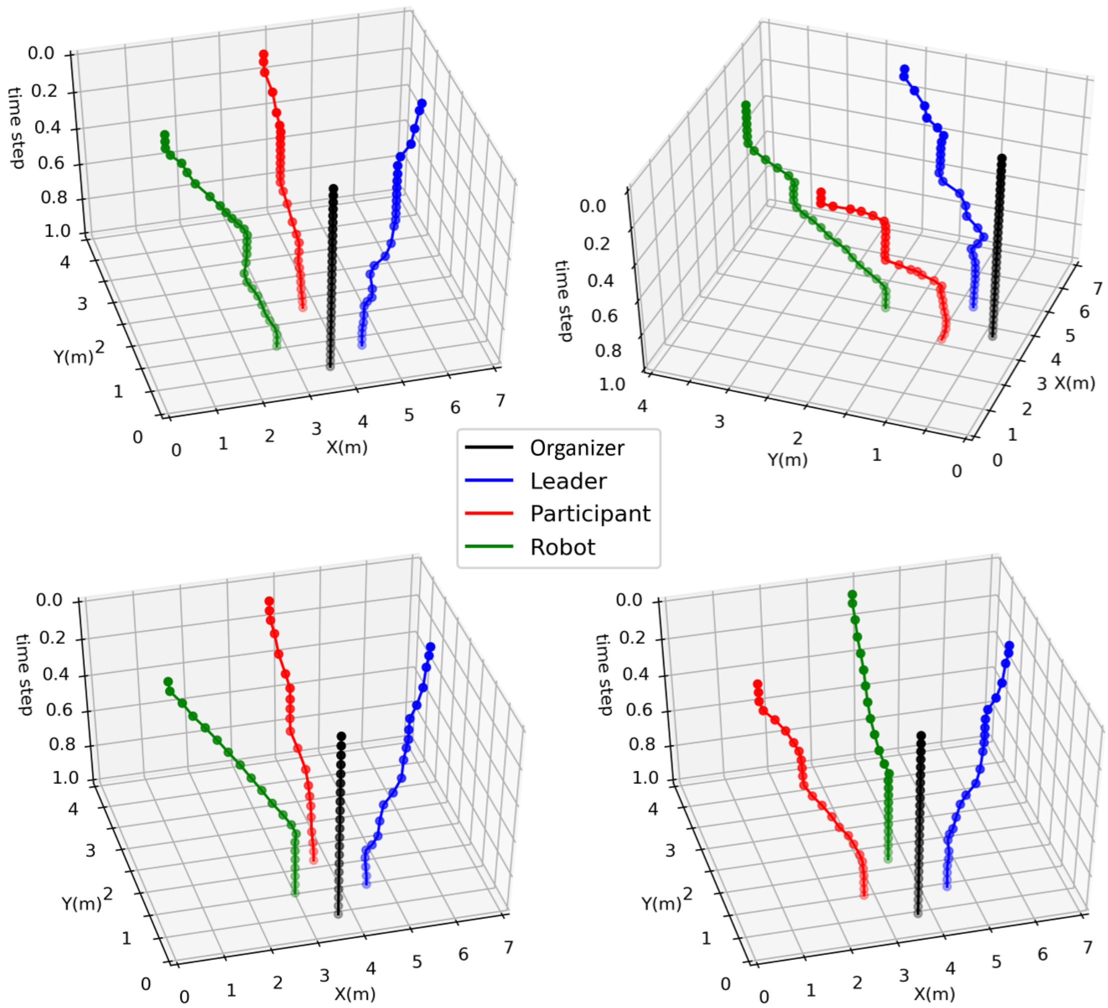

Figure 6.7: Four typical movement paths of experimental group members. The robot in the top two graphs used the proposed model, whereas that in the bottom two graphs was used for comparison. “Leader” in the legend was played by experimental collaborators.

6.3.5 Discussion

As shown in Fig. 6.5, the robot embedding the proposed model statistically outperformed the comparison robot in terms of overall adaptability. The high scores of items 1, 2, and 3 in Table 6.3, coupled with the low scores of items 4, 5, and 6 seem to suggest that the proposed robot was well-adapted to the human–robot group. In addition, as shown in Fig. 6.6, there were significantly higher scores for intelligence, responsiveness, and intimacy for the robot embedding the proposed model. However, as shown in Table 6.6, because Cohen’s d of *"mechanical"* tended to be lower than other evaluation adjectives for the robot equipped with the proposed model, it is possible that the robot was not able to display a natural motion that would be identical to a living person. Therefore, from the results of the questionnaire, it appears that the robot with the proposed model moved more adaptively than the comparison robot, and that the robot was able to impress the participants by conveying a certain level of intelligence, responsiveness, and intimacy.

Table 6.6 shows the effect sizes of the differences between participants' impressions of the two robots. Differences concerning four adjectives—4: rigid, 7: mechanical, 9: conscious—had small effect sizes. This suggests that the difference in terms of participants' impression on these "adjectives" was smaller those that of the rest, so some of the participants tended to feel that the robot embedding the proposed model was rigid. This might be due to the robot's inability to respond immediately to the leader as he started moving. Although the human participants immediately adapted to the movements of the leader, there was a small lag before the robot could respond adaptively. This delay was due to the small amount of time necessary for the robot to calculate and decide where it should stand, given other members' positions. In addition, a part of participants also tended to feel that the robot using the proposed model was mechanical and not conscious. This might have resulted from the simplicity of the robot design and the straightforward nature of the experimental task. It seems that the experimental scenario made it difficult for the participants to evaluate the robot in terms of the two adjectives; mechanical and conscious.

The top two graphs show that the robots using the proposed model also stopped at suitable locations when the leaders (collaborators) stopped. The robot searched for an appropriate location as a group member, and it adapted to the changes in physical distances or interpersonal distances caused by the leader. Although the leader stopped during the process of gathering around the static organizer, it can be seen that the comparison robot approached the organizer regardless of the surrounding situation or the movement of the other members. Therefore, based on the recorded movement paths coupled with the results of the questionnaires, we can conclude that the robot embedding the proposed model was able to adapt to the anomalous movement of the group and thus constantly maintained a suitable distance from the other group members despite moving by only referring to distances between group members.

Although some attributes (such as the ratio of male to female and the majors of the participants) were unbalanced, we do not think that these factors posed an inherent problem for the claims of this paper. We agree that these attributes were unbalanced and acknowledge that familiarity with robots may influence how people feel about, or behave toward robots. Such factors may come into play in experimental conditions where robots are evaluated independently or compared with other artifices such as computer agents. However, we do not think that these factors pose an inherent problem for the claims made in this paper. We would like to point out the employed experimental method (i.e., a comparison of two robots) in this study, which allowed us to limit or rule out the hypothesis that obtained results (i.e., preference of the robot embedded with the proposed model) were only driven by the familiarity factor. Therefore, although we agree that in general, some attributes may affect experimental results, we believe that the nature of our experimental design relatively tempers the impact of these factors in the context of our study, as we explain below.

- First of all, the design of the two robots was extremely simple and the only difference between them was the way they moved. They did not express emotions or other non-verbal information. In other words, during the experiment, there was no direct verbal or non-verbal communication between the robot and the participants. Therefore, it is quite unlikely that the design of the robots influenced participant impressions. Even if shortcomings arose from the attributes of the subjects (e.g., participant gender, background, familiarity with robots, etc.), we can assume that any evaluation bias such shortcomings might create would be directed to areas other than robots movement.

- Secondly, the value of the effect sizes (i.e., Cohen's d) for the comparisons between the two robots is sufficiently large, as shown is Table 6.6. Hence, we believe that obtained results cannot reasonably be explained only by eventual bias among participants. Even if there were participants who had a bias caused by their affinity for robots (and some of them showed responses to the questionnaire that were not favorable to us), we do not think that the overall tendency of the participant responses would change. Therefore, our claim that there was a significant difference between both robots was not significantly affected.

It follows that (from the standpoints of robot design, interaction design, or statistical analysis) we do not believe that the factors are severe. It seems that familiarity with robots may influence how people feel about, or behave towards robots. Such factors may come into play under experimental conditions where communication-related aspects of human–robot interactions are targeted or when robots are compared with other artifices (such as computer agents), which is not our case. Moreover, we believe that the small sample size is not a problem, as the Brunner-Munzel test available for small sample sizes confirms that there is a significant difference. Therefore, we have obtained valuable knowledge in this experiment for the practical application of our proposed model.

6.4 Summary

When interacting with others in a community or a group, human beings tend to be aware of the distance between themselves and others. The amount of distance required varies among situations and depends on several factors, including the social contexts in which people interact. In order to maintain an adequate distance between one another, group members tend to implicitly occupy their own spaces while sharing implicit rules about interpersonal distances. In addition, humans behaving socially might need to tolerate and cope with unacceptable distances for themselves, although they feel discomfort. In spaces shared by humans and robots, it is paramount for robots to move and behave in a socially acceptable manner. For instance, it is necessary for the robots to recognize the distance that humans think they should keep from one another.

Building on our proposed method that enables a robot to obey unspoken and unwritten social rules in a human–robot group, in this study, we developed a navigation model to enable a robot to determine its own position as a member of human groups, wherein the members' interpersonal spaces change. We implemented the proposed navigation model in a real robot and, by means of questionnaire, evaluated its performance. The results showed that the human participants felt that the robot using the proposed model behaved more adaptively to interpersonal distance changes than the comparison robot although the former moved only by estimating an appropriate distance from only distances between group members. The results and records obtained from the experiments suggest that the robot utilizing the proposed model moved appropriately within the environment to find its own position by obeying group norms regarding physical distances of group members.

In future works, we will continue to improve the proposed model and investigate whether it can be adapted to human–robot environments by executing experiments in various situations. We will also develop the model further to allow a robot to adjust to space in which both group members and non-group members exist.

Chapter 7

Conclusions

This chapter summarizes the findings of the study and discusses the remaining issues for the future.

We presented experiments in which robots followed group norms in human–robot groups. The first scenario comprised people and a robot taking a quiz in a group with no apparent correct answer. The second scenario concerned the distance conventions when a person and an autonomous mobile robot interact through an experimental setting. Furthermore, we investigated how the creation of human–robot group norms, in which a robot capable of making judgments based on group norms makes decisions alongside a human, influences human decision-making and thinking in the first experimental scenario. The following important research findings were provided in this study.

First, we suggested a decision-making model for a robot that learns implicitly produced group norms in a human group, and we tested the model's performance. In this experiment, we built a group with two humans and one person who behaved according to the decision-making model. Next, we evaluated if the group norm, or an implicit understanding to be followed, could be developed in the experimental setting. The findings revealed that group norms were developed statistically in the group, implying that the suggested model can learn implicit group norms and make judgments.

Next, we suggested an enhanced decision-making model for robots that learns group norms in human groups. We investigated whether group norms form in a group of one robot and two people using the model. The findings revealed that a mixed group of people and robots produced a group norm, which the enhanced decision-making model could learn. In this experiment, it was discovered that humans behaved in a way that considered robot judgments.

Furthermore, we explored the social effect of group norms on human decision-making in a group of two robots and a human learning group. Based on the results of the human behavior in the experiment and the subject questionnaire, it was discovered that there was a shift in how the human subjects acted and thought in the experimental setting soon after the experiment began and after the appearance of group norms. As a result, we infer that the robot's attempt to follow group standards has a social influence on human decision-making.

We also evaluated the performance of an autonomous mobile robot that considers the distance that should be maintained in a continuously changing group of people and robots coexisting in a virtual space. We conducted a questionnaire survey after the group members moved according to the experimental scenario in a group of three people and one autonomous mobility robot outfitted with the suggested model. Based on the questionnaire responses and the robot's movement route, it was evident that the robot could interact per the group standard to maintain the distance.

Finally, we hope to create an autonomous mobile robot that can account for dynamically shifting distances in a community of humans and robots. When sharing space with others, individuals attempt to maintain a feeling of distance that varies according to the context. However, in a world where people and robots coexist, human-group robots need to adjust to a perception of space that fluctuates depending on various conditions. As a result, we created an autonomous mobile robot for adaptability and performed verification trials. The trials demonstrated that the robot could move and adapt to changing distance perception.

In the future, we will investigate human–robot group norms while taking into account their social interactions. When a group is created, the people who make up the group frequently have social interactions. For example, some members may be friends while others may be strangers if you belong to a group. Social interactions may impact how group norms are developed and whose viewpoints are valued in decision-making in such a circumstance. In prior experiments, we used robots that made judgments based on group norms without considering social interactions. As a result, to contribute to the emergence of a human–robot symbiotic society, we need to research robots that make judgments based on group standards while taking social interactions into account.

In addition, we will develop a decision-making model to enable robots to behave according to belief-level group norms. As explained in Chapter 2, there can be different dimensions of norms within a group, ranging from action-level to belief-level norms. In this study, robots using the proposed model tried to behave socially based on an action-level group norm by observing group members' actions. The robots just pretended to understand the meaning of the group norm, although humans saw the robot obeying the group norm on the spot. To make sociable decisions in human–robot groups, robots need to behave based on both action-level and belief-level group norms. This can make robots look more sociable and acceptable in human–robot symbiotic society. To develop robots based on belief-level group norms, the robots need to infer the group members' beliefs from their actions. In the future, we will develop a model to enable robots to make decisions while considering group norms and inferring the internal states of other group members. Then, we will assess the developed model through human–robot experimental scenarios.

Furthermore, we will develop a decision-making model that also accounts for the robots' personalities in addition to group norms. Herein, we developed robots that just obey group norms in human–robot groups. In other words, the robots do not have their own opinions based on thier personalities in experimental scenarios. In human society, it is important to follow group norms. This behavior of each member of a human group is the basis for maintaining groups. On the other hand, few people do not follow group norms. Each group member can adhere to some but not all group norms. However, breaking the group norms may be regarded as a part of one's personality. Moreover, in informal settings, it is not always necessary to follow the group norms. Therefore, we will examine whether a robot that follows group norms will appear rude to humans if it deliberately does not follow certain group norms, or whether such norm violation will be perceived as part of the robot's personality. This may contribute to the design of more complex personalities for robots and computer-based agents and the improvement of their presence in a society where people and robots coexist.

The results of this doctoral thesis have the potential to contribute to the development of a broader expression of social robots' behavior. Most of the current research on social robots has focused on the existence of a human as a communicating partner in interaction scenarios and how to make robots interact naturally with humans. However, in human society, even in the absence of direct communication, if there are other people in the same space, humans can still perceive the existence of the other people, and the same goes for the other people. Then, an implicit group norm, i.e., a way of behaving that is expected by each other, can be generated. In a society where humans and robots coexist, robots should behave appropriately according to the social norms of groups they belong to. Thus, our research on implicit norms in groups may contribute to the realization of more human-like and social robots as well as computer-based agents.

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