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Research Article

Analysis of a Visual Imitation Algorithm on a Robot Swarm

Ferhat DEMİRAY [a], Mehmet Dinçer ERBAŞ [a,*]

[a] *Department of Computer Engineering, Faculty of Engineering, Bolu Abant İzzet Baysal University, Bolu, TURKEY*
** Corresponding author's e-mail address: dincer.erbas@ibu.edu.tr*
First author's e-mail address: ferhatdemiray@ibu.edu.tr
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ABSTRACT

In this research, we examined a visual imitation algorithm on a group of real robots and analyzed the source of copying errors that are made by the robots visually learning by using this algorithm. As the two possible sources of the copying errors, the actuators of the demonstrator robot and the sensors of the learner robot were specified. First, it is calculated the amount and frequency of errors due to the actuators and we showed that errors due to actuators of the demonstrator robot were minimal. Second, it is examined the errors due to the sensors by using two different trajectory similarity metric in an experiment scenario and we discussed the origin of this kind of imitation error. In this way, we were able to model a source of behavioral diversity in a robot collective, which is similar to the natural systems, which results from errors that emerge during imitation activity.

Keywords: *Visual imitation, Multi-robot systems, Swarm robotics*

Bir Robot Sürüsünde Görsel Kopyalama Algoritmasının Analizi

Öz

Bu çalışmada gerçek robotlar üzerinde bir görsel kopyalama algoritması incelenmiş ve bu algoritmayı kullanarak birbirlerinden görsel yolla öğrenen robotların yaptıkları imitasyon hatalarının kökeni araştırılmıştır. İmitasyon hatalarının olası kaynakları olarak, gösterici robotun eyleyicileri ile izleyici robotun algılayıcıları belirlenmiştir. Öncelikle eyleyici kaynaklı hataların miktarı ve sıklığı ölçülmüş ve bu hata türünün minimal ölçüde gözlemlendiği belirtilmiştir. Daha sonra algılayıcı kaynaklı hatalar bir deney senaryosu içerisinde iki farklı güzergâh karşılaştırma metriği kullanılarak incelenmiş ve bu tür hataların kökeni tartışılmıştır. Böylece, gerçek robotlar üzerinde yapılan deneylerde, doğal sistemlerdekine benzer şekilde, imitasyon sırasında ortaya çıkan hatalardan kaynaklı davranış çeşitliliği gözlemlenebildiği belirtilmiştir.

Anahtar Kelimeler: *Görsel imitasyon, Çok-robotlu sistemler, Sürü robotlar*

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I. INTRODUCTION

Imitation is an important social learning method that allows individuals to learn from other individuals in a group. Due to this feature, imitation has been studied by biologists for many years and it has been claimed that imitation ability increases the adaptability of individuals to their environment [1]. For this reason, many studies have been conducted on the origin and functions of imitation ability. The main aim of these studies is to observe the effect of this ability on individuals by studying organisms with the ability to imitate in their natural environment.

Throughout the research on imitation, some definitions have been made to explain this ability. The most well-known of these definitions was made by Thorndike in the 19th century, and it is the learning of a behavior by seeing how it is done [2]. This definition states that imitation is a method that is usually used to acquire behaviors that the individual does not have. Imitation differs from other adaptive learning methods because, through imitation, individuals benefit from their social interactions and can learn from others the skills and behaviors they do not possess. Thus, Thorpe [3] argues that when imitation occurs, individuals can copy new or unexpected behaviors. There may not be any instinctive tendency that triggers the newly learned behaviors. Mitchell [4] describes important parts of the imitation mechanism. For example, during imitation, a copy behavior emerges, which is similar to the observed original behavior. Furthermore, the original behavior must have been perceived at the time of the appearance of the copy behavior. Finally, the individual performing the imitation activity should try to make the copy behavior resemble the observed original behavior. In other words, the imitating individual should aim to elicit an intrinsically similar behavior. According to Mitchell, if these conditions are met, it can be said that imitation is actually performed.

In light of the above-mentioned definitions, biologists have conducted observational studies on many different animals, looking for traces of imitation ability [5]. Birds, mice, monkeys and chimpanzees are among the animals claimed to have this ability ([6], [7], [8], [9]). On the other hand, it is known that human beings have the ability to imitate from birth. It has also been claimed that the ability to imitate has a key function in the emergence of human culture, which we can define as the common behaviors and beliefs that human communities have [10]. For this reason, many studies conducted by biologists have examined the meaning and importance of imitation in human development. In these studies, it has been shown that through imitation, certain behaviors can be learned by many individuals in a community and this leads to the formation of a common behavioral repertoire over time. In this way, it has been emphasized that people can become a part of human society, which includes very complex rules [11].

An important step in human imitation research was the discovery of mirror neurons. These neurons are activated when an individual performs a certain behavior and observes another individual performing the same behavior. Neurons with this property are found in animals (birds and primates) and humans, which are claimed to have the ability to copy. For this reason, it has been claimed that these neurons are neural structures that enable imitation [12].

Following the discovery of the neural infrastructure that enables imitation, research on the links between imitation and cultural activities has gained momentum. One of the most important human cultural activities is the formation of natural languages. Imitation must have an important function in the emergence, development and, spread of natural languages. Research on this topic has argued that learning and use by many individuals over time plays a key role in the origin of languages [13]. Based on this view, Kirby [14] proposed a method called iterative learning. Iterative learning occurs when an individual learns certain behaviors through imitation by observing another individual; this other individual has learned the same behavior by observing someone else. In this way, common behaviors can emerge through recurrent learning chains consisting of a high number of observation-learning-use steps.

Cornish et al. [15] modeled the emergence of natural languages through iterative learning. One of the important elements of this model is the copying errors that occur during learning with inter-individual imitation. Accordingly, individuals may make errors during copying due to their own biases or memory-based constraints. As a result of these errors, behaviors learned during iterative learning chains become different. Over time, the differentiated behaviors become more easily learnable by the individuals forming the group and spread to all individuals. It has been claimed that this mechanism allows the formation of natural languages. In controlled experiments on humans, it has been shown that simple proto-languages developed through iterative learning can be learned by human groups with increasing accuracy.

Another research area where the direct relationship between imitation and learning has attracted interest is robotics and several recent studies in the field of robotics have investigated imitation learning [16]. This is because robots with imitation capability have several theoretically important advantages. Today, robots can work in many different dynamic environments that can change over time. It is a laborious activity to think in advance about all the situations that the robot may encounter in a changing environment and, accordingly, to program the control architectures needed for the robot to respond appropriately to the changing situations. From this point of view, the ability of robots to learn from their environment in changing environments will increase their adaptability to their environments. In this way, it will not be necessary to pre-program all the behaviors that robots should have. In addition, if robots can learn by imitation, there is no need to spend extra effort or energy to train robots, because robots can learn new behaviors by observing individuals in a working system.

Some mechanisms have been proposed to perform imitation on robots. For example, Bakker and Kuniyoshi [17] claimed that the imitation activity consists of three different phases. These are *"observe the action"*, *"represent the action"* and *"reproduce the action"*. As can be seen, these stages are highly similar to the observe-learn-use steps of the iterative learning method. In another study, Dautenhahn et al. [18] state that for imitation to take place on robots, it is necessary to create a system that answers five different questions. These questions are who to imitate, when to imitate, what behavior to imitate, how to imitate the chosen behavior, and how to define a successful imitation.

The process of representing the observed behaviors by the robot and translating them into actions that the robot can perform is called the correspondence problem [19]. Accordingly, the observed behaviors must first be transformed into a structure that can be understood by the robot. Then, this structure should be translated into a collection of actions that can be performed by the robot. In this way, robots can reproduce and perform the actions they observe in their environment. The correspondence problem is usually solved by automatic translation methods.

As can be seen, imitation has practical benefits and a wide range of applications in robotics. For this reason, imitation learning has been the subject of many studies in recent years (e.g. [20], [21], [22], [23] and [24]). In these studies, robots have attempted to accomplish a task by copying the behavior of another robot or a human demonstrator. Thus, a research field called learning by observation emerged [25].

As mentioned above, there have been many studies on the impact of the ability to imitate on the formation of human culture and natural languages. These studies often focused on modeling with humans or groups of simulated agents. Experiments with humans have shown that prior cognitive biases [26], [27], [28] or memory-based [15] constraints cause copying errors during imitation, and that these errors have an important function in the development and propagation of natural languages. In the case of groups of agents in simulated systems, artificially induced errors have been introduced into the imitation process [29], and thus the evolution of linguistic items that change during imitation has been studied. From this point of view, robot groups consisting of individuals who can imitate each other offer an alternative method for studying the meaning and function of imitation. Compared to humans, mobile robots have very limited sensor and actuator capabilities. Therefore, when imitation is performed entirely on robots, spontaneous sensor and actuator errors can be observed. Modeling research with this approach has been able to study the development of simple proto-languages on robots. For example, Steels [30] used imitation-based social learning to develop a grounded communication system for humanoid robots. In the system, the robots interacted with each other during experiments called "talking heads" and thus agreed on a common lexicon that they could use during their communication. In another study, Steels and Spranger [31] modeled the spontaneous emergence and development of a common lexicon within a group of robots capable of copying each other's actions. In their experiments, robots observed the body images of other robots and matched these images with their own action sequences. In this way, agreement on the content of a common symbolic language between robots was achieved. Erbas [32] developed a visual copying based algorithm on real robots and investigated the evolution of an artificial proto-language in a group of mobile robots. The experiments showed that the symbols of the artificial antecedent language became more easily understandable during multiple iterative learning chains, thus increasing the transferability of the evolving artificial proto-language.

In this study, we investigate an embedded copying algorithm on real robots and investigate the origin of imitation errors made by robots that learn visually from each other using this algorithm. There are two possible sources of imitation errors. The first of these sources is the actuators of the robots. In order to observe the errors caused by the actuators, the robots were programmed to follow certain movement trajectories and the success rate of the robots in following the specified movement trajectories correctly was calculated. The second possible source of imitation errors is the robots' sensors. In order to observe sensor-related errors, imitation experiments were conducted using more than one robot. In these experiments, one robot was assigned as a demonstrator and programmed to follow some predefined movement trajectories. Another robot followed the movement trajectories displayed by the demonstrator and replicated them using a visual imitation algorithm [32]. The movement trajectory followed by the demonstrator robot and the copy obtained by the tracker robot were compared with two different trajectory similarity metrics and the cause of the resulting sensor-related errors was investigated.

The rest of the paper is organized as follows: Section 2 introduces the robots used in the experiments and the visual imitation algorithm to be studied on the robots. Section 3 describes the experiments conducted to investigate the errors that occur during imitation and presents the results of these experiments. Finally, in section 4, the results are discussed and new research questions that may arise in the light of the findings are mentioned.

II. EXPERIMENTAL SETUP

A. ROBOTS

In the experiments conducted in this study, e-puck miniature robots were used [33]. The robots are 7 cm in diameter and 5 cm in height. Thanks to their microprocessor and two-step motor, they can be programmed to follow predefined movement trajectories. There is also an image sensor on the front of the robots. The images obtained by the robot using this sensor are used by the visual imitation algorithm. Furthermore, to facilitate on-board image processing, the processing power of the e-puck robots are enhanced with a Linux extension board [34] and ROS [35] is installed on the extension board of the robots. All programming on robots is done in C Programming Language.

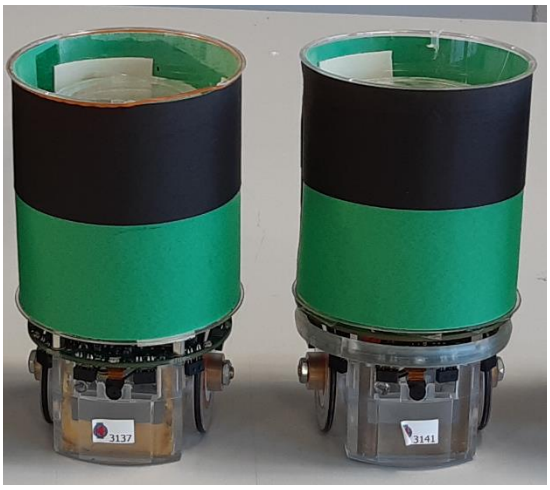


Figure 1. *E-puck miniature robots. The figure shows the robots and their colorful heads*

The bodies of the robots are partially made of transparent material. In order to facilitate image processing operations on mobile robots, a colored head was placed on the robots. The Blobfinder module of ROS [35] is used to detect the predefined color of this head so that it is possible for the robots to detect each other on the image they obtained.

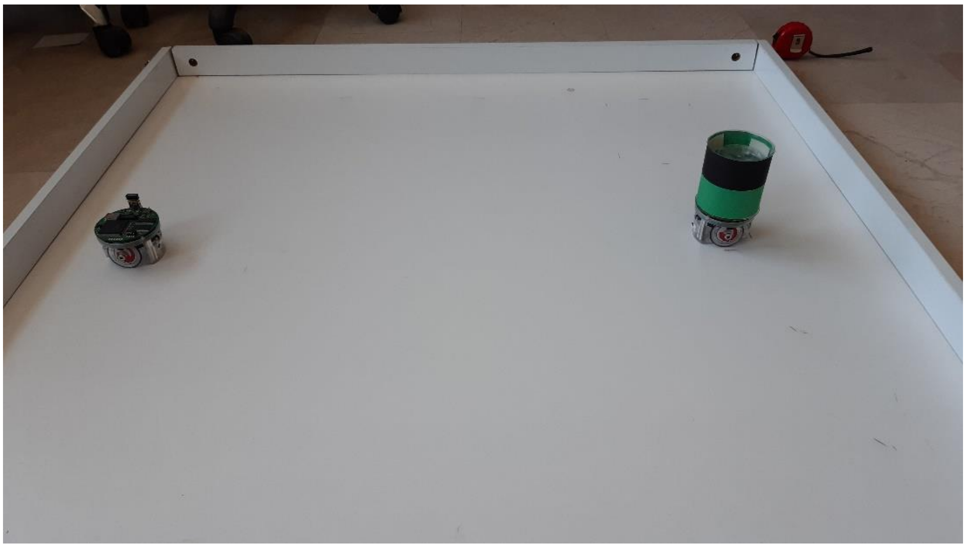


Figure 2. *Two e-puck robots on the experimental setup. The one on the left is programmed as a tracker and the one on the right as a demonstrator.*

B. VISUAL IMITATION ALGORITHM

Using a visual imitation algorithm [32], a follower robot can replicate the movement trajectory followed by a demonstrator robot in its environment. The algorithm consists of steps corresponding to the observation - learning - replication phases specified in imitation mechanisms. The operations performed during these steps can be summarized as follows:

- Observation: During the movement of the demonstrator robot, the tracker robot acquires two images per second using its image sensor.

- Learning: The tracker robot calculates the size of the head on the demonstrator robot and its relative position on each acquired image.

- Replicate: The trajectories that are demonstrated by the robots consist of straight movements and turns on the spot between those straight movements. In order to estimate the length and direction of straight movements that are demonstrated by the robots, a linear regression method [36] is applied to the positions calculated in the previous stage and the trajectory followed by the demonstrator robot is reconstructed.

- Translation: Finally, the movement trajectory generated in the previous stage is translated into motor commands that can be executed by the tracker robot. Thus, the correspondence problem mentioned above is solved.

At the end of these steps, the imitation activity is completed by the tracker robot. As can be seen, the imitation algorithm works entirely based on the sensors and actuators on the robot's body. No other means of communication between the robots was allowed during the experiments. Further technical details on the specific operations that are part of the imitation algorithm can be seen in [32].

Figure 3 shows a movement trajectory followed by the demonstrator robot and a copy of this movement trajectory generated by the tracker robot. As can be seen in the figure, there is a difference between the original trajectory and the replicated copy. The original movement trajectory is a square with 20 cm sides, consisting of straight movements and 90° counterclockwise turns. The reproduced copy consists of an 18 cm straight movement, 81° counterclockwise rotation, and finally 23 cm straight movement, 89° counterclockwise rotation, 16 cm straight movement, 73° counterclockwise rotation and finally 23 cm straight movement. The rest of the paper will analyze the origin of this type of copying error.

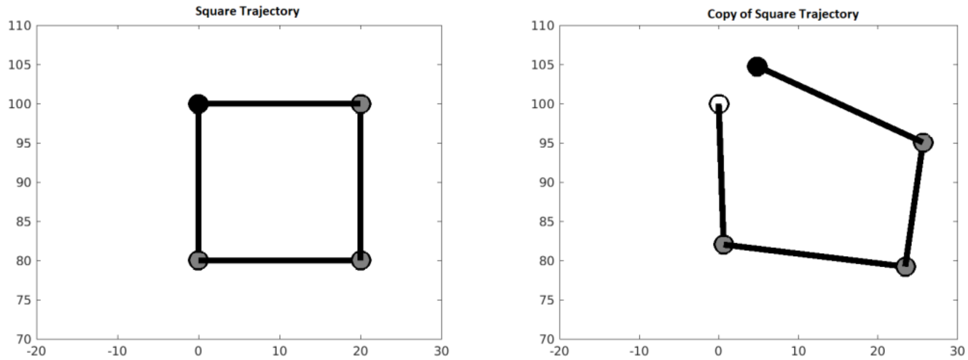


Figure 3. *On the left is the trajectory followed by the demonstrator robot and on the right is the copy of this itinerary created by the tracker robot. The starting positions of the trajectories are indicated by the white circle, the turns by the gray circle and, the ending position by the black circle.*

III. IMITATION EXPERIMENTS

As mentioned in the previous section, during imitation, the tracker robot makes some errors when copying the movement trajectory followed by the demonstrator robot. During the imitation activity, two different pieces of hardware are involved. These are the actuators (motors) of the demonstrator robot and the image sensor of the tracker robot. Therefore, the source of the imitation errors should be the mentioned hardware parts. The aim of this research is to investigate the source and content of the imitation errors. For this purpose, the following experiments are organized.

A. IMITATION ERRORS DUE TO ACTUATORS

The robots have a microprocessor and two stepping motors. As mentioned before, robots can be programmed to move in certain movement trajectories. The purpose of the experiments conducted in this chapter is to calculate the extent to which the robots can successfully perform the movement trajectories that they are programmed to follow, consisting of straight movements at certain distances and turns at certain angles, in a physical environment. In this way, the amount and content of actuator-related imitation errors in a swarm of e-puck robots will be determined.

For the detection of actuator-related errors, a demonstrator robot is programmed to move 10 times along the trajectory shown in Figure 2. During this movement, each straight movement and turn of the robot was examined externally and the amount of the physically performed turn or straight movement was compared with the programmed movement trajectory. In this way, the imitation errors caused by the actuators of the demonstrator robot were analyzed. The results obtained are shown in table 1. As can be seen, there is minimal error in the robot's turns. A deviation of ±1° was observed for 90° turns. In addition, the errors have a normal distribution around the actual rotation angle and are not statistically significant.

When the straight movements that the demonstrator robot is programmed to follow are examined, it is observed that the straight movement of 20 cm in length can be performed with an error of approximately 1 mm. The error is distributed between 0 and 0.1 mm. In the light of these findings, the following conclusions were drawn:

- The robots used in the experiments can perform the movement trajectories they are programmed to follow with high accuracy.

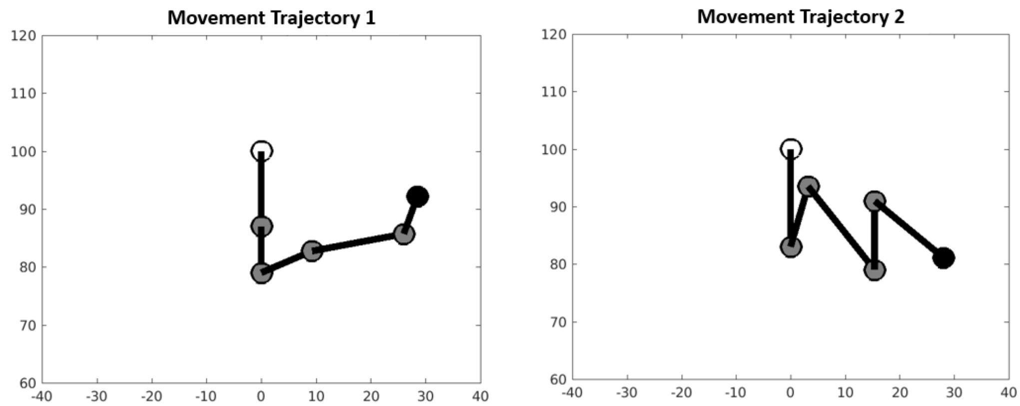
- The observed actuator related errors are very low and do not affect the overall shape and structure of the pre-programmed movement trajectory.

Table 1. *Actuator-related errors.*

Programmed movement type	**Performed average movement**	**Standard deviation**	**Mean error**
90° rotation	90.2333°	0.6789°	0.5°
20 cm straight movement	20.0125 cm	0.0335 cm	0.0125 cm

B. SENSOR RELATED IMITATION ERRORS

The robots copy the movement of another robot using the visual imitation algorithm introduced in the previous section. The visual imitation algorithm is executed by using the images captured by the robots with the image sensor on their bodies. In this section, some experiments are conducted to investigate the sources and effects of sensor-related errors. Two robots were used in the experiments. One of these robots is defined as a demonstrator and is programmed to follow the randomly generated movement trajectories shown in Figure 4. The other robot was defined as a follower and was programmed to copy the movement trajectory exhibited by the demonstrator robot using the visual imitation algorithm.



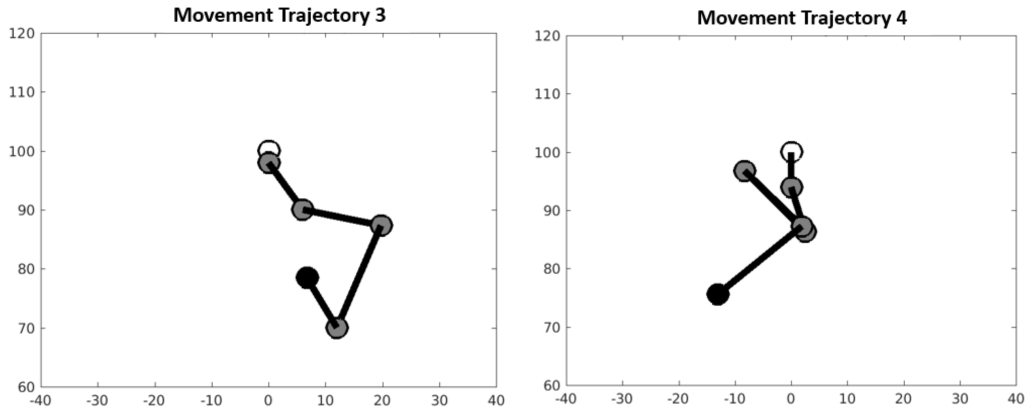


Figure 4. *Randomly generated movement trajectories to be exhibited and replicated.*

Each experimental set consists of the following steps:

- The demonstrator robot and the tracker robot are placed on a 120 cm x 120 cm robot arena as shown in Figure 2, with 100 cm between them.

- The demonstrator robot chooses one of the movement trajectories shown in Figure 4 and announces the start of the demonstration by turning on the LEDs on its body.

- The tracker robot detects the LEDs and starts the visual imitation activity.

- The demonstrator robot turns off the LEDs and demonstrates the selected movement trajectory. Meanwhile, the tracker robot copies the movement trajectory of the demonstrator robot.

- When the demonstrator robot completes the defined movement trajectory, it turns its LEDs back on and announces that the demonstration is completed.

- The tracker robot saves the observed movement trajectory in its memory.

- The demonstrator robot returns to the starting point where it was previously placed.

During the experiments performed in this way, each movement trajectory shown in Figure 4 was displayed 10 times by the demonstrator robot and copied by the tracker robot. The flow-chart of the experiment setup is given in figure 5.

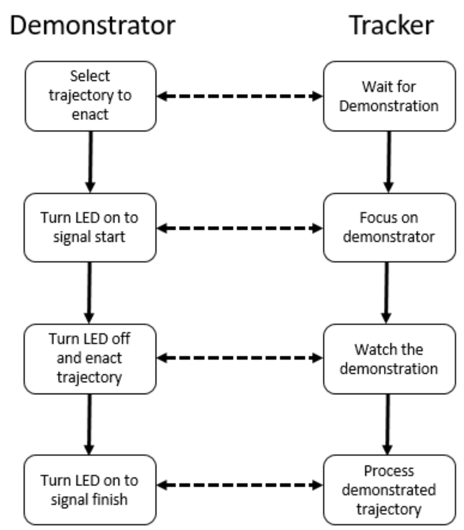


Figure 5.*Flow-charts of the demonstrator and the tracker robots during the experiments*

In order to quantify the amount of sensor-related errors that occur during imitation, it is necessary to calculate the similarity between the demonstrated movement trajectories and the generated copies. There are many trajectory comparison methods designed for this purpose [37]. In this study, sensor-related imitation errors will be analyzed using two different methods.

The first method is the piecewise similarity function, which is similar to the method we used to measure actuator-related errors [32]. This method treats each straight movement and turn as a separate part, matches the demonstrated trajectory with the straight movements and turns of the copy, respectively, and calculates the difference between them. Accordingly, each copy has three different similarity measures to be calculated. The first one is the quality of move length and is calculated as follows:

$$Q_l = 1 - \frac{\sum_n |l_n^D - l_n^C|}{\sum_n l_n^D} \qquad (1)$$

In the formula, l_n^D is the length of nth straight moves in the demonstrated trajectory and l_n^C is the length of nth straight moves in the copy trajectory. If two trajectories contain a different number of straight moves, the comparison is made for the number of straight moves of the trajectory containing the least number of straight moves. Similarly, turn similarity is calculated as follows:

$$Q_a = 1 - \frac{\sum_n |a_n^D - a_n^C|}{\sum_n a_n^D} \qquad (2)$$

In the formula a_n^D is the turn angle following nth move in the demonstrated trajectory and a_n^C is the turn angle following nth move in the copy. Finally, the quality of the segment number is calculated as follows:

$$Q_s = 1 - \frac{|N^O - N^C|}{N^O} \qquad (3)$$

In the formula, N^O is the number of straight movements in the exhibited trajectory and N^C is the number of straight movements in the copy. As a result, the similarity between the demonstrated trajectory and its copy is calculated by combining three different quality measures:

$$Q_P = \frac{Q_l + Q_a + Q_s}{3} \qquad (4)$$

The copy obtained as a result of the imitation activity shown in Figure 3 has a Q_l value of 0.8605, a Q_a value of 0.9, a Q_s value of 1 and so a Q_p value of 0.9202.

The second method used to quantify sensor-related errors is the edit distance function [38]. Accordingly, the edit distance between the demonstrated movement trajectory O consisting of ($o_1,o_2,o_3,...,o_m$) vectors and the copy movement trajectory C consisting of ($c_1,c_2,c_3,...,c_n$) vectors is calculated as follows:

$$Diff(O,C) = \begin{cases} \sum_{i=1}^{m} dist(o_i, 0) & if\ n = 0 \\ \sum_{i=1}^{n} dist(c_i, 0) & if\ m = 0 \\ min \begin{cases} Diff\big(Rest(O), Rest(C)\big) + dist(o_i, c_i) \\ Diff(Rest(O), C) + dist(c_i, 0) \\ Diff\big(O, Rest(C)\big) + dist(o_i, 0) \end{cases} & else \end{cases} \qquad (5)$$

In the formula, Rest(O) and Rest(C) denote the respective trajectories except their first vectors and dist(o_i,c_i)is equal to the distance between vectors o_i and c_i . Based on the calculated difference value, imitation quality between the demonstrated trajectory and its copy is calculated as follows:

$$Q_T = 1 - Diff(O,C) \qquad (6)$$

The Q_T value of the copy obtained during the imitation activity shown in Figure 3 was calculated as 0.7333.

Figure 6 shows the imitation success rates of the copies created as a result of the imitation activities performed during the experiments, calculated with $Q_P$and Q_T metrics. When both results are analyzed, it is seen that the tracker robot makes some sensor-related errors during imitation, similar to natural systems. The reason for this situation can be explained as follows:

- Image capture is performed from a single point and with relatively low resolution (320 x 240 pixels). For any movement of the demonstrator robot to be detected by the tracker robot, this movement must cause a change in the captured image. Otherwise, that is, if the movement does not cause any change in the pixel values on the image, the tracking robot can't detect this movement. For this reason, it was observed that some of the movements in the exhibited trajectories could not be detected and some of them could be partially detected.

- During the image capture process, the demonstrator robot is in motion. Compared to a static target, the fact that the demonstrator robot is in motion may cause some perceptual error in the captured image. As a result, it was observed that the turning and straight movements of the exhibited movement trajectory could be reproduced with some error.

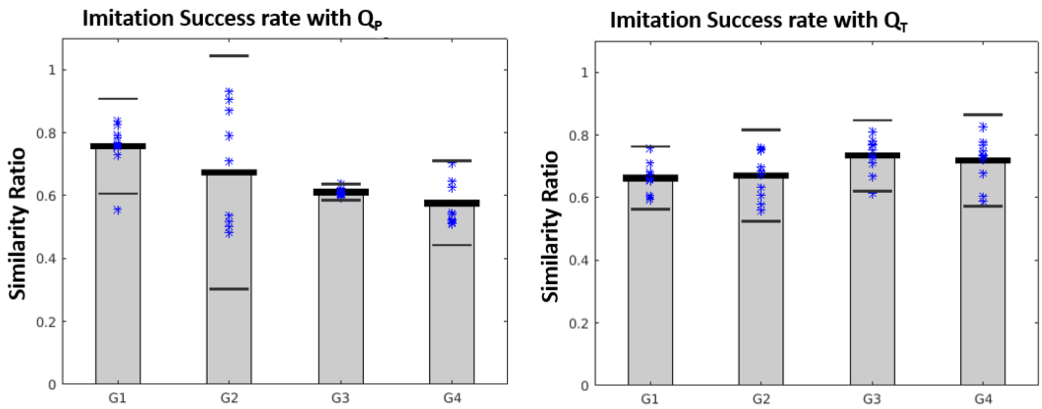


Figure 6. *On the left is the similarity ratios of the copies obtained in the imitation experiments calculated with the Q_P metric). On the right is the similarity ratios of the same copies calculated with the Q_T metric. The copies of each trajectory are shown in a separate column (G1 = trajectory 1, G2 = trajectory 2, G3 = trajectory 3, G4 = trajectory 4).*

Although a certain amount of sensor-related error is observed in each imitation activity, an analysis of the copies of randomly generated trajectories shows that some trajectories can be replicated with statistically higher accuracy. To analyze the reason for this, Figure 7 shows the exhibited movement trajectories and a randomly selected copy of these trajectories. As a result of this analysis, the findings listed below were obtained:

- When trajectory 3 shown in Figure 6 and its copies are examined, it is seen that although the copy resembles the exhibited movement trajectory in general shape, it does not include the first action in the demonstrated trajectory, the 2 cm straight movement. When all copies of trajectory 3 were analyzed, it was observed that the tracker robot had difficulty in copying this action, which has a relatively short length. From this point of view, it can be said that the straight movements with relatively short distances in the demonstrated trajectories are more affected by sensor-related errors. Trajectories 3 and 4 contain relatively more of these types of short straight movements, so the imitation accuracy rates of the copies of these trajectories calculated with the Q_P metric are relatively lower. Trajectory 1, on the other hand, does not contain these types of straight movements, so the accuracy of the copies of this trajectory calculated with the Q_P metric is higher.

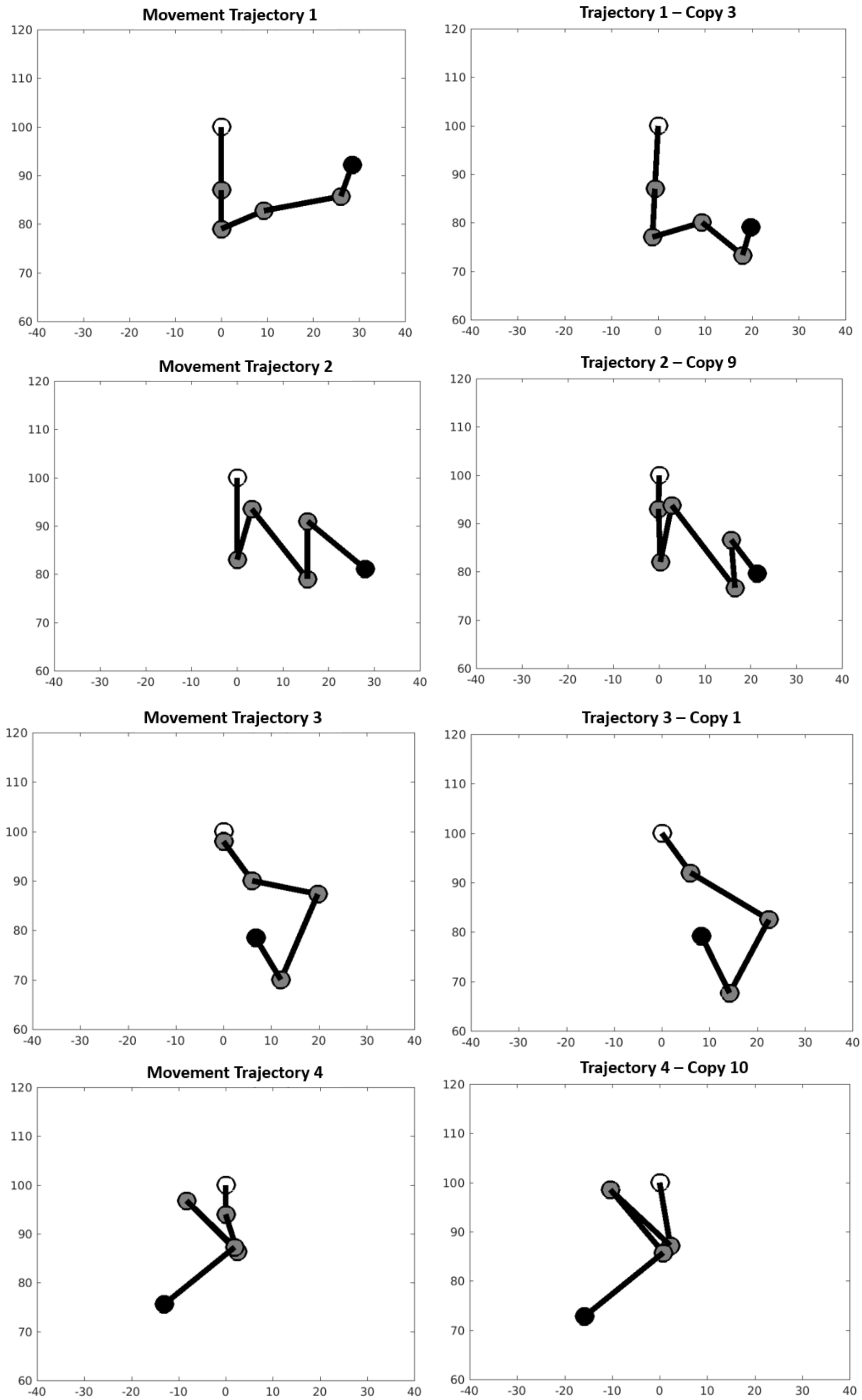


Figure 7. *On the left is the exhibited trajectory and on the right is a randomly selected copy of the exhibited trajectory.*

In the cases described above where short distance movements cannot be replicated or a long vertical movement is split into multiple segments, the overall shape of the copies of the demonstrated trajectory remains unchanged. Therefore, theQ_T metric is not affected by such errors and the geometric properties of the demonstrated trajectories and their copies can be compared efficiently with this function. When the imitation accuracy rates calculated with the Q_T metric are analyzed, it is seen that similar imitation accuracy rates are calculated for the copies of different trajectories. When the accuracy rates of the different trajectories are statistically compared with the paired t-test method, it is seen that only the copies of trajectory 1 can be replicated with statistically low accuracy, while there is no statistical difference between the accuracy rates of the copies of the other trajectories. In order to analyze the reason for this situation, the geometric properties of trajectory 1 and other trajectories were compared, and the following observations were made:

- The demonstrated movement trajectories contain 90° or wider turns, which cause significant changes in direction. Movement trajectories containing such turns can be copied by the tracker robot with higher accuracy. When the randomly generated movement trajectories are analyzed, it is seen that trajectory 1 contains only one wide-angle turn, while the other trajectories have a relatively higher number of wide-angle turns. This made trajectory number 1 more difficult to replicate.

- When the demonstrated movement trajectories contain straight movements with vertical and horizontal components, the start and end points can be replicated with relatively high accuracy. When trajectory number 1 is examined, it is seen that it contains a relatively large number of straight movements with only vertical or horizontal components. For this reason, the similarity ratios of the copies of this trajectory calculated with the Q_T metric were relatively low.

IV. CONCLUSION

In this study, we analyze a visual imitation algorithm on real robots. For this purpose, it is first shown that when imitation is performed on robots, the movement trajectories learned by imitation differ between robots during learning. The possible sources of the differences are the actuators of the demonstrator robot and the sensors of the tracker robot. First, the errors due to the actuators of the demonstrator robot are analyzed and it is shown that such errors are minimal. Then, the errors due to the tracker robot's sensors were analyzed in an experimental scenario and the errors due to sensors during imitation were measured with two different similarity metrics. By analyzing the results obtained, it is seen that movement trajectories with certain geometric features can be replicated with relatively low accuracy in the experiments performed. It has been shown that trajectories exhibited with the effect of the listed geometric features can be learned with different accuracy rates.

In order to calculate the copying accuracy rates, two different trajectory comparison functions commonly used in the literature were used to calculate the similarity of the demonstrated and learned trajectories. It was observed that each function prioritizes different geometric features during the comparison and calculates different accuracy rates accordingly. From this point of view, it should be noted that the comparison method used to measure learning success is of high importance in research using imitation learning. In research on physical systems, a comparison function should be chosen that is appropriate for the intended goal of imitation and the meaning and accuracy of imitation should be explained with the measurements made with the chosen function.

As mentioned above, the ability to imitate and the variety of behaviors that emerge during imitation are thought to be of great importance in the emergence and development of natural languages. In modeling studies on this topic, mobile robot collectives that can learn from each other through imitation provide a very important research environment. As shown in this study, in experiments on real robots, similar to natural systems, behavioral variation due to errors made during imitation can be observed. This is an important research topic that can help in the development of efficient robot-to-robot or robot-to-human communication systems.

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