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Modeling Active Learning in a Robot Collective

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Abstract

In this research, we model an active learning method on real robots that can visually learn from each other. For this purpose, we initially design an experiment scenario in which a teacher robot presents a simple classification task to a learner robot through which the learner robot can discriminate different colors based on a predefined lexicon. It is shown that, with passive learning, the learner robot is able to partially achieve the given task. Afterwards, we design an active learning procedure in which the learner robot can manifest what it understand from the presented information. Based on this manifestation, the teacher robot determines which parts of the classification system are misunderstood and it rephrases those parts. It is shown that, with the help of active learning procedure, the robots achieve a higher success rate in learning the simple classification task. In this way, we qualitatively analyze how active learning works and why it enhances learning.

Keywords: Active Learning, Learning by Demonstration, Multi-Robot Group, Robot Learning.

1. INTRODUCTION

Active learning is a well-known teaching method that is widely accepted to enhance the learning activities of students. The basic idea behind active learning is that the students are able to understand and later recall the information that is presented to them if they, instead of passively listen, get involved in the learning process [1]. As the students actively participate in the learning process, their experiences support the grounding of the perceived information. Therefore, it is seen as a key mechanism that can transform students

from passive listeners to active information gatherers. It is generally compared with traditional lectures in which students passively listen and possibly get notes about the newly presented information. According to Kyriacou [2], when active learning is utilized, the students should be given a degree of control over the learning activities such that they can have a sense of ownership on what is learned and how it is learned. In addition, he claimed that through active learning, the learning experience should be open-ended instead of predetermined so that the

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active participation of the students can shape the learning process.

A number of basic student activities, including reading, writing, discussing, asking, explaining, form the basis of any active learning method. In particular, the students are expected to engage in high-level cognitive tasks, such as analysis, synthesis and evaluation so that they can think, understand and finally learn the information that is presented to them [3]. Although these activities can be included in traditional homework practices, active learning is generally implemented during lectures in a classroom. In an active learning environment, the main objective is to draw the students' attention as high as possible while keeping them engaged [4]. For this purpose, students are encouraged to think critically, communicate their opinions with classmates or teachers, express their understandings through writing and most importantly provide feedback about their ongoing learning process [4].

It may be beneficial to list some other well-known teaching techniques that can be used in accordance with active learning. For instance, collaborative or cooperative learning is a method in which students work in small groups in order to achieve a common goal [5]. The students are encouraged to form small groups and cooperate with others to solve some specific problems that can be partitioned into a set of distinct issues for which each member of the group can contribute. Another well-known teaching method, problem-based learning (PBL) [5] aims to present a set of relevant problems that shape the learning process at the beginning of every learning activity. Both collaborative and PBL methods increase student engagement and cooperation; therefore they are widely used as a part of active learning methods.

As active learning methods can be designed with a variety of different approaches, there have been some efforts for formalizing the main principles of active learning. For instance, Barnes [6] defined seven principles of active learning as:

- Purposive: The content of the learned task should be relevant to the learner's concerns. In effect, the learner should

intentionally participate in the learning process.

- Reflective: The student should be allowed to reflect his/her own opinion about what is learned. Instead of passively listening, the student should be allowed to openly express what he/she understands from the presented information.
- Negotiated: The teacher and the student should negotiate the objective and methods of learning.
- Critical: The students should possess ways of appreciating different methods of learning.
- Complex: The students should be able to compare what is learned with the complexities encountered in the real life.
- Situation-driven: The task that is learned should be a part of a specific situation.
- Engaged: The task that is learned should correspond to a real life activity.

Barnes claimed that the first four principles encourage the participation of the students while the last three enhance the realism of the learning process. Kyriacou [2] identified five key concepts for active learning:

- Concrete materials should be used as a part of direct experience.
- Problem-oriented techniques should be utilized.
- Students should work in small groups.
- Students should own the learning process.
- Learning process or task should be relevant and personally focused.

He stated that the application of at least one of these concepts to a learning activity implements an active learning process. Felder and Brent [7] designed distinct steps which they claimed that an active learning process should include. These steps had detailed timings and objectives that are implemented to increase the level of participation of students in a classroom.

Active learning methods are designed and tested on some student communities in a number of researches. Some of these researches reported an enhanced level of success. For instance, Laws et

al. [8] examined the effects of active learning methods on students in a course in physics. They reported that the students managed to get a better learning rate when they had interactive engagements during the lectures. The number of students that could understand the basic concepts of physics, such as force and acceleration was two to three times higher with the help of active learning methods. Freeman et al. [9] examined the learning performance of students in primary and secondary level students with active learning methods. They reported that the students had a higher mean score of success compared to their performance with traditional passive learning methods. Marcondes et al. [10] attempted to utilize active learning methods for undergraduate psychology classes. They stated that simple puzzles can be utilized to explain cardiac cycle to students.

Although many teachers have become interested in active learning in recent years and some reports claimed high success rate of certain active learning methods, there are still some issues that makes its implementation hard for new practitioners. For instance, Borrego [11] stated that there is a lack of consensus about the exact definition of active learning. As a result, its implementations in different disciplines possess many uncertainties. Konopka et al. [4] claimed that many teachers who are interested in active learning have no clear understanding about what active learning means and how it is different from the traditional teaching methods. Furthermore, many teachers do not know the meaning and use of different active learning techniques and so cannot use them effectively based on the students' needs. Additionally, Prince [5] claims that there is a significant problem in the assessment of the outcomes of active learning methods. For instance, some researchers declared improvement in the learning performance with active learning; however they did not mention the improvement was in fact small. Konopka et al. [4] claimed that the effectiveness of any active learning method is difficult to measure because many different methods were compared on different metrics. As a result of these difficulties, although many teachers feel that the current educational methods should be improved, they avoid trying active

learning methods and pursue the traditional teaching activities.

The issues that make the implementation and evaluation of active learning methods are partly due to the fact that these methods have never been mathematically modeled and examined on any platform. A number of adaptive learning algorithms, including reinforcement learning [12], supervised learning [13], learning by demonstration [14] or deep learning [15], have been implemented, tested and examined on simulations or robotics platforms. There is continuing effort in modeling some of the well-known human cognitive processes, such as language acquisition on simulation or real robot experiments [16]. These models explain the mechanisms that allow humans to gradually develop a shared and complex communication system in noisy social learning environments. The systems that model noisy social learning environments are particularly significant for active learning research because active learning attempts to improve the quality of learning in noisy learning environments that may cause misconception or partial retention of the information that is presented with the traditional teaching methods. If we can model an environment in which robots or simulated agents learn from each other, though imperfectly due to their limited perceptual abilities and noisy interactions, we can examine and then explain how and why active learning methods enhances learning.

In this research we attempt to model an active learning method on real robots that can visually learn from each other. For this purpose, we design an experiment scenario in which a teacher robot presents a simple classification system to a learner robot through which the learner robot can discriminate different colors based on a predefined lexicon. It is shown that, with passive learning, the learner robot is able to partially comprehend the presented classification system. Afterwards, we design an active learning procedure in which the learner robot can manifest what it understand form the presented information. Based on this manifestation, the teacher robot determines which parts of the

classification system is misunderstood and it rephrases those parts to make them more suitable to the perceptual abilities of the learner robot. As a result of this active learning procedure, it is shown that the presented classification system can be fully comprehended by the learner robot. We qualitatively analyze how the procedure works and why it enhances learning.

The article proceeds as follows: section 2 presents the robots and the visual learning algorithm that are used to model active learning. Section 3 presents our method of passive and active. Finally, section 4 discusses the experiment results and concludes the article.

2. ROBOTS AND VISUAL LEARNING ALGORITHM

To model learning between robots, we use two e-puck miniature robots that are shown in figure 1 [17]. The robots are programmed to visually learn from each other by using their on-board image sensors. One of the robots is declared as the teacher and it can follow predefined movement patterns that can be learned by the learner robot. The learner robot can learn a demonstrated movement pattern by using a movement imitation algorithm [18]. The algorithm works as follows:

- As the teacher robot moves on a predefined movement trajectory, the learner robot captures multiple frames from its image sensor.
- The robots wear a colorful hat to enhance on-board image processing. On each frame, the learner robot determines the relative position of the hat of the teacher robot and saves this information in a list of relative positions.
- When the movement pattern is completed, the learner robot processes the relative position list in order to reproduce the demonstrated movement pattern of the teacher robot.
- The learner robot saves the reproduced movement pattern in its memory so that it can be executed at a later time.

In this way, the learner robot is able to observe and learn the movement patterns that are demonstrated by the teacher robot. Further details about the movement imitation algorithm and an analysis on the type of copying errors can be seen in [18].



Figure 1. Two E-puck robots that are used in the experiments. As can be seen in the figure, the robots are fitted with a colorful hat to make it easier for them to detect each other.

The learner robot watches a demonstrated movement pattern from a single point of view; hence it has monoscopic vision. Furthermore, it can capture relatively low resolution image frames (320 x 240 pixels). As a result of these facts, the learner robot may have perceptual errors due to imperfect sensor system, therefore we have noisy social learning among the robots. For instance, figure 2 shows a movement pattern that is followed by the teacher robot and its reproduced copy by the learner robot. When we compare two movement trajectories, it can be seen that the reproduced copy has some discrepancies. For instance, in comparison with the original movement pattern, the first straight line segment is partitioned into two parts, the second straight line segment becomes slightly longer, third turn has a wider angle, fourth straight line segment is slightly longer and the last straight line segment is shorter in the copy.

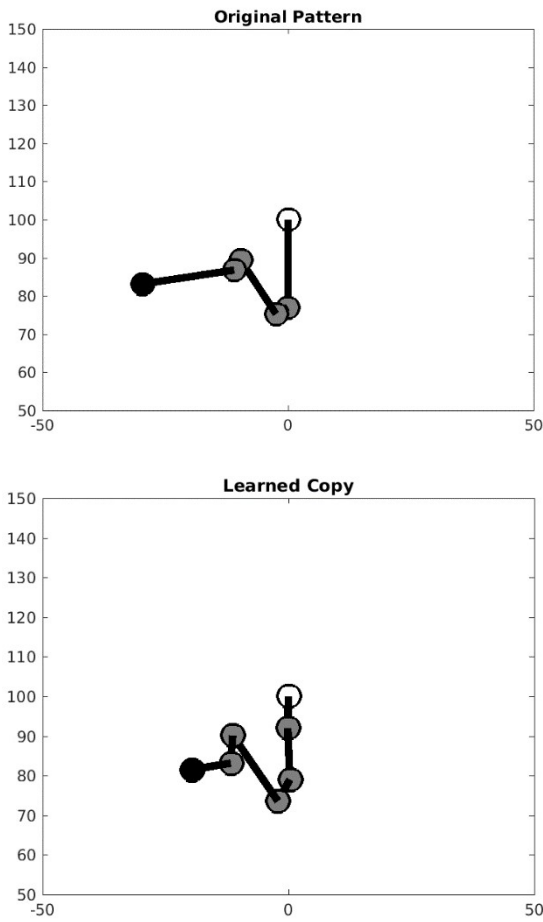


Figure 2. An original movement pattern that is followed by the teacher robot and its reproduced copy. The original pattern consists of 23 cm straight move, 54° clockwise turn, 3 cm move, 99° clockwise turn, 16 cm move, 128° counter-clockwise turn, 3 cm move, 54° clockwise turn and 19 cm move. Its copy consists of 8 cm move, 3° counter-clockwise turn, 13 cm move, 26° clockwise turn, 6 cm move, 127° clockwise turn, 19 cm move, 148° counter-clockwise turn, 7 cm move, 75° clockwise turn, 8 cm move. The trajectories are shown in cm.

In order to qualitatively determine how accurately a demonstrated movement pattern is learned by the learner robot, we need a quality of learning metric that compares two distinct movement patterns. For this purpose, we devise Edit Distance with Penalty metric (ERP) that is widely used as a trajectory similarity measure [19]. Based on ERP metric, the difference between an original pattern O which consist of a list of vectors $(o_1, o_2, o_3, \dots, o_m)$ and its copy C , which consist of a list of vectors $(c_1, c_2, c_3, \dots, c_n)$ is calculated as follows:

$$ERP(O, C) = \begin{cases} \sum_{i=1}^m dist(o_i, g) & \text{if } n = 0 \\ \sum_{i=1}^n dist(c_i, g) & \text{if } m = 0 \\ \min \begin{cases} ERP(Rest(O), Rest(C)) + dist(o_i, c_i) \\ ERP(Rest(O), C) + dist(o_i, g) \\ ERP(O, Rest(C)) + dist(c_i, g) \end{cases} & \text{oth.} \end{cases} \quad (1)$$

in which $Rest(O)$ and $Rest(C)$ are the O and C with the first element removed, $dist(r_i, s_i) = |r_i - s_i|$, the Euclidean distance between the vectors r_i and s_i , $dist(s_i, g) = |s_i - g|$ and $dist(r_i, g) = |r_i - g|$ where g is the gap constant which is set to 0 vector. Based on this metric, the distance between the movement patterns that are shown in figure 2 is equal to 0.3225. An ERP value that is less than 0.5 is accepted as a high quality copy.

At this point, it should be noted that the robots are not allowed to communicate in any other way except visual learning. For instance, they cannot send any message or executed motor commands to other robots. Therefore, they can only interact through a noisy channel by using their on-board image sensors.

3. MODELING LEARNING METHODS

3.1. Modeling Passive Learning

To model passive learning, we designed experiments in which the learner robot attempts to learn and then tested on a lexicon. The lexicon consists of 5 different randomly generated movement patterns and each movement pattern is matched with a specific color. Figure 3 shows the randomly generated movement patterns and their corresponding colors. The passive learning experiment starts with teaching procedure during which the teacher robot teaches the learner robot each of the movement patterns and their corresponding colors. This is done by the following steps:

- At the start of each teaching procedure, as shown in figure 4, the teacher robot and a block with the specific color are placed 1 m away from the learner robot on a 120 x 120 cm robot arena.
- The learner robot captures a frame and determines the color of the presented block.

- The teacher robot then turns its LEDs on for two seconds to signal movement pattern start. The learner gets ready for the demonstration.
- The teacher turns its light off and follows the movement pattern that is matched with the presented color, while the learner robot learns the movement pattern by using the movement imitation algorithm presented in the previous section.
- When the execution of the movement pattern is completed, the teacher robot turns its lights on for two seconds to signal movement pattern completed.
- The learner robot saves the reproduced movement pattern as the meaning of the presented color in its memory.

The above steps are repeated for all of the 5 colors so that the learner robot learns the pattern of each color.

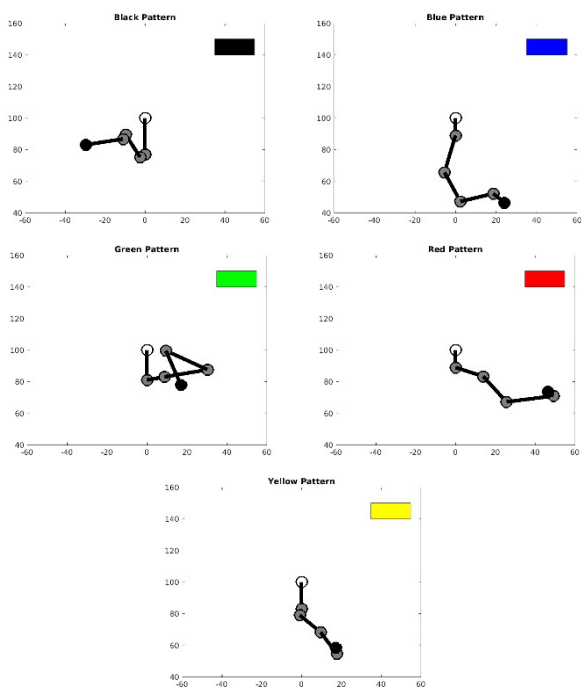


Figure 3. The randomly generated movement patterns of colors.

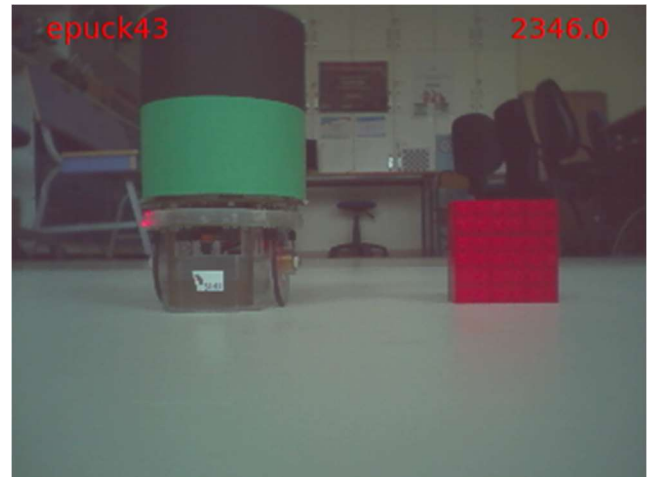


Figure 4. A captured image from the image sensor of the learner robot. In the figure, the teacher robot and the red block can be seen.

At this point, it should be noted that so far, with the passive learning method during which the learner solely observes the presented information through noisy learning channel, the teacher has no clue about how accurately the presented information is comprehended by the learner. In order to test the learning success of the learner, the teaching procedure is followed by an examination procedure. For this purpose, the following steps are applied:

- The teacher robot selects one of the colors and follows its matched movement pattern.
- The learner robot copies the pattern. Then it compares the newly reproduced pattern with the movement patterns of each color that it saved in its memory during the teaching procedure, by using the ERP function.
- The learner robot determines the pattern that is most similar pattern (lowest ERP value) to the newly reproduced pattern and declares its corresponding color as its answer.
- The teacher compares the answer of the learner to the actual color that it previously choose. If it is the same color, the learner is given 1 point.

During the examination procedure, the teacher robot selects and executes the patterns of each color 10 times. In this way, we are able to check

if the learning activity in the teaching procedure is successful.

Figure 5 shows the results of the examination procedure. As can be seen, the learner robot can detect the patterns of the black, blue, green and yellow; however it has a low performance when it needs to detect the pattern of red.

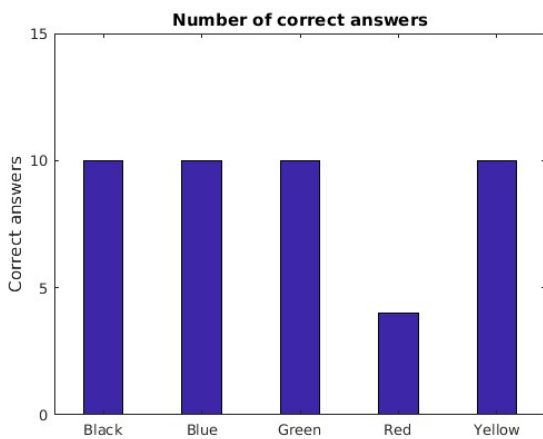


Figure 5. The results of examination procedure with passive learning.

In order to observe the reasons of the results shown above, we examine how accurately the presented patterns are learned by the learner robot. Figure 6 shows the learned patterns of the learner robot after the teaching procedure. When we apply the ERP function to compare the original and learned movement patterns, it reveals that four of the patterns, namely patterns of black, blue, green and yellow, are learned with relatively low error (ERP value 0.3225, 0.2425, 0.3415, 0.2343, respectively), while the pattern of red can be learned with a much higher error (ERP value 1.0564). This fact explains why the learner robot has a low performance when it needs to detect the pattern of red. As it is learned with high error, the robot cannot detect it in the examination procedure. A visual inspection of the learned patterns also reveals that the learned version of the pattern of red is highly dissimilar to its original. In fact, some geometrical properties of the pattern of red make it harder to learn. For instance, its first straight line segment is shorter compared to other patterns which make it harder to detect. Furthermore, the teacher robot seems to move on the same direction while it executes pattern of red

as there is only one distinct change of direction in this pattern. Other patterns that are learned have sharper turns which are much easier to detect. As a result of these unique geometrical properties, overall shape of the copy of the pattern of red is highly dissimilar to its original demonstration.

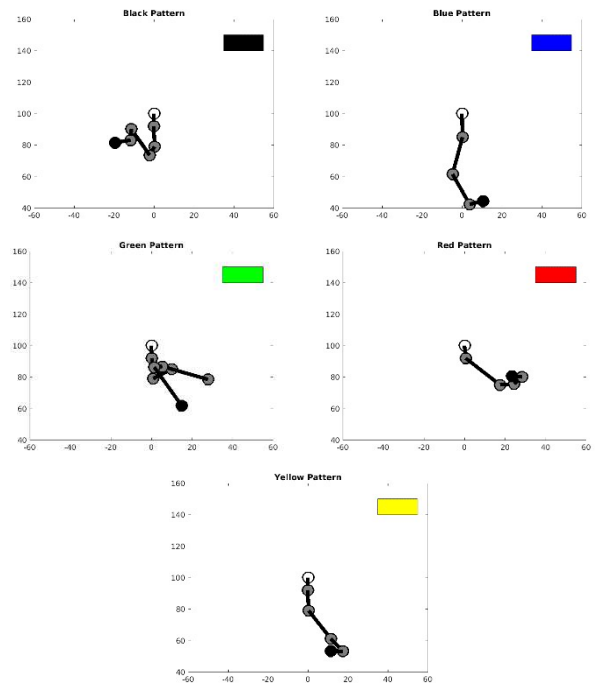


Figure 6. Reproduced patterns of the learner robot.

As stated above, with traditional passive learning methods, as the learner robot just observes and does not actively participate in the learning process, there is no way for teacher robot to detect the fact that four of the presented patterns are learned accurately while one of the patterns is not. The noisy learning channel may have different effects on the learning process of different subjects and it may cause principal differences between how a subject is explained by the teacher and how it is understood by the learner. Unfortunately, there is no way that an excessive error in learning can be detected and corrected.

3.2. Modeling Active Learning

As stated above, the main issue about the passive learning is that for the teacher, there is no feedback mechanism from the learner. The learner may misunderstand some parts of the information that is presented; however, as it only

passively listen, they cannot declare the issue to the teacher. Actually, the learner may not be aware that it misunderstands something. Therefore, as a part of the active learning, there needs to be a procedure that allows learner to actively declare what it understands. To model this, we present a feedback procedure after the teaching procedure. During the feedback procedure, the learner robot declares what it has understood from the presented patterns of each color by executing all patterns that it previously saved. In effect, the robots change roles and the teacher robot watches the demonstrations of the learner robot. When the teacher robot gets the feedback by copying the demonstrated patterns of the learner robot, it compares the copied patterns with what it previously presented, by using the ERP function. This comparison immediately reveals that the patterns of the four colors, namely black, blue, green and yellow, are learned accurately (ERP value 0.4545, 0.2953, 0.4747, 0.2723, relatively) while there is a high error in the learned version of the pattern of red (ERP value 1.2137). As a result of the feedback procedure, the teacher robot now can determine which part of the presented information is misunderstood by the learner robot.

Obviously, as the pattern of red cannot be accurately learned by the learner robot, this pattern should be reconfigured and re-thought. The ERP value reveals that there is a high error in the copies of the pattern of red; however, it does not indicate the specific parts of the pattern in which the errors occur. For the reconfigured version of the pattern of red, we program the teacher robot to utilize the pattern that it copied during the feedback procedure. As this pattern was previously reproduced by the learner robot, we assume that it is a pattern that can be accurately learned by the learner. In this way, we are able to model an active learning procedure in which the feedbacks received from the learners are utilized to achieve enhanced learning. The teacher robot presents the new version of the pattern of red, which is shown in figure 7, along with the patterns of other colors to the learner. After this modification, when we check how accurately the 5 patterns are learned by the learner robot, it can be seen that now all the patterns are

learned with high fidelity (ERP value for black, blue, green, red and yellow are 0.2757, 0.1152, 0.3706, 0.3495, 0.1196, respectively). Finally, we repeat the examination procedure to check if the learner robot can discriminate all colors based on the learned patterns. Figure 8 shows the results for the second examination procedure. As can be seen, with updated learned patterns, the learner robot has the correct answer for all colors.

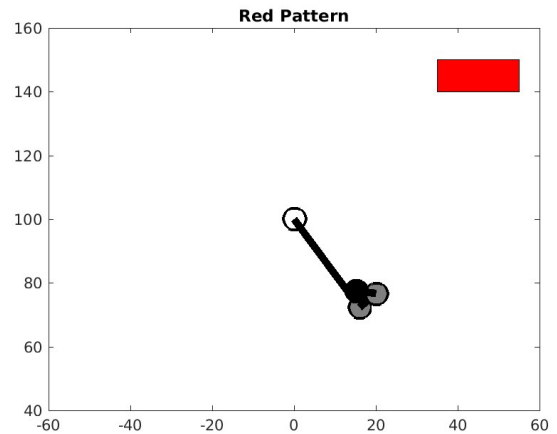


Figure 7. Reconfigured pattern of red.

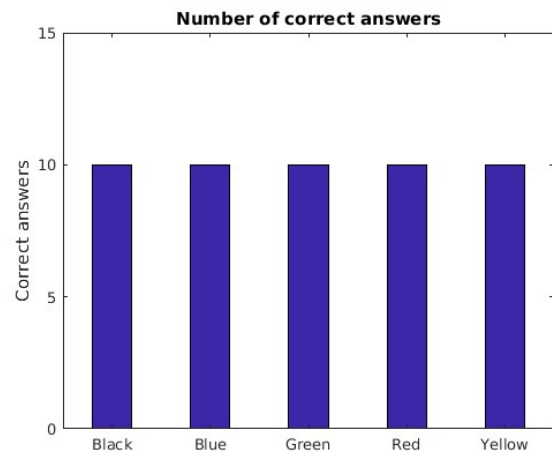


Figure 8. Results of examination procedure with active learning.

4. CONCLUSION

In this research, we aimed to utilize robotic experiments to model a well-known learning method, namely active learning. For this purpose, we initially designed a noisy social environment where mobile robots can visually learn from each other, albeit imperfectly due to uncertainties in

their perceptual system. It is shown that, as the robots learned from each other, the movement trajectories contained some copying errors. In this noisy learning environment, we designed a passive learning procedure in which a teacher robot presented a lexicon that can be used to categorize multiple colors. Based on this method, the learner robot passively observed the movement patterns and then it was tested to determine if the presented information was accurately learned. The experiments revealed that due to copying errors, the learner robot had low performance in detecting the movement pattern of one of the colors. With passive learning method, the learner passively observed, therefore there was no way to overcome this issue. Later, we designed an active learning method that includes an extra feedback procedure during which the learner robot declared what it understood from the presented information. Based on the feedback that it received from the learner robot, the teacher robot was able to determine which part of the presented information was misunderstood by the learner robot. As the teacher robot reconfigured the misunderstood parts, an increase in the learning performance was observed. In this way, we were able to model an active learning method in which the learner actively participated in the learning process. Based on our model, we were able to qualitatively show how and why active learning approach enhances learning.

The active learning method that is modeled in this research involves two of the principles that were presented by Barnes [6]. First, the method is reflective as the learner robot was allowed to express what it understood during the feedback procedure. Second, the method is negotiated as the final reconfigured version of the pattern of red was determined based on the feedback from the learner robot. Therefore, in effect, the teacher and the learner negotiated the objectives and the methods of learning. It should be possible and testable to model and examine other active learning principles on robotic platforms that involve noisy social learning between robots.

In our experiments, robots learned a simple categorization task. The robots were able to achieve a high performance with the help of one

feedback procedure. However, with a more complex learning task, we may need to run multiple feedback procedures to achieve an enhancement in learning. In this respect, the feedback procedure should be designed as a feedback loop so that it can be repeated until an agreement on the content of the presented information can be achieved.

Our analysis reveals some important deductions about active learning methods. As other researches strongly suggested, the participation of the learners in the learning process is a crucial factor for enhancing learning. The learners should definitely possess ways of expressing themselves and they should be able to clearly explain what they understand. For this purpose, students should be encouraged to write, talk and discuss from an early age so that they can effectively be a part of an active learning environment.

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