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Robots That Think Fast and Slow: An Example of Throwing the Ball Into the Basket

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ABSTRACT Can a robot think like a human being? Scientists in recent years have been trying to achieve this dream, and we are also committed to this same goal. In this paper, we use an example of throwing the ball into the basket to make the robots process with human-like thinking behavior. Such thinking behavior adopted in this paper is divided into two modes: fast and slow. The fast mode belongs to the intuitional reaction, and the slow mode represents the complicated cogitation in human brain. This fascinating human thinking concept is inspired by the book, *Thinking, Fast and Slow*, which explains the process of the human brain. In addition, the psychology theories proposed in this book are also adopted to realize the thinking algorithms, and our experiments verify that the thinking mode of human beings is reasonable and effective in robots.

INDEX TERMS Anchoring effect, fast and slow systems, FIRA, humanoid robot, learning algorithm, peak-end rule, psychology.

I. INTRODUCTION

An interesting concept of human thinking has been proposed in *Thinking, Fast and Slow* [1], and it explains the process of the human brain. This concept divides human thinking into two modes, fast and slow. The fast mode, System 1, belongs to the intuitional reaction, and the slow mode, System 2, represents the complicated cogitation in human brain. However, can a robot think like a human being? Here we show an example of throwing the ball into the basket to make the robots implement the human-like thinking behavior. In this study, we built two humanoid robots, David Junior and David II [2], to accomplish the experiments. Robots are asked to place on the basketball field to learn the best shooting motion by the fast-slow system. The establishing and correcting procedure of System 1 and System 2 are fully presented in the experiments. In addition, some psychology theories are also adopted to realize the thinking algorithms [3]–[5]. Our results demonstrate that though the human thinking behavior is certainly effective in a robot, peak-end rule [3],[4] and anchoring effect [5], which are seemingly defective, are helpful in the procedures. In recent years, many of intelligent methods are derived from biological effects similar to animals' distinctive behaviors [6], such as genetic algorithms [7]–[11], particle swarm optimization [12]–[16], artificial bee colony optimization [17]–[19], ant colony optimization [20]–[24], or other developed robots with animal behaviors [25]–[27]. Nevertheless, human thinking is the most intelligent and complicated type of thinking. The powerful deep learning method [28]–[32] is also inspired by the process human brain. So it is worth adopting human psychological theories to develop a novel machine learning method to solve other complex engineering problems, and make the machines more intelligent in the future.

Due to the explosion of knowledge, scientists can barely do research manually today [33]. Even though the processing speed of computers nowadays is much higher than that of the human brain, the functions of computers, such as recognition and navigation, still cannot compare with those of human beings [34]. And scientists continue to enhance the intelligence of robots to improve our living environment [35]. They are committing themselves to promoting creativity [36], interaction ability [37], natural language speaking ability [38], and collective intelligence [39] in the robot, and so on.

Furthermore, brains are the fountain of wisdom of this world. In order to forage, avoid predators, mate and protect offspring, the brains of our ancestors became more intelligent over hundreds of millions of years of evolution [34]. Nevertheless, we still do not understand our brains well enough. The potential of the human brain is very powerful, but we have no efficient way to explore it. Therefore, building a brain-based robot to understand the whole process of the human brain is important and urgently needed [40]. In the case of the robot, its artificial brain ought to understand itself to be able to handle all kinds of missions. In order to be able to coexist with robots in the future, cognitive algorithms and the personality of robots can also be achieved through experiments [41]. Furthermore, the machine learning methods of robots have caused a revolution in education. Psychology, neuroscience, and machine learning are considered among the principles of human learning [42]. All in all, the brain-based robot provides a pipeline for exploring the process of the human brain, and this learning concept can be employed in other applications. We believe that when the psychological learning theories of human beings and robots are consummated, the interactive and cooperation mode between humans and robots will be entirely changed in the future.

The major contributions of this paper are 1) using an example of throwing the ball into the basket to make the robots process with human-like thinking behavior; 2) adopting the proposed cognitive learning algorithm to construct the experience curve of the shooting postures for basketball games; 3) unprecedentedly utilizing the concepts of peak-end rule and anchoring effect to enhance the learning process and final results; and 4) presenting the feasibility and practicality of the proposed novel learning algorithm.

This paper is organized as follows. In Section II, the background knowledge in *Thinking, Fast and Slow* are introduced. The architectures of the basketball learning system are described in Section III. The learning methods for the basketball competitionare depicted in Section IV. In Section V, the experimental results are presented to verify the feasibility and practicality of the proposed method. The discussions of the proposed method are addressed in Section VI. Finally, Section VII concludes the paper.

II. BACKGROUND KNOWLEDGE

A. THE TWO SYSTEMS

From the point of view of psychology, thinking behavior can be divided into two modes, fast and slow, and psychologists have been intensely interested in this behavior for several decades. These two thinking modes are named ''System 1'' and ''System 2,'' and they play different roles in the human brain. These two modes in our brain also have different personalities and functions; they usually take turns dominating our thinking behavior. System 1 belongs to automated operation mode, in which the reaction time in this thinking is very fast and does not involve spending a lot of effort during the operation. And because it is autonomous, we cannot control what it does at all. System 2 involves laborious and time-consuming work; its operation is logical and complicated. We have to spend a lot of extra effort when System 2 is in operation. Therefore, System 2 can also be regarded as the aspect of rational thinking in the human brain.

Generally speaking, System 1 has the characteristics of intuitive thinking, and System 2 has the characteristics of logical thinking. At first glance, System 2 seems to be much more reliable than System 1. But human beings almost entirely use System 1 for thinking in daily life. For instance, we do not have to pay much attention to thinking when we walk over to the table and drink a cup of coffee. Moreover, we do not have to think hard about running or riding a bicycle while doing these actions. In other words, System 1 is the industrious worker in the brain. Precisely since its operation does not take much effort, it can run almost all day and does not get tired at all. On the other hand, System 2 does not appear frequently. And it usually does not interfere with determinations made by System 1 or accept decisions easily. Therefore, System 2 is called ''The Lazy Controller [1].'' All in all, System 1 and System 2 have different roles and functions in the brain.

TABLE 1. The operating occasions of System 1 and System 2.

System 1	System 2
Answering 1+1=?	Answering 52×48=?
Catching a falling vase.	Memorizing a speech draft.
Dodging a flying tennis ball.	Overtaking on the highway.
Drinking a cup of water.	Searching for a lost friend in a crowd.
Understanding the title of a book.	Planning the cost of next month.

The operating occasions of System 1 and System 2 are illustrated in Table 1, where System 1 is suitable for handling simple problems and some reflex actions which need to be performed quickly, while System 2 is usually used for solving complex problems. Furthermore, when a decision made by System 1 is wrong, or the situation is too complex to solve, System 2 will take over to resolve the problem. Based on the above, the thinking behavior of human beings is processed by these two cores. However, they cannot work alone in one human being because both of them are not perfect at all. We can obtain the most efficient way to make a right decision only through the proper division of labor on the part of System 1 and System 2. Therefore, it is important to select a suitable thinking mode at the appropriate time in our daily lives.

B. PEAK-END RULE

Kahneman's colonoscopy experiments give interesting results [1]. As shown in Fig. 1, why does patient A, who has a shorter pain time, feel more miserable than patient B? The experimental results tell us a surprising fact: The length of the process has no effect on the rating. No matter how long the pain time is, the overall rating only depends on the most painful moment of the experience and its end. That is to say, the average intensity of feeling will not be influenced by the length of the process [3], [4]. Such a phenomenon always follows the ''peak-end rule.''

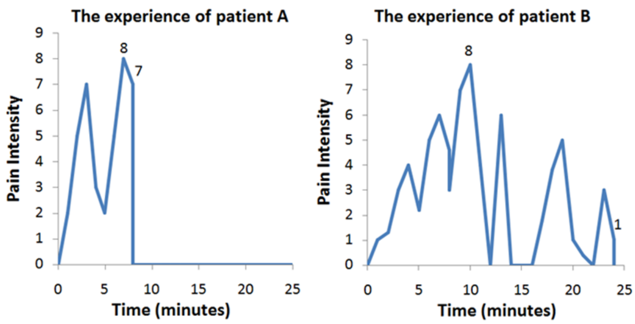

FIGURE 1. Kahneman's colonoscopy experiments [1].

C. ANCHORING EFFECT

The anchoring effect is already widely used in commercial fields. The promotional advertising of Campbell's soup in Sioux City is a good example [1]. The sales with a "limit of 12 per person" are two times larger than the sales with "no limit per person." No matter whether "12 cans" is the result of a precise calculation or random generation, this will become an anchor and produce an anchoring effect subconsciously in consumers. Furthermore, Kahneman's experiment on "wheel of fortune [1]" has a very amusing result. Why is the percentage of African nations in the United Nations related to a wheel of fortune? Participants' judgments were influenced by an obviously uninformed number5. These seemingly absurd results show that the anchoring effect does absolutely and constantly happen today.

III. ARCHITECTURES OF THE BASKETBALL LEARNING SYSTEM

Computer analogy involves developing computational models to understand human or animal cognition. With human beings as an example, the aim of this discussion is to describe the similarities that might exist between algorithms and the way people think. This approach can be applied to imitating the operation of the human brain. In this section, the architectures of the basketball learning system will be described as follows.

A. ROBOT ARCHITECTURES

Since David Junior is a humanoid robot, he possesses a human-like appearance. David Junior has 26 Degrees of Freedom (DOF). He weighs 9.6 kg and is 95 cm tall. The material of mechanism consists of Al-Mg alloy, Acrylonitrile Butadiene Styrene (ABS), and Polyoxymethylene Resin (POM).

Aluminum-magnesium is widely applied to David Junior, especially in the skeleton, because of the high stiffness and light weight. However, there are many series of Al-Mg alloy. The parts, including the hip and ankle, are made of A7075 alloy since these parts require the highest stiffness and strength. Other parts such as the arm and body are made of A6061 alloy. In order to reduce the weight of the robot, the parts that sustain light loading are made of ABS such as the hands, head, and so on. All the gears of David Junior are made of POM rather than steel because the strength of POM is enough for the load of David Junior. David Junior has 26 DOF in total, and most of the joints are actuated by one motor. However, some joints of the robot such as the knee sustain high loading, and the power of a single motor is insufficient for these parts. Therefore, the high loading parts are actuated by two motors, which are connected by a synchronization cable or actuated by one motor with a gear to enhance the torque.

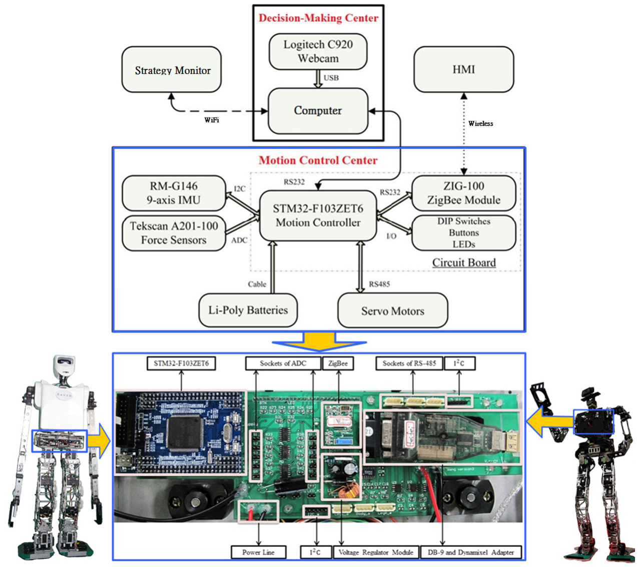

FIGURE 2. The system architecture of David Junior and David II.

To meet all the requirements of our own robot, the best way is to design the peripheral circuit board for all the required parts. The system architecture and the integrated circuit board are shown in Fig. 2. The architecture of David Junior and David II includes two main parts: One is the Decision-Making Center and the other is the Motion Control Center. Besides, we put an emphasis on the autonomy of the robots, so it is important that the robots have a brain to decide "what to do." In the robots, this part is called the Decision-Making Center and consists of a webcam as the robot's eye for vision and a laptop associated with image processing, logical strategies, and some other computations. If the robot knows what to do, the commands will be transferred to the next indispensable unit, which tells the robot "how to do" something. We call this unit the Motion Control Center.

B. LEARNING ENVIRONMENT

As with athletes, the aim of their training is to help their actions become intuitive motions. In other words, these practices help them to construct the experience database for System 1. In the same way, the goal of the issue addressed here is to build the experience curve to give David Junior the ability to shoot the ball into the basket from any angle. System 1 is also an intuitive thinking process. Its thinking movement is not only very fast but also effortless. In addition, it can be thought of as the accumulation of the experiences of human beings. When System 1 is dealing with a problem, it

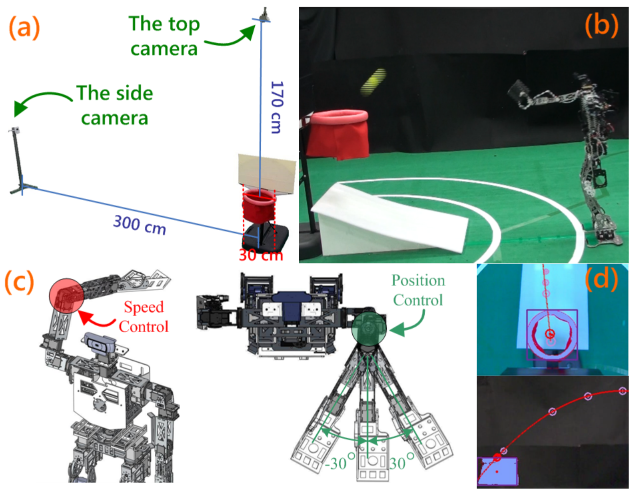

FIGURE 3. **Learning environment and control systems of David Junior.**

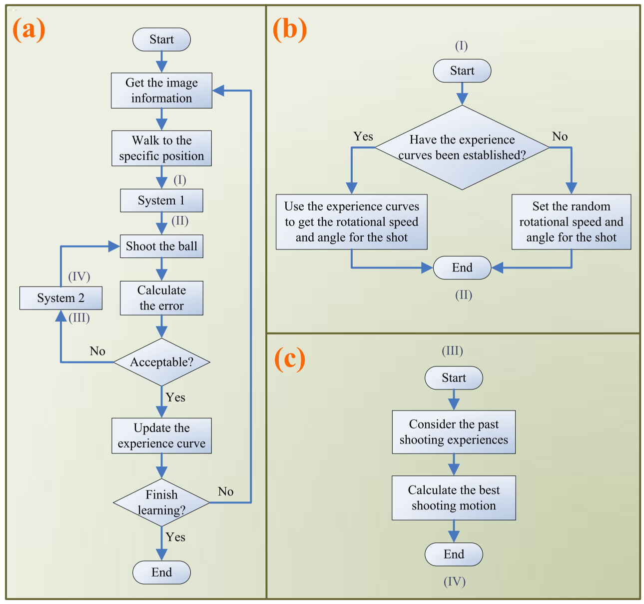

FIGURE 4. **The system flowcharts of the proposed learning algorithms.**

wants to use a look-up table approach to get answers from past experiences. In this issue, two polynomials represent the rotational speed and angle experimental functions, respectively. Therefore, the rotational speed and angle decisions made by System 1 can be obtained easily by inquiring about these two experimental functions.

David Junior is a humanoid robot, as shown in Fig. 3(b). He is equipped with a 9-axis inertial measurement unit including web camera, accelerator, gyroscope, and electronic compass. Fig. 3(a) shows the learning environment and the relative position of the basket and two IP cameras. One camera is mounted on the left side of the basket and is 300 cm from the basket. The camera is held in place by an aluminum structure. The other camera is installed in the ceiling and is positioned directly above the basket, which is 170 cm distant from the top camera. As for the basket, it is 30 cm in diameter and is fixed on the plastic structure. Its image data can be transmitted to David Junior to recognize the shooting error. Like human beings, David Junior can make decisions using System 1 or System 2 after these images are captured by the camera on the robot's head. If he makes a decision, whether with System 1 or System 2, his brain will send a message to the motion control center to perform the corresponding motions. The server motor control methods of David Junior's shooting motion are illustrated in Fig. 3(c). We can use the speed and position control to modify the trajectory of the ball. In Fig. 3(d), the upper and lower partitions show the detected ball path in red, the recognized rim framed in purple, and the purple circles representing when the ball has gone through the hoop and been captured by the IP cameras. The red circles denote the calculated falling position of the ball. After that, David Junior can recognize the shooting error so as to adjust his shooting motion for another try.

IV. LEARNING METHODS FOR PLAYING BASKETBALL

The system flowcharts of the proposed learning algorithm are shown in Fig. 4(a). First, the procedure of the image processing will be executed. The main goal in this step is to get information on the target as long as the object has been recognized. According to the values of the distance and direction between the basket and David Junior, he will step forward, step back, turn left, or turn right autonomously to meet the requirements of the distance and the direction. For example, the robot will keep turning left or right until the angle between the basket and himself is smaller than the threshold. Before deciding the shooting motions, the robot will execute the position adjustment depending on the information on the basket. After that, David Junior will utilize System 1 to decide on the rotational speed and angle he should perform.

David Junior will shoot the ball according to the rotational speed and angle which has just been obtained from System 1 or System 2. After the ball is shot, David Junior will check whether the accuracy meets the requirement or not. The falling location of the ball is used to calculate the shooting error, and the error will be the distance between the center of the basket and the center of the ball. If the ball falls into the region within the quarter of the basket radius, this is called a good shot. If the accuracy situation meets the requirement, the experience curves can be updated. Otherwise, the robot will go to a step in System 2 to have another try at the same position.

As long as the accuracy and the times do not meet the requirement, System 2 will operate. System 2 is logical and is continuously monitoring the human brain. When a decision made by System 1 is wrong, System 2 will take over the thinking behavior and support more detailed and specific processing to solve the problem. However, if the accuracy meets the requirement, the experience curves of the rotational speed and angle will both be updated. The final step is to check whether the experience curves of the power and the direction are completed or not. If the experience curves are completely trained, the learning ends. Otherwise, the distance between the basket and David Junior will change and the learning algorithm will restart from the beginning.

A. THE MODELS OF SYSTEM 1

The models of System 1 can be defined as the following equations.

$$S_{sys1} = c_{s0} + c_{s1}l + c_{s2}l^2 + c_{s3}l^3 + \cdots + c_{sn}l^n \quad (1)$$
$$A_{sys1} = c_{a0} + c_{a1}l + c_{a2}l^2 + c_{a3}l^3 + \cdots + c_{an}l^n \quad (2)$$

where S_{sys1} and A_{sys1} are the output values of the shooting rotational speed and angle decided on by System 1, and l denotes the location where the robot stands. c_{s0} to c_{sn}, and c_{a0} to c_{an} are the coefficients of the fitted experience curves. The number of the coefficients is $n + 1$. Because the robot trains the shooting motions at six positions, in this study, n is set to be 5. By the experimental points which have existed, the experience curves can predict the appropriate rotational speed and angle for shooting.

The flowchart of System 1 is shown in Fig. 4(b). First, System 1 will check whether the experience curves have been established or not. As a result, if the experience curves have been established, David Junior will acquire the next rotational speed and angle by inquiring about the two experience curves, respectively. On the other hand, if there are no established experience curves, random rotational speed and angle will be performed for shooting the ball. It is worth noting that random rotational speed and angle are all in the limited ranges constrained by the specification of the motors.

B. THE METHODS OF SYSTEM 2

The flowchart of System 2 is depicted in Fig. 4(c). The aim of System 2 is to find the best shooting motion for the robots. According to past experiences, the robots can use several methods to estimate the optimal motion. However, the methods of System 2 can be changed. In this paper, three methods of System 2 (short-term memory, long-term memory, and peak-end rule) are adopted for the experiments.

The short-term memory method is constructed by simple artificial intelligence. The robot can only remember the last experience to adjust the motion of the next shot. The adjustment of the next rotational speed and angle scales depend on the specification of the server motors, and the correction rule is described in equations (3) and (4).

$$S(t+1) = \begin{cases} S(t) - \Delta S_3 \times \operatorname{sgn}(e_y), & \text{if } |e_y| > R \\ S(t) - \Delta S_2 \times \operatorname{sgn}(e_y), & \text{if } R \geq |e_y| > (R/2) \\ S(t) - \Delta S_1 \times \operatorname{sgn}(e_y), & \text{if } (R/2) \geq |e_y| > (R/4) \\ S(t), & \text{if } |e_y| \leq (R/4) \end{cases} \quad (3)$$

$$A(t+1) = \begin{cases} A(t) - \Delta A_3 \times \operatorname{sgn}(e_x), & \text{if } |e_x| > R \\ A(t) - \Delta A_2 \times \operatorname{sgn}(e_x), & \text{if } R \geq |e_x| > (R/2) \\ A(t) - \Delta A_1 \times \operatorname{sgn}(e_x), & \text{if } (R/2) \geq |e_x| > (R/4) \\ A(t), & \text{if } |e_x| \leq (R/4) \end{cases} \quad (4)$$

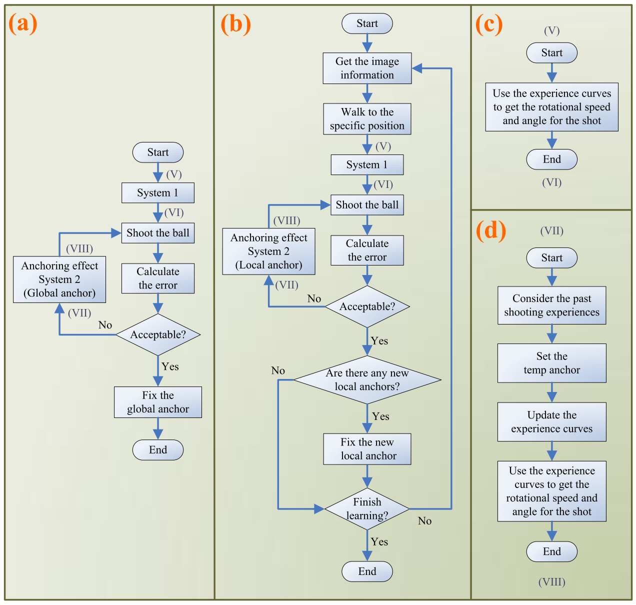

FIGURE 5. The system flowcharts of the anchoring effect adjustments.

where R represents the radius of the basket, e_x and e_y are the errors from the center of the basket to the falling location of the ball, and $S(t+1)$ and $A(t+1)$ are the next output values of the rotational speed and angle at time t. $\triangle S_1$, $\triangle S_2$, $\triangle S_3$, $\triangle A_1$, $\triangle A_2$, and $\triangle A_3$ are the adjusting parameters for the shooting rotational speed and angle.

In aspect of the methods of System 2, both the long-term memory type and the peak-end rule type can remember all the past experiences. However, the estimating method of the long-term memory type is obtained by a regression line, and this regression line is calculated from all the shooting experiences. Although these three methods all give acceptable results, the performances of the long-term memory type and peak-end rule type are better than those of the short-term memory type. On the other hand, the peak-end rule type just uses the best and the last experiences to correct the shooting motion. The calculated amount of the peak-end rule type is lower than that of the long-term memory type.

C. ANCHORING EFFECT

The anchoring effect has been widely used in the commerce field. However, this is the first paper which has adopted the concept in robots. The adjusting process of the anchoring effect (global anchor) is illustrated in Fig. 5(a). If the voltage of the batteries is insufficient, the robot will start the adjusting process of the global anchor. After the robot shoots the ball using System 1, the shooting error will be calculated. If the error is not acceptable for the robot, the anchoring effect of System 2 will be enabled to modify the effect of System 1 by a global anchor. Because the robot cannot ensure the best position of the global anchor, System 2 will continuously adjust the global anchor to obtain the most appropriate value. If the adjustment is completed, then the global anchor will not be modified until the status of the robot is restored.

The adjusting procedure of the anchoring effect (local anchor) is depicted in Fig. 5(b). Unlike the global anchor, many local anchors can be added into the experience curves. In addition, because of the damage to the robot, the robot cannot throw precisely from some specific positions using the old System 1. Therefore, if the robot cannot perform a good shooting motion, a local anchor will be added into System 1. Then, the anchoring effect of System 2 will start to adjust the position of the local anchor. After several adjustments, the robot will be able to shoot precisely, and the local anchor will also be fixed. If all the distances in which the robot stands are adjusted, the adjustment is completed.

The process of the anchoring effect of System 1 is denoted in Fig. 5(c). The robot will perform the shooting motion by the rotational speed and angle from the experience curves. On the other hand, the process of the anchoring effect of System 2 is shown in Fig. 5(d). According to past shooting experiences, a temporary anchor can be added or modified to update the experience curves. Then the updated System 1 is used to obtain the next shooting motion. Besides, without a complicated retraining process, all the anchors can be removed to perform the original System 1 if the robot reverts to the initial condition.

V. EXPERIMENTAL RESULTS

In this section, three parts of the experiments are presented. Part A is the basketball learning process. A comparison of the three types of System 2 is shown in Part B. Furthermore, the tuning processes of anchoring effect are revealed in Part C.

A. BASKETBALL LEARNING PROCESS

The primary purpose of the issue is to make the robot learn the shooting rotational speed and angle by himself. Here we adopt two robots, David Junior and David II, to accomplish this task.

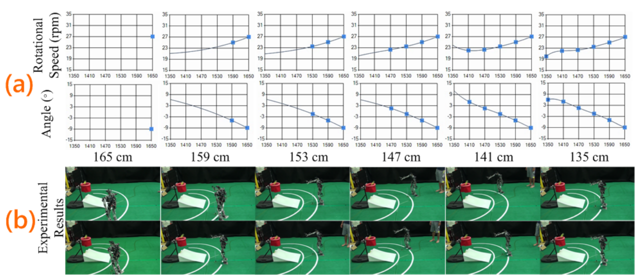

FIGURE 6. The learning process and final results.

The construction process of System 1 is illustrated in Fig. 6(a). The upper and lower figures belong to the shooting rotational speed and angle, respectively. Initially, David Junior stands at the position where the distance between the basket and the robot is 165 cm. In general, David Junior acts like a human being, and his decisions are instinctively made by System 1 at first. However, the decisions made by System 1 may not always be reasonable [43]. If a decision is wrong and unacceptable, System 2 has some ability to change the ideas produced by System 1, and it will take over to solve these problems. No matter the desired shooting motion obtained by System 1 or System 2, the optimal shooting rotational speed and angle will be remembered by an "anchor," as shown in the blue circles in Fig. 6(a). After the memory anchors are remembered, David Junior will construct a new experience curve and walk forward to another position for the next learning step. Finally, the learning process will be completed when the robot establishes all the experience curves at 135 cm. After the learning process, we place the ball randomly at 12 different positions. Then David Junior gets the ball and utilizes the established System 1 to shoot the ball into the basket, as shown in Fig. 6(b).

The learning environment of David II is presented in Fig. 7. In Fig. 7(c), the trained experience curves are different from those of David Junior because the robot model and the shooting motion of David Junior and David II are different. Furthermore, the effects of the changes in the rotational speed and angle are dependent. In other words, the increased rotational speed may change the shooting direction, and the changes in the shooting angle may also influence the shooting power. Therefore, the experience curves may not be linear at all. The cognition of human beings may be different, which is also true for robots. And for different robot models, various motions, or various tasks, System 1 can be established in different ways to achieve specific assignments.

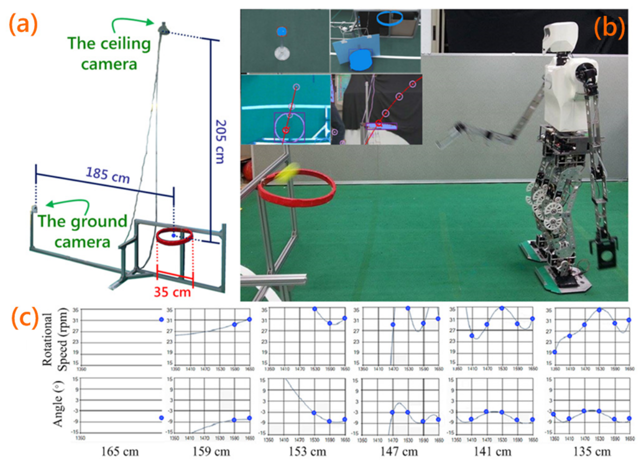

FIGURE 7. The learning environment and the results of David II.

B. PEAK-END RULE

The detailed thinking methods of System 2 can change. For example, the street parking skills of everyone are different, and they also consider the specific subjects they want for the driving references. Even though the thinking methods of System 2 are different, they can still achieve the same goal. Here we utilize three types of System 2. For the short-term memory type, the robot can only remember the last shot, and he only uses the last experience to adjust the shooting motion. For the long-term memory type, the robot can remember all the shots, and he can calculate the best shooting motion by the regression line of all the shooting experiences. For the

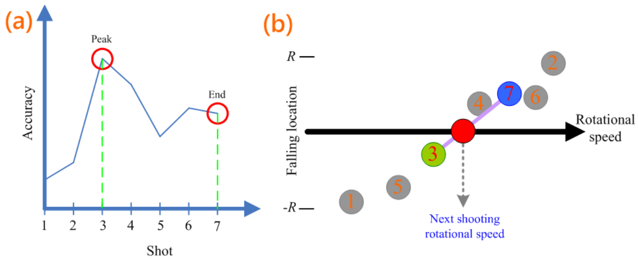

FIGURE 8. **Peak-end rule based System 2.**

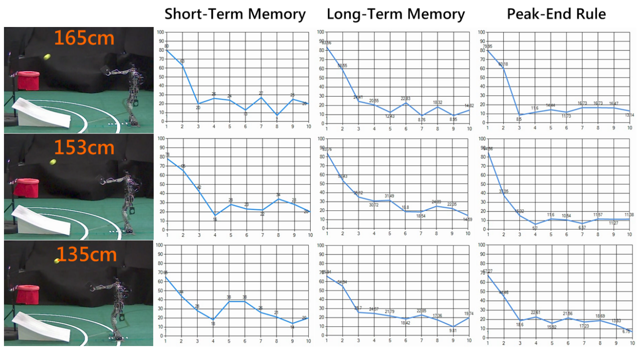

FIGURE 9. **The experimental results of three types of System 2.**

peak-end rule type, the robot can remember all the shots, but only the best and the latest shot are considered for finding the optimal shooting motion, as shown in Fig. 8(a) and (b). Fig. 9 shows the experimental results of the three types of System 2. In this experiment, David Junior stands at three different positions and uses the three types of System 2 to estimate the optimal shooting motion. For these three cases, David Junior can obtain acceptable results from all types of System 2. Obviously, the performances of the long-term memory and the peak-end rule types are about the same, but better than the short-term memory type. However, the calculated amount of peak-end rule type is lower than the long-term memory type. Consequently, the peak-end rule type of System 2 is suggested to be applied for this issue. Surprisingly, the concept of peak-end rule, which is seemingly defective in human beings, is helpful in the process.

C. ANCHORING EFFECT

After the learning process, the shooting motion may change due to a variety of factors, such as the charge of the batteries, the aging of the mechanism, the flatness of the ground, and so on. These factors will change the shooting motion and cause unexpected results. Besides the experience curves representing the angle and rotational speed with which the robot should perform, the optimal angles and rotational speeds in the impression are also assembled by the anchors of the robot. When the robot's old cognition already cannot fit in with the actual environment, it is time to adjust the cognition of the robot. Based on the adjustability of the anchors in the human brain, we establish a learning procedure for David Junior by altering the anchors to overcome these problems. Following are two types of external anchors the robot may adopt.

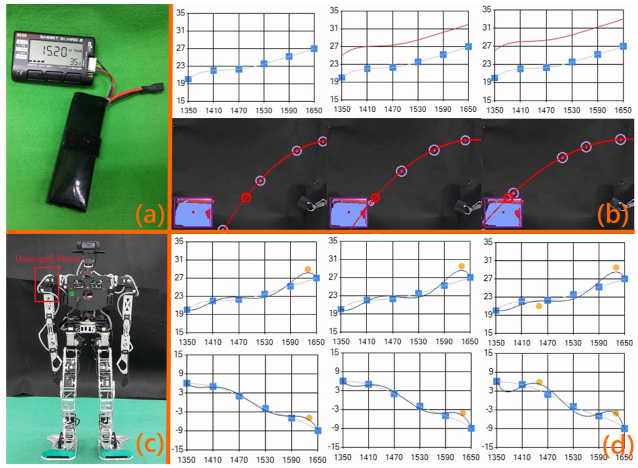

FIGURE 10. **The adjusting process of anchoring effect.**

1) GLOBAL ANCHORS

When we walk to the brand counters, we naturally feel that the commodity prices are much more expensive here than in other areas. This means that in order to meet the reality of the situation, our consumption anchors improve comprehensively. Similarly, if the robot has low battery voltage, as shown in Fig. 10(a), the overall shooting rotational speed will be reduced. Therefore, in order to make the robot meet our expectations, adding a global anchor to the robot is an efficient way. All the values will be shifted higher or lower by the global anchor to correct the shooting motion. According to the shooting errors, David Junior can also adjust the value of the global anchor. The adjusting process is shown in Fig. 10(b).

2) LOCAL ANCHORS

When we walk in an environment which is surrounded with brands, sometimes we wonder why certain commodities are still cheap there. Therefore, at this time, some anchors of these certain commodities will be reduced automatically. Similarly, if the robot is damaged by an accident, as shown in Fig. 10(c), the robot may not perform well in some specific cases. Therefore, placing local anchors on the robot is a good choice for solving this problem. As shown in Fig. 10(d), the experience curves will be revised precisely by the local anchors (the orange circles). The adjusting process of the local anchors is shown in Fig. 10(d).

As basketball players do, if their physical condition is not very good or the competition environment is not familiar to them, the players will try to adjust their playing motions to keep up their skill level. However, if the players come back to the accustomed environment in good physical condition, they can simply remove the adjustments and not have to relearn all of their basketball playing skills to play the game. This is the same with robots; if all the situations of the robot are restored, the added anchors can be removed immediately. The robot's System 1 will also revert to the initial situation. Besides, in order to verify the feasibility of the proposed learning concept in other robot models and motions, David II participates in experiments. David II is also a humanoid robot, but he is higher than David Junior. In addition, the throwing motion of David II is different from that of David Junior. No matter what robot we use, or what throwing motion it performs, the throwing task scan still be achieved by the proposed learning concept. Moreover, the models of System 1 and the adjusting method of System 2 can be modified for different cases. For the reasons above, the proposed learning concept is practical and can also be utilized for many applications in the future.

VI. DISCUSSIONS

Previously, the conventional method to achieve this task was dealing with human-in-the-loop testing, and the tuning time was about 90 minutes. The proposed method provides an autonomous learning procedure for a robot, and the learning time is within 20 minutes or even faster. The operating efficiency is much improved, and the robot can shoot precisely from any distance and direction after the learning process. In the experiment, the robot can shoot precisely at 12 random positions. Besides, the competition results also validate the robustness of the proposed method. If the charge of the batteries or the flatness of the ground is changed, the anchoring effect method can be immediately adopted for the correction of the robot's experience curves. In System 2, the concept of peak-end rule used in the algorithm can also reduce the computational cost. Since the first international robot competition was held at KAIST, Daejeon, Korea in 1996, the FIRA RoboWorld Cup [44] has become an important indicator of international robot contests in the world. Our laboratory, aiRobots, has been actively involved in this contest for a decade. Moreover, we have won the championship in the basketball event for six consecutive years and the all-round championship for last three years. Obviously, such an algorithm which mimics human thinking is feasible and practical. The experiments also verify that the thinking mode of a human brain is reasonable, and it can also be applied to make the robot think more like a human being.

The proposed learning algorithm is similar to the internal and external control loops in a complicated control system. Nevertheless, in the field of system control, some theories and control methods also include the analogous concepts of fast and slow, such as implicit and explicit control [45], slow-fast systems in singular perturbation theory [46], and cascade control [47]. However, these concepts must involve a system model and so are hard to apply in this work. The autonomic nervous systems and higher cognitive functions in animals are one kind of neurological cognition. In this paper, the proposed algorithm emphasizes the learning of cognitive behaviors to establish a human-like learning system in a humanoid robot.

In order to reduce the effect of the luminance variations, HSV [48] color space is used in the searching, and matching process of this work. However, if the complexity of the searched object is getting higher, the Binary Robust Invariant Scalable Keypoints (BRISK) [49] can be applied in the future work. Besides, the model of System 1 can also be changed. In order to improve the accuracy of the System 1 in the future work, the established experiences curves can be represented by Extreme Learning Machines (ELMs) [50], which tries to make human like machines with minimum training.

For scientists, one of the main goals of robotic development is for robots to be made to more closely resemble human beings. The proposed learning method is very close to that of human thinking, and these thinking behaviors have already been proved by psychological theories. Moreover, the celebrated phenomena in psychology called peak-end rule and anchoring effect are also utilized in this cognitive learning algorithm in an unprecedented way to improve the learning process and the final results. For a basketball player, the training process for the shooting motion must be executed from every orientation. However, David Junior can be trained in just one direction, and he performs the precise shot in all the orientations through the proposed method. In the experiments and competitions, there are many good validations showing that the proposed novel learning method is feasible and practical, and it indeed enhances the intelligence of the humanoid robot in the basketball training event.

D. Kahneman began surveying the thinking systems of human beings in 1979, and he was awarded the Nobel Memorial Prize in Economics in 2002. In 2011, he wrote a book, *Thinking, Fast and Slow*, to systematically address these research achievements. The current paper continues to use these appellations, which are unprecedented, to design a novel learning method for humanoid robots. In this paper, the theoretical evidence and empirical proofs of the thinking systems have already been proved by psychologists in many research studies [3]–[5]. The evidence is quite strong and exact, and it has matured in psychology in the past few years. Moreover, these psychological concepts used in basketball learning events have also been validated in experiments and robot competitions. As a result, this paper adopts these concepts in reasonable ways. From the standpoint of engineering, at least the proposed learning algorithm is feasible for realization in a humanoid robot.

Up to now, the literature on basketball learning applications is still quite scarce. Classical methods have been unable to solve shooting motion learning from a practical standpoint. In terms of learning, any method can be utilized for the fixed shooting position, but these methods are hard to integrate into System 1 and System 2 since the proposed learning method is not only a process of finding the best parameter or solution, but also an entire thinking framework in robot intelligent systems. In the aspect of the basketball learning event, the construction procedure of the experience curves requires two reflecting cores. One is the instinct response (System 1) for testing; the other one is the rational thinking (System 2) for supervising and correcting. If and only if the experience curves are comprehensively established can the robot shoot precisely from various distances. However, the general classical methods do not consist of two such computing cores. Due to this issue, classical methods are hard to apply in this case. A specific problem may be solved by several methods. However, this is the first paper which has adopted the concepts of cognitive psychology from *Thinking, Fast and Slow* to develop a learning method for a humanoid robot.

The learning algorithm proposed in this paper is inspired by the concept of human thinking systems, and this learning method can be further used in many applications. For example, when a small child is learning to catch an object, he or she may perform imprecisely at the beginning. This is because the System 1 of the child is not well established in this state. Therefore, System 2 will take over the decision process to "think" how to accomplish this task. In the process of dealing with the correction by System 2, System 1 is also modified according to the experiences of the child. After several tries, the System 1 of the child will be well established, and she or he can finally catch the object intuitively without any misses. However, this thinking method not only works in human beings, but also in robots. The ability to catch an object is an important issue in robotics, and the proposed method can also be used for this function in future work. This is the first paper to adopt the concepts of cognitive psychology, which may provide a different and efficient way to solve learning problems in the future.

The proposed concept applied in robots is novel, and the basketball event is chosen for the validations. However, besides the applications of basketball events and catching an object, there are still many functions which can adopt this learning method. As long as the behavior can be executed by a fitting model (even just a lookup table), the fitting model can be treated as System 1. Then complicated calculations (System 2) can be established to monitor and modify the decisions of System 1. As a result, the learning effect is already achieved, and this learning method can easily be utilized in many applications. Moreover, the model of System 1 and the calculating method of System 2 are changeable, depending on the experimental environments or different cases. For other applications, the proposed algorithm may provide a good solution for robotic learning issues in the future.

VII. CONCLUSIONS

A novel psychology learning algorithm has been proposed in this paper. This algorithm is derived from *Thinking, Fast and Slow* by Daniel Kahneman, the Nobel Memorial Prize winner in 2002 for Economic Science. Like a human being, the developed humanoid robots, can apply the thinking modes, System 1 and System 2, to accomplish the learning process for basketball games. The concepts of peak-end rule and anchoring effect are unprecedentedly used to enhance the learning process and final results. What is noteworthy is that these two phenomena are seemingly defective in human beings, but are very helpful in the learning procedures. Furthermore, the performance and practicality of the proposed cognitive learning algorithm has had good validations at FIRA RoboWorld Cup 2015. By the construction of the cognitive learning algorithm, this concept can be applied to many applications in the future, and the preliminary step of the investigation of a robot's cognitive psychology is demonstrated in this paper.

APPENDIX

In the aspect of controlling the falling position of the ball, inverse kinematics cannot provide the entire solution for adjusting the shooting motion because this motion must involve the speed and angle control of the server motors. Nevertheless, inverse kinematics still plays an important role in this study. As shown in the supplementary video, there are many hand motions David Junior must perform, such as catching the ball, raising the ball for shooting, and so on. Except for the final state of the shooting motion, all the hand motions of David Junior are controlled by inverse kinematics.

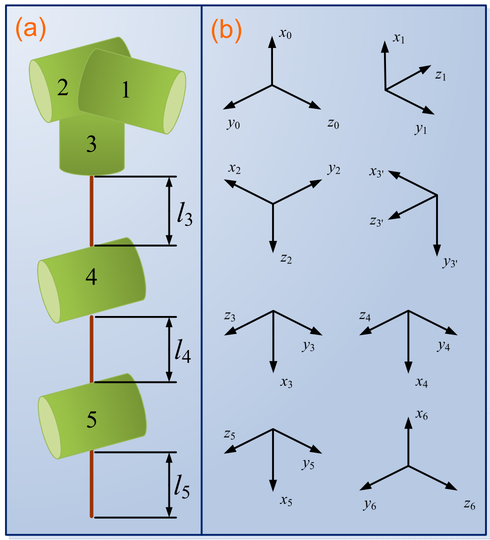

FIGURE 11. The coordinate frames and joint definition of David Junior's hand.

TABLE 2. D-H parameters of David Junior's hand.

i	θ_i	α_i	a_i	d_i
1	θ_1	90°	0	0
2	θ_2-90°	90°	0	0
3'	θ_3	90°	0	l_3
3	90°	0°	0	0
4	θ_4	0°	l_4	0
5	θ_5	0°	l_5	0
6	180°	90°	0	0

The coordinate frames and the joint definition of David Junior's hand are illustrated in Fig. 11. According to these definitions, the Denavit-Hartenberg (D-H) parameters of David Junior's hand can be established, as shown in Table 2. Therefore, the transformation matrices can also be obtained as follows.

$$H_i^{i-1} = \begin{bmatrix} \cos\theta_i & -\cos\alpha_i \sin\theta_i & \sin\alpha_i \sin\theta_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\alpha_i \cos\theta_i & -\sin\alpha_i \cos\theta_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_1^0 = \begin{bmatrix} \cos\theta_1 & 0 & \sin\theta_1 & 0 \\ \sin\theta_1 & 0 & -\cos\theta_1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_2^1 = \begin{bmatrix} \cos(\theta_2 - 90^\circ) & 0 & \sin(\theta_2 - 90^\circ) & 0 \\ \sin(\theta_2 - 90^\circ) & 0 & -\cos(\theta_2 - 90^\circ) & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \sin\theta_2 & 0 & -\cos\theta_2 & 0 \\ -\cos\theta_2 & 0 & -\sin\theta_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_{3'}^2 = \begin{bmatrix} \cos\theta_3 & 0 & \sin\theta_3 & 0 \\ \sin\theta_3 & 0 & -\cos\theta_3 & 0 \\ 0 & 1 & 0 & l_3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_3^{3'} = \begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_4^3 = \begin{bmatrix} \cos\theta_4 & -\sin\theta_4 & 0 & l_4\cos\theta_4 \\ \sin\theta_4 & \cos\theta_4 & 0 & l_4\sin\theta_4 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_5^4 = \begin{bmatrix} \cos\theta_5 & -\sin\theta_5 & 0 & l_5\cos\theta_5 \\ \sin\theta_5 & \cos\theta_5 & 0 & l_5\sin\theta_5 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$H_6^5 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Then, we can define the matrix P to represent the transformation matrix H_5^0. According to the position (P_x, P_y, P_z) and the orientation matrix we gave, all the rotational angles of each server motor can be obtained, as shown in the following equation.

$$H_5^0 = H_1^0 H_2^1 H_{3'}^2 H_3^{3'} H_4^3 H_5^4 H_6^5 = P = \begin{bmatrix} r_{11} & r_{12} & r_{13} & P_x \\ r_{21} & r_{22} & r_{23} & P_y \\ r_{31} & r_{32} & r_{33} & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Fig. 12 shows the geometric relationships among the links. According to the relationships, l_{05} can be obtained by the following equations. Then, we can use the cosine theorem to calculate θ_4, and determine the plus or minus sign of θ_4.

$$H_4^0 = P\left(H_5^4 H_6^5\right)^{-1} = \begin{bmatrix} * & * & * & P_x + l_5 \times r_{11} \\ * & * & * & P_y + l_5 \times r_{21} \\ * & * & * & P_z + l_5 \times r_{31} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$l_{05} = \sqrt{(P_x + l_5 \times r_{11})^2 + (P_x + l_5 \times r_{21})^2 + (P_x + l_5 \times r_{31})^2}$$

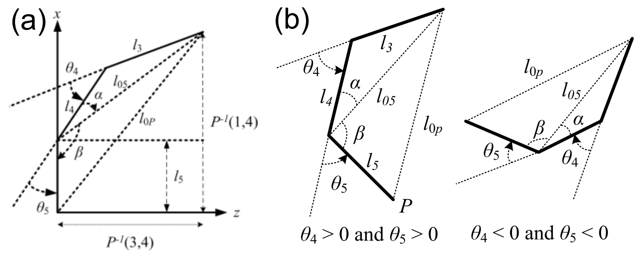

FIGURE 12. The geometric relationships among the links.

$$\theta_4 = \pm\cos^{-1}\left(\frac{l_{05}^2 - l_3^2 - l_4^2}{2 l_3 l_4}\right)$$

In order to obtain the angles of α and β, l_{0P} must first be calculated. As depicted in Fig. 12(a), we can also figure out the relationship of θ_5, α and β. Then, the plus or minus sign of θ_5 is determined by θ_4.

$$l_{0P} = \sqrt{P_x^2 + P_y^2 + P_z^2}$$
$$\alpha = \cos^{-1}\left(\frac{l_{05}^2 + l_4^2 - l_3^2}{2 l_{05} l_4}\right)$$
$$\beta = \cos^{-1}\left(\frac{l_{05}^2 + l_5^2 - l_{0P}^2}{2 l_{05} l_5}\right)$$
$$\theta_5 = \operatorname{sgn}(\theta_4) \times \left(180^\circ - \alpha - \beta\right)$$

Considering the following equation, θ_3 can be obtained by the left hand side and right hand side of H_3^0.

$$H_1^0 H_2^1 H_{3'}^2 H_3^{3'} = P\left(H_4^3 H_5^4 H_6^5\right)^{-1}$$

$$LHS = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & \cos(\theta_2) \times \cos(\theta_3) & -\cos(\theta_2) \times \sin(\theta_3) & * \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$RHS = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & r_{33} \times \cos(\theta_4 + \theta_5) - r_{31} \times \sin(\theta_4 + \theta_5) & r_{32} & * \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\sin(\theta_3) = \frac{-r_{32}}{\cos(\theta_2)}$$
$$\cos(\theta_3) = \frac{r_{33} \times \cos(\theta_4 + \theta_5) - r_{31} \times \sin(\theta_4 + \theta_5)}{\cos(\theta_2)}$$
$$\theta_3 = \tan^{-1}\left(\frac{-r_{32}}{r_{33} \times \cos(\theta_4 + \theta_5) - r_{31} \times \sin(\theta_4 + \theta_5)}\right)$$

Furthermore, the left hand side and the right hand side of matrix H_2^0 can be calculated as the following equations.

$$H_1^0 H_2^1 = P\left(H_{3'}^2 H_3^{3'} H_4^3 H_5^4 H_6^5\right)^{-1}$$

$$LHS = \begin{bmatrix} * & \sin(\theta_1) & * & * \\ * & -\cos(\theta_1) & * & * \\ -\cos(\theta_2) & * & -\sin(\theta_2) & * \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$RHS = \begin{bmatrix} * & a & * & * \\ * & b & * & * \\ c & * & d & * \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where

$$\begin{aligned} a &= r_{11} \times \sin(\theta_4 + \theta_5)\sin(\theta_3) \\ &\quad - r_{13} \times \cos(\theta_4 + \theta_5)\sin(\theta_3) - r_{12} \times \cos(\theta_3) \\ b &= r_{21} \times \sin(\theta_4 + \theta_5)\sin(\theta_3) \\ &\quad - r_{23} \times \cos(\theta_4 + \theta_5)\sin(\theta_3) - r_{22} \times \cos(\theta_3) \\ c &= r_{32} \times \sin(\theta_3) - r_{33} \times \cos(\theta_4 + \theta_5)\cos(\theta_3) \\ &\quad + r_{31} \times \sin(\theta_4 + \theta_5)\cos(\theta_3) \\ d &= -r_{31} \times \cos(\theta_4 + \theta_5) - r_{33} \times \sin(\theta_4 + \theta_5) \end{aligned}$$

Finally, θ_1 and θ_2 can be obtained by the following equations.

$$\begin{aligned} \sin(\theta_1) &= a, \quad -\cos(\theta_1) = b \\ \theta_1 &= \tan^{-1}\left(\frac{-a}{b}\right) \\ -\cos(\theta_2) &= c, \quad -\sin(\theta_2) = d \\ \theta_2 &= \tan^{-1}\left(\frac{d}{c}\right) \end{aligned}$$

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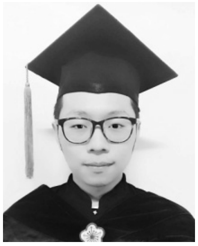

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