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ORIGINAL RESEARCH ARTICLE

A novel human-to-robot interaction model based on transfer expert reinforcement learning with recurrent neural network

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ABSTRACT

The control tasks related to interaction tracking are mainly limited in robot manipulators-based traditional applications. In this, the desired motivations are specified based on the trajectories and the desired positions. The robots are programmed by using the teach-and-playback method in such applications that are assumed to be more convenient. Moreover, the advancements in sensing and robotic methodologies fulfill the satisfactory requirements of more demanding tasks. Several instructions are provided for interacting robots with humans in order to perform a sequence of more difficult tasks. It does not require learning the motions, but it only requires learning the positions of the motions in such applications, and this position is learned by using the robot controller. The major aim of this research work is to develop a new Transfer Expert Reinforcement Learning (TERL) method to offer efficient interaction between humans and computers. In this developed model, Reinforcement Learning (RL) is utilized to observe the movement of the robotic arm. Then, robot movement is considered with the help of a deep learning approach named Recurrent Neural Network (RNN) along with inputs of kinematic movement. Finally, the proposed model achieves a superior rate than conventional approaches in human to human-to-robot interaction model.

Keywords: human to robot interaction model; skill transfer knowledge; transfer expert reinforcement learning; reinforcement learning; recurrent neural network

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1. Introduction

During the last decades, autonomous robots have held a better place in a variety of industrial domains, especially in Industry 4.0 practices[1]. Robots are mainly useful in many daily life activities in addition to industrial applications. In complex environments, robots are used to tackle various tasks, which include household management, eldercare assisting, transferring parcels in natural urban environments, and interacting autonomous robots with humans[2]. To process these application domain requirements, the robots are needed to process a large amount of data during the accomplishment of hundreds of various manipulation and motor skills in a noisy sensor environment, which may depend on the desired tasks' complexity[3]. Moreover, the system can be more complex with the addition of intrusive objectives like disturbance compensation and obstacle avoidance in dynamic environments[4]. Manual programming skills are not sufficient for the development of intelligent autonomous systems under these circumstances, and they can assist humans in supporting daily life tasks in complex environments[5]. The nature of the interaction is the other challenge aroused in this situation, and user experience should be considered here to provide higher integration in day-to-day life activities[6]. Furthermore, the quality of life may also be improved by using this user experience robot activity[7]. When the robot is functioning in a nearby place, the user should feel very comfortable and safe[8].

In this instance, human-related factors like pleasantness and controllability due to user feedback might be helpful for enhancing the human–Robot Interaction (HRI), which may depend on factors like shared autonomy[9]. High dimensional data are processed to obtain the robot skill learning approaches from the robotic arms[10]. The teaching process should be more complex in humanoids when the learning skills are processed through large dimensional datasets[11]. In various robotic assistance strategies, the determination of human feedback is in high demand for a very detailed selection of content and amount of transferred knowledge skills[12]. Most Artificial Neural Networks (ANN) use closed-loop feedback control methodologies to process huge amounts of parameters[13]. In this skill transfer knowledge, the synaptic weights from various layers are chosen to provide efficient interaction[14]. In the autonomous adaptation methodologies, the cognitive models of the multisensory integration and the probabilistic models of the human feedback are utilized instead of broadly using psychometric questionnaires[15], and this may enhance the robot strategies, where the main objective is to learn the transfer knowledge related motor skills from newly adapted samples.

The main contributions of the developed skill transfer knowledge model for providing efficient human-to-robot interaction are given as follows:

- To develop a new TERL method for providing efficient interaction between humans and computers. The concept of skill transfer knowledge by integrating the concept of TERL with the consideration of the robotic arm movement.
- To introduce RL for attaining action features from the robotic arms to maximize the reward signals.
- To develop an RNN network for effectively learning the transfer skill knowledge from the robotic arms for providing better human-to-robot interaction.
- To train the RNN network to decrease the error difference between the desired and predicted movements for a robot.

The overall sections used to arrange this skill transfer knowledge learning model are described as follows. Section II points out the description of traditional human-to-robot interaction models with skill transfer knowledge and its merits as well as demerits. Section III gives a description of the proposed model and the principles behind TERL. Section IV enumerates RNN-based skill transfer learning. Finally, Sections V and VI explain the results and discussions as well as the conclusion.

2. Literature survey

2.1. Related works

In 2017, Ramirez-Amaro et al.[16] presented a human activity recognition framework based on the observation of semantic representations. The difficulties and the challenging issues aroused during the transfer of skills and tasks were addressed in this model. The demonstrator's behaviors have been determined by robots with a higher-level understanding of semantic representations. The essence of the activity has been captured from these observations, and it should indicate the aspect of the demonstrator's actions to be performed to achieve the specified activity. According to the object properties and human motions, an essential semantic representation was obtained. Furthermore, the semantic rules accomplished in distinct conditions were validated. Different labeling strategies, time restriction capabilities, and various execution tasks of different participants were demonstrated by using quantitative and qualitative analysis. This analysis proved that the obtained rules were valid for new situations, and the inferred representations depended on the performed task. Analyzing the implementation results, the developed model attained highly recognized human behaviors with high accuracy. Moreover, the dynamic growth of the ontology-based knowledge representation has been improved using the accomplished semantic rules. The flexibility and the capability of inference have been increased using this developed model.

In 2021, Jayaratne et al.[17] designed a new unsupervised skill transfer learning-based distributed algorithm to provide better human-to-machine interaction in real-life scenarios. This newly developed distributed algorithm has been applicable for skill transfer learning schemes, which needed incremental, unsupervised, and ongoing self-learning of multi-tasks for the transfer of knowledge. Moreover, the data parallelization algorithm has been utilized to find scalable and distributed properties that have been very helpful in handling large volumes of data. This extensive amount of data might be helpful for skill transfer learning based on an unsupervised learning algorithm. Here, multiple maps were generated for the representation of specific skill knowledge, and then a single embedding was used to project these skills. Within an autonomous developmental robotics approach, several algorithms have been demonstrated for skill transfer learning and knowledge acquisition. Finally, three computing platforms such as Spark, Hama, and Hadoop, were adapted to perform empirical evaluations for validating the computational efficiency of the developed unsupervised skill transfer learning framework.

In 2022, Abiodun et al.[18] developed a learning framework for the replication of new skills that have been attained from a human demonstration in order to enable robotic arms. The online data to be obtained from the wearable devices formed an interactive interface that has been helpful for giving anticipated motion in a user-friendly and efficient way. Moreover, appropriate human tutors have been introduced to accomplish complex manipulations and control all joints in the real-time robotic manipulator. For instance, low-cost wearable devices were used to control the robotic manipulator remotely to enhance sensitivity, adaptability, and human-robot skill learning. In addition, it provided continuous motion mapping and easy calibration. The human-robot interaction has been improved when compared to existing models according to repeatability and skill transfer without the need for complex coding skills.

In 2022, Bhatu et al.[19] implemented an effective skill knowledge transfer framework with the help of TERL within humans and computers. The robotic arm movement has been attained by using the advanced RL concept. The Fitness-based Coyote Optimization Algorithm (COA) has been introduced to optimize the action features from the RL algorithm. Moreover, the Deep Neural Network (DNN) has been adopted to find the robot movement with the involvement of kinematic movements. The important contribution of this developed approach was to decrease the error that has occurred between the predicted and desired movement for increasing the reward. The results demonstrated that the developed model attained more benefits than the traditional models.

In 2020, Zahedi et al.[20] proposed a kinesthetic human-robot interaction approach that depended on the machine learning algorithm with virtual training simulations. The skill level of users has been discriminated by using the learned force positional skills. The force data has been attained from the virtual forces that have been designed on the basis of Computed Tomography (CT) data in real-time instead of developing from force sensors. The practice environment has been achieved by using femur bone drilling, and the residents were provoked by haptic feedback, which activated the bone layers' variable stiffness. Here, machine learning tools were used for discriminating the skill level of users, and also the performance has been enhanced via the resident models. The implementation results ensured that the machine learning framework had proven its effectiveness based on the resident models.

2.2. Problem statement

The unstructured and unsupervised learning of complex structures makes it difficult to identify the transfer of knowledge skills from robots. Moreover, several complex coding rules are required for learning the transfer knowledge skills, and hence, this may increase the computational complexity of the models. Hence, several skill transfer knowledge learning approaches are developed for providing the interaction between robots and humans, where the merits and disadvantages of these models are summarized in **Table 1**. Transfer learning[16] allows the flexible imitation of observation-based human behaviors. In addition, it effectively captures the essence of human activities by using semantic rules. But it produces high errors, and also it does not provide better learning results over new behaviors. SOM[17] effectively identifies the transfer of knowledge skills from a large amount of data. Furthermore, it provides high computational efficiency. Yet, it needs grid-based algorithms to reduce the dimension of the large data. The interaction algorithm[18] accomplishes complex manipulations in real time. Therefore, the cost required for using wearable devices is very low. COA[19] highly decreases the error difference in between the predicted and the desired moment. Moreover, the efficiency of the system is highly increased by optimizing the action features. But it requires a high cost to provide the interaction between humans and robots. Neural networks[20] enhance the resident's performance with respect to parameters like temperature and completion time. Yet, it needs more realistic virtual simulations to provide better learning skills. These issues have promoted us to develop a new human-to-robot interaction model based on a deep learning structure.

Table 1. Features and challenges of traditional human to robot interaction models.

Author [citation]	Methodology	Features	Challenges
Ramirez-Amaro et al.[1]	Transfer learning	• It allows the flexible imitation of observation-based human behaviors. • It effectively captures the essence of human activities by using semantic rules.	• It produces high errors. • It does not provide better learning results over new behaviors.
Jayaratne et al.[2]	SOM	• It effectively identifies the transfer of knowledge skills from a large amount of data. • It provides high computational efficiency.	• It needs grid-based algorithms to reduce the dimension of the large data.
Abiodun et al.[3]	Interaction algorithm	• It accomplished complex manipulations in real time. • The cost required for using wearable devices is very low.	• The time consumption is high to provide flexible task execution in this model.
Bhatu et al.[4]	COA	• It highly decreases the error difference between the predicted and the desired moment. • The efficiency of the system is highly increased by optimizing the action features.	• It requires a high cost for providing the interaction between humans and robots.
Zahedi et al.[5]	Neural networks	• It enhances the resident's performance with respect to the parameters like temperature and completion time.	• It needs more realistic virtual simulations to provide better learning skills.

3. Architectural view of TERL with RNN for skill transfer knowledge

3.1. Proposed model and description

The movement of the robotic arm is guided by using the RL network. It mainly ensures the actions to be accomplished by the agents in a real-time environment, and hence, this RL algorithm is described as a well-performing machine learning algorithm. The major objective of using this RL algorithm is to increase the reward. The action-based features of the robots are effectively learned using the deep learning structure in this model. Moreover, the kinematic movement of the robotic arms is obtained by using the RNN network, and the skill forces are obtained from the final layer. The desired angle and the torque are measured using this deep-learning structure. Moreover, the transfer knowledge-related skills are obtained using this RNN, and finally, the error between the predicted as well as the desired movement is determined using the learned transfer knowledge skills. The feedback from the environment is observed using the RL, and the maximized reward signals are obtained by using the changes in the state of actions. The architectural representation of the skill transfer knowledge based on the RL network is given in **Figure 1**.

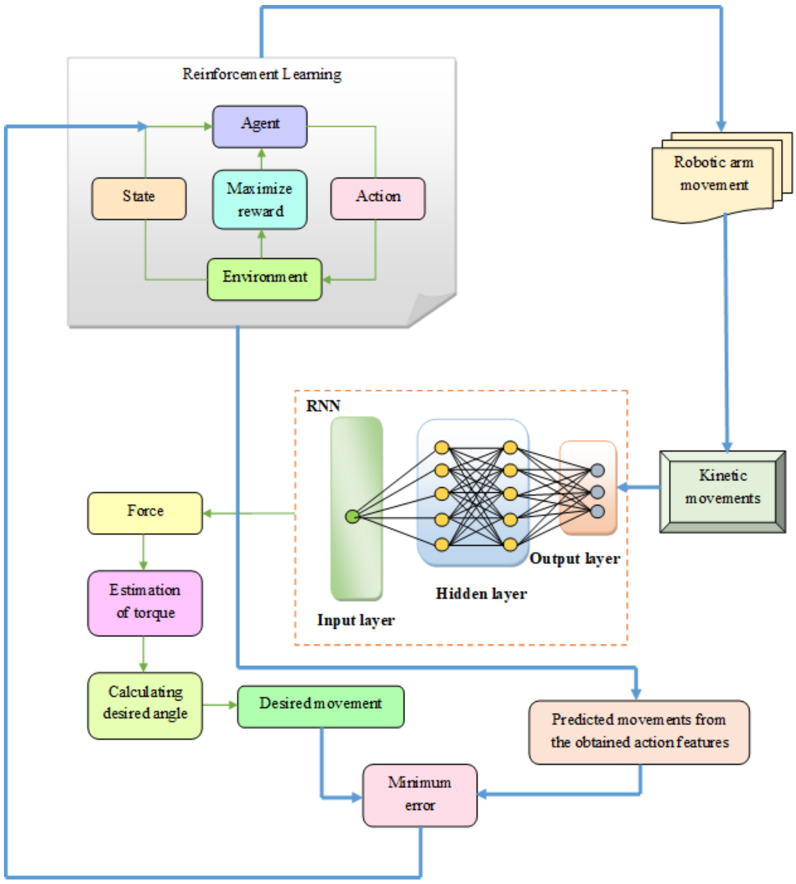


Figure 1. Structural illustration of the developed skill transfer knowledge in robotic arm based on RL.

3.2. TERL principle

The TERL framework is used to solve the source-task selection problem, and the inspirational things utilized to formulate the TERL architecture are the extracted features from the robotic arms. In the future, multiple-skill learning abilities will be faced by using several constraints of animals.

Approximation of functions: In RL and TERL systems, the natural setups are worked with the function approximation in the embodied and robotic models, which consists of continuous states and action spaces. The usage of linear function approximators provides several advantages like stability, simplicity, convergence speed, and learning speed. The kernel functions and the modularities are leveraged to solve the issues of the linearly separable problems. Furthermore, the biological plausibility of the models is enlarged with the help of the learning rules accomplished from the locally available information among the linear function approximators.

Actor-critic architecture: The most commonly adopted actor-critic RL method is the TERL approach, where separate data structures are used for saving the action policy and valued functions. This is done via the temporal difference algorithm and is explicitly used to describe the procedures for solving continuous actions, such as costly and complex. The trial-and-error learning ability of organisms is reproduced precisely by using the dynamics of the phasic dopamine and neuromodulator.

Eliminating source-task selection problem: The components of TERL are effectively classified using a mixture-of-experts-based deep learning structure. Here, the neural network classifier is personalized, and it is prior to TERL with RL. Here, the source task selection problem is eliminated by using this TERL network, which depends on the personalized morality of several applications. Two levels of hierarchies are used for producing Critics and Actors, which are a high-level gating network and a low-level experts network. In this, the genuine capacity of new tasks is effectively handled by using the two gating networks.

Determine similarity among source and target tasks without any prior information: Here, the sampling among the previous skills is utilized for solving the problem of source-task selection. This can be resolved by situating target objects in several positions, and then the representation is tested with different robot arms. Moreover, various opportunities are used for forwarding the knowledge, and hence, diverse resemblance among these locations is provided by using this approach. The algorithms have the ability to transfer the robot's knowledge. The tasks are defined based on the situation that is used to reflect the information between the source and target.

Redundant experts face catastrophic interference: In this, the chance of catastrophic problems has been reduced, and it is an important advantage for this solution. Here, new mechanisms are introduced to eliminate the catastrophic interference problem and decoupling is used to select the experts for doing the implementation, and deep learning is assisted in providing better knowledge results based on the liability signals. The advantages of these solutions are given below.

- More tasks are effectively learned by using the developed deep learning-based mechanism to model the brain images.
- From the beginning of the models, it utilizes experts to solve novel tasks from the previously learned skills.
- Here, the copy experts have existed to provide the system robustness.
- Based on the specialization and temporal activation, the same set of features is utilized and then classified in space.

4. Recurrent neural network with TERL for skill transfer knowledge

4.1. Recurrent neural network

RNN structures[21,22] are mainly used for learning the ictal parameters very efficiently because of their ability to encode the hidden layers. The transfer knowledge skills are efficiently determined from the large dimensional data obtained from the robotic arms. The previous layer input is considered for taking the resultant output. There are three layers mainly present in the RNN network such as batch normalization, maximum pooling, and independent RNN. The input sequence is subjected to the independent RNN layer to process them in forward order. In the independent layer, the time depends on features extracted from the input features, and this dependent feature extraction process is given in below Equation (1) and Equation (2), respectively.

$$Hi_r = \vartheta_{Hi}(we_{Hi} * In_r + recn_{Hi} \circ Hi_{r-1} + F_{Hi}) \tag{1}$$

$$op_r = \vartheta_{op}\left(we_{op} * Hi_r + F_{op}\right) \tag{2}$$

The hidden layer, input layer, and output layer vectors are indicated by the terms Hi_r, In_r and op_r. The recurrent unit vectors are indicated by $recn_{Hi}$ the weight matrix of the input layer is indicated by the term we_{Hi}, and the output layer weight matrix is indicated by the term we_{op}, respectively. The rectified linear unit activation functions are indicated by the terms ϑ_{Hi} and ϑ_{op}, respectively.

Here, the training is provided to the RNN for learning the efficient features, and hence the convergence speed of the learning process is improved. Moreover, the usage of the RNN network for learning skills may avoid overfitting issues as well as generalization issues. To accomplish this, the batch normalization layer is inserted into the independent layer separately, and then the maximum pooling layer is added to this layer. Here, the relevant behaviors are retrieved by using the maximum pooling layer, where the specific temporal value is assigned for extracting the features with high sensitivity. The final classification of features is performed using the fully connected layer in the RNN. The efficiency of the skill-learning process is highly enhanced by using this RNN network. By using this feature extraction, the reward gets increased, and the error between the predicted and desired value gets decreased.

4.2. RNN-based arm movement

Motor babbing data are used in the RNN to train the features obtained from the robots. Here, the input given for the RNN process is kinematic movement, and the output obtained from the RNN network is skill forces. Moreover, the computation torque is performed in the RNN network, and the determination of desired angles is also done in this network. By using this obtained desired angle value, the entire target movements are to be trained from the robotic arm. Best transfer knowledge skills are attained by using this RNN model. Finally, the minimum error is obtained by using this RNN-based skill transfer knowledge learning. The error is determined between the predicted as well as desired movement values. The RNN-based skill transfer learning process to provide better human-to-robot interaction is given in **Figure 2**.

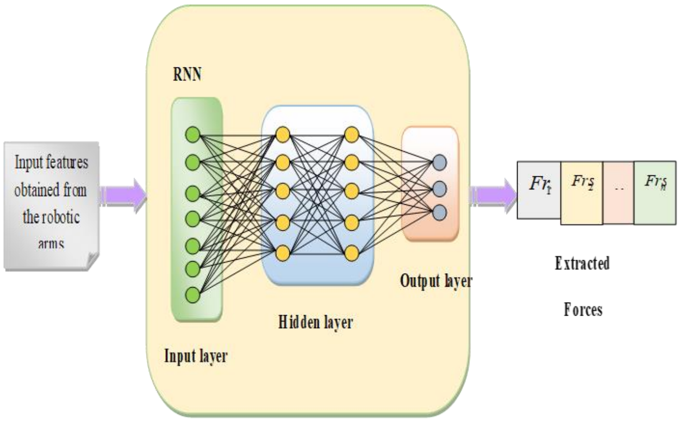


Figure 2. Diagrammatic representation of RNN-based skill transfer knowledge in TERL.

5. Results and discussion

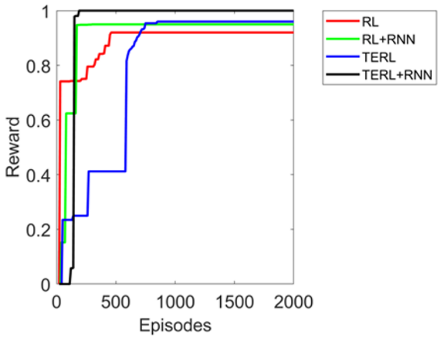
5.1. Experimental setup

The developed skill transfer knowledge-based human-to-robot interaction model has been executed in MATLAB 2020a, and two test cases were taken to evaluate the performance of the implemented TERL-RNN. The reaching time analysis and the reward analysis over two test cases were considered for validating the effectiveness. Moreover, the robotic arm movement of the developed TERL-RNN among RL, RL+RNN, and TERL was utilized to test the performance.

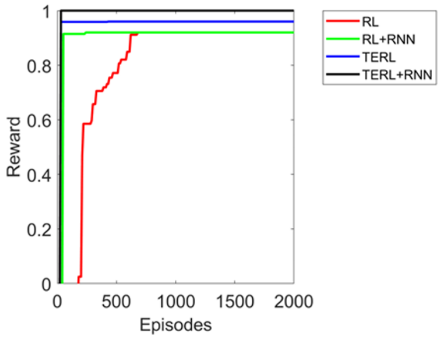
5.2. Reward and reaching time analysis

The performance of the developed TERL-RNN-based human-to-robot interaction mechanism is validated with respect to reward and reaching time given in **Figures 3** and **4**, respectively. Here, two test cases are considered for conducting this experiment. The developed TERL-RNN model provides better effectiveness in terms of reward when compared to other models. Moreover, the reaching time is also very low when compared to other RL-based models. The implemented TERL-RNN-based model attained 84.61%, 54.54%, and 77.77%

improved reaching time than RL, RL+RNN, and TERL concerning test case 1. The main aim of this computation is to maximize the rewards and also to minimize the reaching time. The maximum rewards generate better communication between human and robots and also the minimum reaching time helps to get the signals in a faster way of robots. While analyzing **Figure 3**, the given designed method clearly shows that it attains minimum reaching time and maximum rewards.

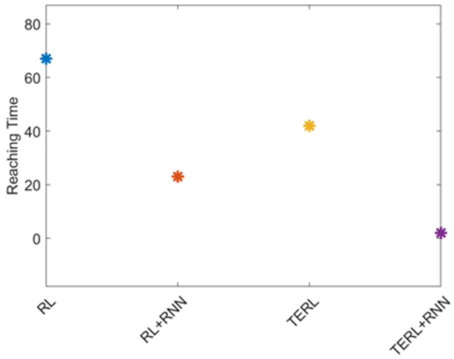


a



b

Figure 3. Reaching time analysis on developed TERL-RNN-based skill transfer knowledge model using **(a)** test case 1; **(b)** test case 2.



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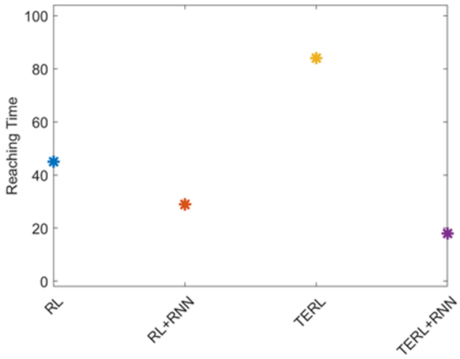

b

Figure 4. Reward analysis on developed TERL-RNN-based skill transfer knowledge model using **(a)** test case 1; **(b)** test case 2.

5.3. Robotic movement analysis

The robotic movement analysis with implemented TERL-RNN is analyzed, which is illustrated in **Figures 5** and **6**, respectively. Here, two test cases are used to get the robotic movement. The actual and the predicted movement of the RL, RL+RNN, TERL, and TERL+RNN are given in the plot. These robotic movement values are more helpful in analyzing the error that occurred after learning the transfer skill from the robots. The X and Y terms used in the plot represent the path for matching the features from the data to find the error.

Here, the communication of knowledge is an important skill among humans for proficiently training the latest theory. The expert network can reveal a robot with the help of the latest theory by using physical movement and written language. Then, the knowledge is transferred to other robots or humans. Especially, the impacts of effective human-to-robot knowledge transmission generate a chance of a robot performing new activities. While taking **Figures 5** and **6**, the simulation outcomes show the robotic movements of the developed and actual model. From **Figures 5** and **6**, the dotted lines are considered as the actual movements of the robots and also the blue lines are considered as the movements of the robots. From the result validation, the designed model like actual robotic movements shows better performance than the other baseline approaches.

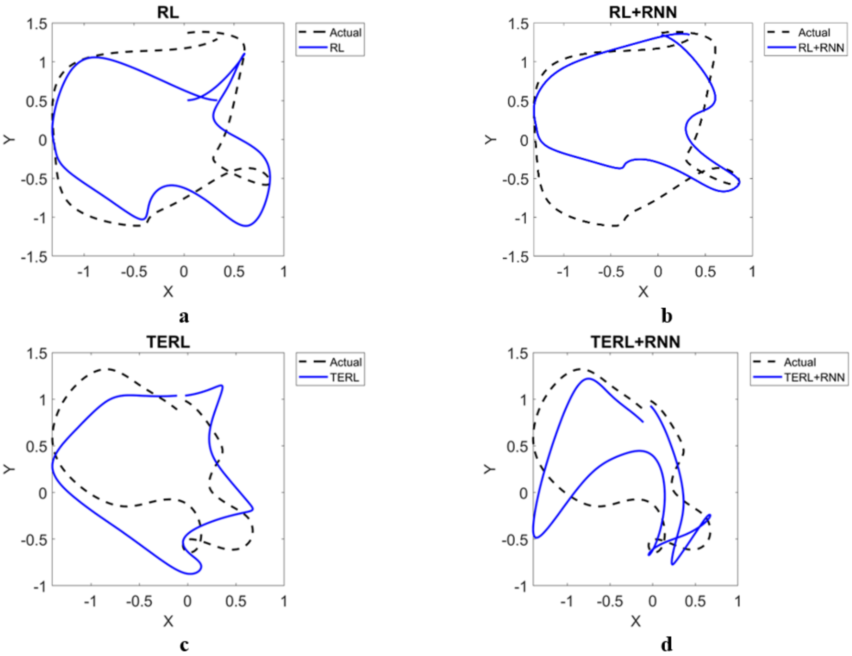

Figure 5. Robotic movement analysis on developed TERL-RNN-based skill transfer knowledge model in respect to **(a)** RL; **(b)** RL+RNN; **(c)** TERL; **(d)** TERL+RNN on test case 1.

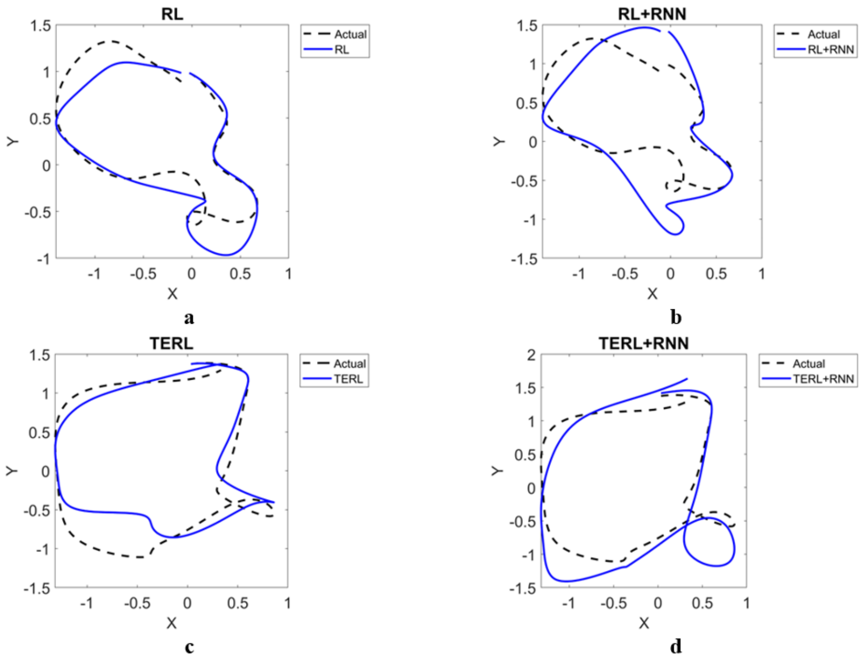

Figure 6. Robotic movement analysis on developed TERL-RNN-based skill transfer knowledge model in respect to **(a)** RL; **(b)** RL+RNN; **(c)** TERL; **(d)** TERL+RNN on test case 2.

5.4. Performance validation in terms of robotic movement

The obtained robotic movement values of two test cases are given in below **Table 2**. Here, RL, RL+RNN, TERL, and TERL+RNN models are used to estimate the effectiveness of the developed human-to-robot interaction mechanism. From the above results, the TERL+RNN-based model provides better robotic movement results than the other models, and the errors are highly reduced using this model.

Table 2. Robotic movements among two test cases.

Obtained robotic movement		
Techniques	**Testcase-1**	**Testcase-2**
RL	0.072893	0.16936
RL+RNN	0.18925	0.19768
TERL	0.20123	0.10631
TERL+RNN	0.040708	0.09229

5.5. Ablation experiment of the designed TERL-RNN-based skill transfer knowledge model

The ablation experiment of the developed TERL-RNN-based skill transfer knowledge model for two test cases is shown in **Table 3**. Thus, the developed model attains elevated outcomes than the other baseline approaches.

Table 3. Ablation experiment of the developed TERL-RNN-based skill transfer knowledge model among two test cases.

Obtained robotic movement		
Techniques	**Testcase-1**	**Testcase-2**
TERL+LSTM	0.07245	0.07021
LSTM	0.07542	0.07487
TERL+GRU	0.05988	0.06154
TERL+SVM	0.05245	0.06845
TERL+ANN	0.06544	0.07845
Proposed TERL+RNN	0.04566	0.05454

6. Conclusion

An efficient skill transfer knowledge-based human-to-robot interaction scheme was developed to learn efficient skills from robotic arms to support various real-time applications. The robotic movement was taken as an important factor in this model. The action features from the robotic arm and the input kinematic movements were evaluated using the RNN model. The significant goal of this developed model was the minimization of error and maximization of reward. The error has been evaluated from the predicted as well as the desired movement. Experimental analysis was considered to validate the effectiveness of the developed model in terms of reward, reaching time, and robotic movement in two cases. The suggested TERL-RNN-based model achieved with 77.77%, 71.42%, and 88.23% improved reaching time than RL, RL+RNN, and TERL according to test case 2. The developed TERL-RNN-based human-to-robot interaction mechanism gave higher effectiveness in terms of maximized reward and minimized error, among other techniques.

Author contributions

Conceptualization, MBG and SSG; methodology, MBG; software, MBG; validation, MBG, SSG, MP, AK; formal analysis, AK; investigation, MBG; resources, MBG; data curation, AK; writing—original draft preparation, SSG; writing—review and editing, MBG; visualization, SSG; supervision, MBG; project administration, MP; funding acquisition, SSG. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest

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