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Result Paper on – "Design and Development of Real Time Trainable Industrial Robotic Arm"

Shruti V Ramteke[1], Kanchan Dhote[2]

[1]*Department of Wireless Communication and Computing, TGPCET, RTM Nagpur University, Nagpur, Maharashtra India, shruti.ramteke90@gmail.com*
[2]*Department of Electronics Engineering, TGPCET, RTM Nagpur University, Nagpur, Maharashtra, India, hod.etrx@tgpcet.com*

Abstract: **Industrial automation requires wide numbers of machines for repeatedly done the same number of actions. The main difficulty to design such a system is complex programming & constant operating speed. So, it can be overcome by design & develop a robotic arm which works on real-time. An industrial robotic arm based on experience reply learning technique. Different techniques are developed previously based on neuro-fuzzy approach to record actions & convert them into devised motion codes and vice-versa. This type of robotic arm has wide variety of applications in industrial automation like open and close bottle neck, cleaning of specific surface or pick and place particular object. To achieve such intelligent robotic arm, algorithm can be developed via which the robot will record the actions when performed by the user during the 'learning phase' which is nothing but when the user is performing the action for the robot for the first time. The prototype of a vehicular arm can be used to demonstrate & developed a system to run robot according to the sequence of recorded motion codes. An additional filter can installed for adding effects.**

Keywords: **Robotic Learning, Motion Codes, Macro Recording, Macro Replay.**

1. INTRODUCTION

1.1 Overview

At present, automation industry has wide number of requirement of machineries which can solve are multiple number of problems and can be operated by any person without having expert knowledge to solve this purpose of repeatedly done the same number of action an algorithm can be developed. The main difficulty to design such a system is complex programming and constant operating speed. So it can be overcome by design & develop a robotic arm based on micro coding approaches which work on real time. An industrial robotic arm based on experience replay learning technique.

In traditional approach the system is designed for dedicated task which has no other use, another disadvantage is user need to have knowledge of programming for reprogram of specific task, so it can be overcome by installing wireless modules to enable wireless control of the robotic arm via developed handheld controller. An algorithm based on neuro-fuzzy approach can be developed to record action & convert them into devised motion codes and vice-versa. Arm has wide variety of application in industrial automations like open and close bottle neck, cleaning of specific surface or pick and place particular object. Filters used to edit and add additional effects during the replay; here effect can be used for editing the speed of robotic arm.

Sander Adam. developed an effective algorithms that can automatically learn optimal control strategies for nonlinear, possibly stochastic systems[1]. With a multitude of developing scenarios of how humans and robots can simultaneously collaborate as a team, it becomes instrumental to assess the performance of such teams.

In human robot interaction a robot should able to infer the user's intention through recognizing the actions, but also to perform appropriate decisions and to learn from the user's feedback. In this paper Shih Huan Tseng1, they propose an integrated strategy of human-oriented perception, user modeling and user sensitivity in a social environment [2]. The robot can analyze a user's feedback to adjust decision. The experimental results show the effectiveness of the proposed approach that enables autonomous adaptation of robot's decision to the user desires.

1.2 Problem Definition:

- At present, industrial automation requires wide number of product for repeatedly done.
- The main disadvantage to design industrial machines is complex programming.
- In traditional approach, the user need to follow same procedure and give instruction every time for similar kind of work done.

- Using various algorithm like supervised learning algorithm and reinforcement learning algorithm object will work only on constant speed.

1.3 Objectives:

- Mimic human action according to the instructions stored by the programmer during the learning phase.
- The objective of the system is to perform one task autonomously and can be reprogramming for different task.
- Another feature of the system is multiple experiences storage capability like cleaning particular surface and pick and place any object.
- Filters used to edit and add additional effects during the replay; here effect can be used for editing the speed of robotic arm.
- Reprogram for various task.

2. LITERATURE SURVEY AND REVIEW

There are various algorithm designed based on experience storage and replay are used for different applications are follows as

2.1 Reinforcement-learning (RL) [1]

The following section guides the user about algorithms that can automatically learn optimal control strategies for nonlinear, possibly stochastic systems. An approach for practical RL is experience replay (ER), in this method the data acquired during the online-learning process are stored and presented repeatedly to the underlying RL algorithm. To increases data efficiency during a process, while exploiting the computational efficiency of the underlying algorithm. ER was introduced by Lin[10] in the context of RL with neural-network approximation. Further, Kalyanakrishnan and Stone illustrated using simulations that reusing data in Q-learning leads to a performance similar to that of batch-RL algorithms [9]. Despite such discouraging results, ER has been continuously studied in the Reinforcement Learning literature, and RL has only few real-time applications as well. In fact, in simulated systems RL applications have so far largely been restricted. To improve the visibility of RL field and to stimulate real-world applications, it is necessary to go beyond simulations and demonstrate that RL methods so that it can be effectively used in the real-time control applications.

Outline of Design Methodology

Experimental evaluation of ER RL, which includes real-time results. here first introduce a general ER framework, which can be combined with incremental RL algorithm. This framework is represented as approximate *Q*-learning and SARSA, and thereby giving ER-*Q*-learning and ER-SARSA.

2.2 Intelligent human robot interaction (HRI) [3]

In HRI a robot should able to infer the user's intention through recognizing the actions, but also to perform appropriate decisions and to learn from the user's feedback. In this paper Shih Huan Tseng1, they propose an integrated strategy of human-oriented perception, user modeling and user sensitivity in a social environment [2]. The robot can analyze a user's feedback to adjust decision. The experimental results show the effectiveness of the proposed approach that enables autonomous adaptation of robot's decision to the user desires. Also, we demonstrate a satisfactory performance in terms of successful inference of human intentions, as well as adequacy of the decisions made by the robot tor meeting user expectation.

There has been a wide interest in robot performance based on human awareness, which implies the robot's abilities in various skills, including three components [2]:

1) Human-oriented perception: the capabilities of human detection and tracking, gesture and speech recognition etc.
2) User modeling: the capabilities of understanding human behaviors and making appropriate decision.
3) User sensitivity: the capabilities of measuring user feedback, adapting robot's decisions to users.

2.3 Online learning Mechanism

The uncertainty in the office environment and wrong predictions of human intention author develop an decision making model based on learning scheme and Decision Network which is based on Reinforcement Leaning with human feedbacks. Decision Network model for the interaction planning, and a leaning mechanism for robot to enable adjust ment of the model's parameters in reacting to human user's feedback [2]. During robot interaction with the user, the robot can team and update the decision network model with the human user's speech feedback. The algorithm shows overall learning mechanism. Based on the inferred human intention and environment context the robot makes interaction decisions. After reacting to the user, it receives and analyzes feedback from the user so that the decision network model can be adjusted to meet the human user's expectations The system architecture of intelligent mobile robotic arm follows that the authors, Schmidt-Rohr et al., proposed in the bottom layer includes the skill control, perception, and actuation, while the middle layer consists of recognition and action executor [7]. The top layer is the Decision Network, it also includes Sensing Skills and Feature Selection.

Here, the robot cannot cope up with multiple users, it deal only with fixed human user. Another disadvantage is language processing ability to enable human user to express their desire on the robot in more natural and simple way. The active learning technology may fail to find out whether the error comes from the consequences of establishing improper training data or recognisation of human context when robot infer wrong intentions.

2.4 Interactive Classifier System[4]

D. Katagami, S. Yamada introduces 'Interactive Classifier System' it is a fast learning method in which a mobile robot to acquire autonomous behaviour interact between human and robot [4]. Here a mobile robot can learn by directly teaching from an operator by quickly learning the rules. In the situation where does not need instruction, robot autonomy is demonstrated by instruction rules stored without putting a burden on human during interaction with people. The robot autonomy can be realized by receiving the instruction information **as** a suitable act from human and gaining act rules evolutionally with the state recognition which can solve a task. In order to measure a teacher's load Interactive Teaching divides the load into mental load and physical load.

The efficiency of Interactive Classifier System is very less as it uses cognitive decision making system which fails sometimes in multi-stimulated environment.

3. METHODOLOGY

3.1 Block Diagram

The block diagram of developed system is shown below which consist various hardware and software connectivity. The following architecture consists of microcontroller 89s51. The model is divided into two parts i.e. hardware part and software part, where hardware part is actual 5axis robotic arm & handheld controller where as in software part coding is done in embedded C

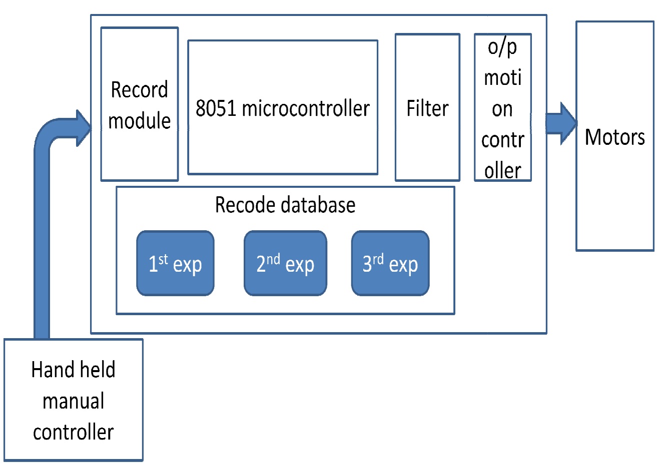

Fig. 1. Block Diagram

Firstly, a circuit diagram is designed which consist of Microcontroller (89s51), record module, recode database and motor drivers IC (L293D). A basic handheld controller is designed which consist 6 different switches for robotic arm movement such as left, right, upward, downward, 360 degree rotation and pause. A reverse switch is also add to reverse all the action if required. An additional filter is attached to control the motion of robotic arm.

3.2 Flow Chart

The flowchart given in the following Figure.2 describes the working principle of how robot should learn & replay the actions.

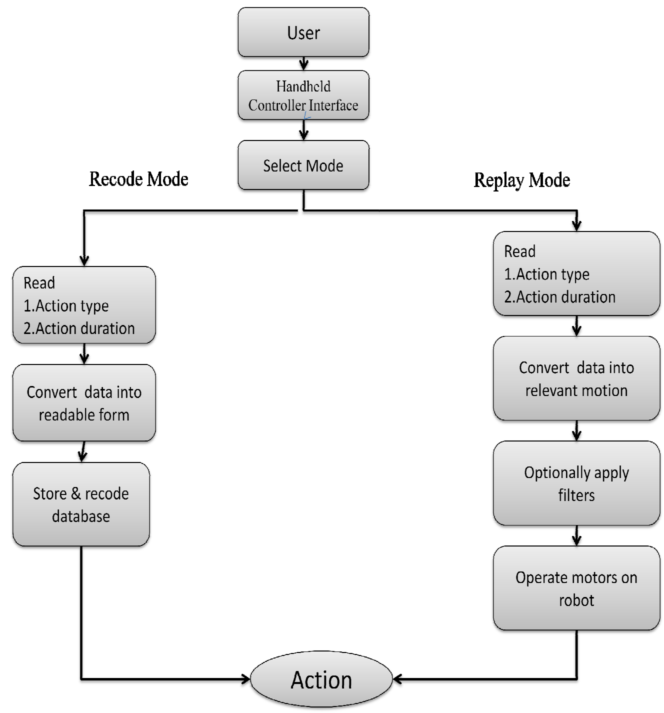

Fig. 2. Flow Chart of robotic Arm Controller

The system archictitecture includes two modes record and replay. Recode mode first read the action for what duration of time it is been pressed and which type of action it is recording followed by convertion of that data into readable form and at the end store that database for future work.

Replay mode contains four different steps to get according output firstly it read the action type & action duration for which action is performed then convert that data into machine understandable code. Filter effect can be optionally added to speed up or down the action motion. Various motors on the robot can be operate according to actions. Finally operator can operate robotic arm from different stored actions during the "learning phase".

4. DESIGN/ IMPLEMENTATION

4.1 Circuit Diagram

The system consists of set of fingerprint sensor, microcontroller and RS232 serial communication. The circuit diagram is constructed as per the block diagram. Figure and shows the following circuit diagram of the system. . The port D pins i.e. pin D0 & D1 is connected to RS232 pins 10 & 9.

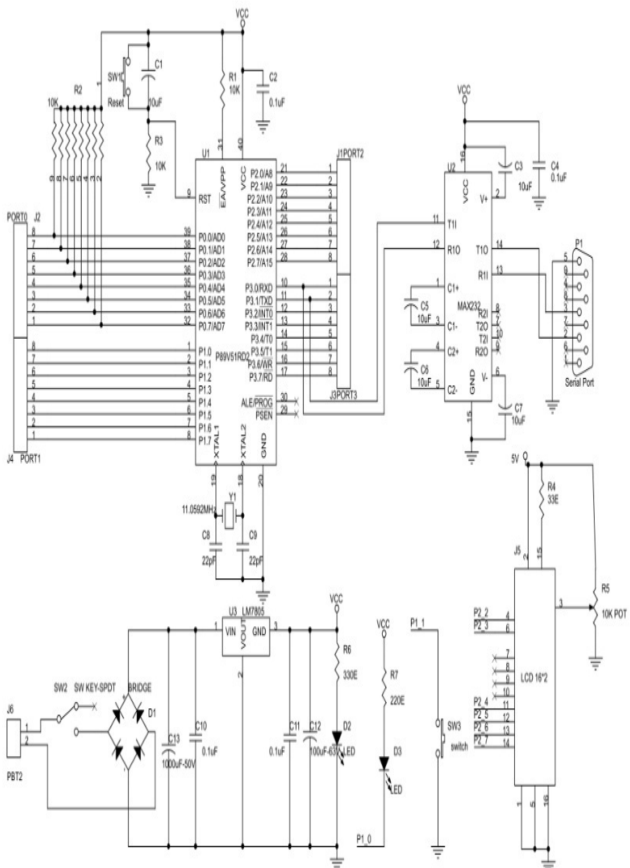

Fig. 3. Circuit Diagram

4.2 Algorithm and Working

4.2.1 Macro based Algorithm

Macros are used to make a sequence of computing instructions available to the programmer as a single program statement making the programming task less tedious & less error prone.

In computer science is a rule or pattern that specifies how a certain input sequence should be mapped to replacement output sequence. Macro is series of steps for record and replay.

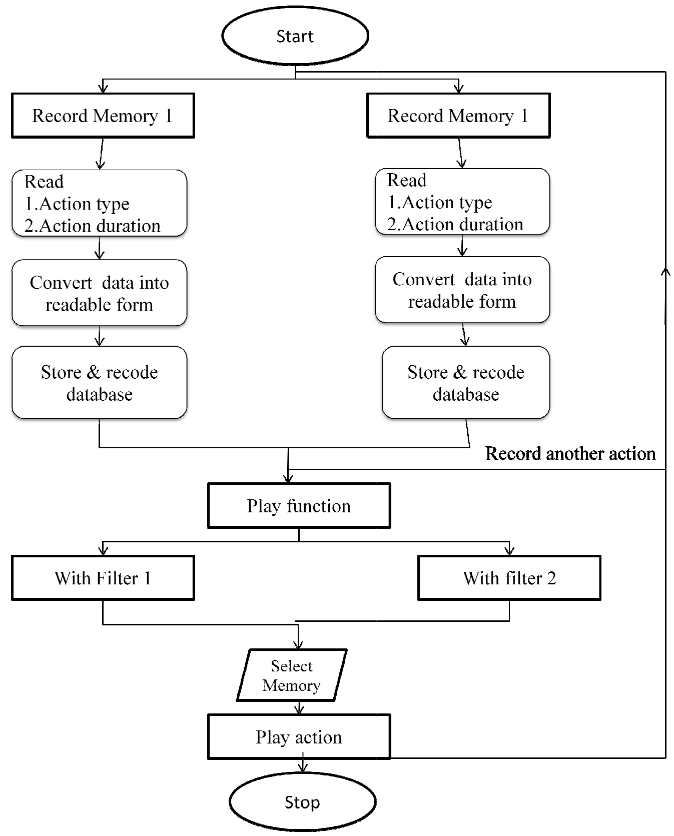

Fig. 4. Learning robot flowchart

4.2.2 Algorithm Implementation steps

1. Start
2. Build 5-axis robotic arm & interface it with controller .
3. Develop controller software in macro to code and control the robotic arm
4. Develop software module to record user action for the first experience.
5. Develop software module to record user action for the second experience.
6. Design & build handheld controller .
7. Design data structure & format to store data information .
8. Design filters module (software) to manipulate stored actions .
9. Design replay module to convert store "experience" to actions .
10. Stop.

5. EXPERIMENTAL RESULTS

Proposed system consist of both hardware and software implementation. Hardware parts consist of robotic arm (RB50), microcontroller and RS232 for serial communication, handheld controller, LCD for display. Software parts consist of keil microvision software for embedded c coding & flash magic tool which used to program hex code in EPROM of uc. The detailed figure of the robotic arm is shown.

The hardware part of project is shown below which consist of 5 axis robotic arm, wired handheld controller with different switches, LCD display & RS 232 IC for serial communication.

Fig. 5. Hardware Implementation

6. CONCLUSION

In this project, we proposed a Active Teaching method for robotic arm for programmer various load, here when a teacher instruct a mobile robotic arm to perform a particular task for one time during the "learning phase" and algorithm can be developed via which the robot will record the actions. This project will provide a wireless module to enable wireless control of the robotic arm via developed handheld controller to record action & convert them into devised motion codes and vice-versa Filter can be installed for adding effect in particular speed of robotic arm.

7. APPLICATION AND FUTURE SCOPE

1) The pick & place mechanism is very helpful in transportation as the variation in the mechanical structure and the angle of movement can be changeable.
2) The robotic arm is also used for the cleaning a particular area on a glass or surface where human hand is difficult to move.
3) For the welding of particular types of sheet metal.
4) To weld straps to nikel-metal hybride cells to make batteries.
5) The robotic arm can be used in automobiles as well as manufacturing industries like opening & closing of bottle neck.
6) The hand is very "user friendly" & capable of being interfaced & networked with other system in the factory to achieve a very high level of integration.

With the development of this project, a neuro-fuzzy algorithm study is done from which a simple embedded C language program is written, which can be used in various modular robot to achieve real-time scalability functionality reconfiguration. This project will provide wireless module to enable wireless control of robotic arm via developed handheld controller to record action and convert them into devised motion code & vice-versa.

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