Self and Mutual learning in Robotic Arm, based on Cognitive systems

Chetan Patil, Sushant Sachan, Rahul Kumar Singh, Kirti Ranjan, and Vikash Kumar

Abstract—**The paper presents a novel implementation of self-learning and mutual learning of the Robotic arm based on Cognitive systems. The proposed arm can learn different motions or tasks in supervisory mode under the supervision of similar master arm having exactly same degrees of freedom at the same places. The cognitive approach results in efficient learning based on past history. The proposed hardware provides cheaper solution to the expensive industrial robotic arms for numerous applications.**

Index Terms—**Robotic arm, Cognitive learning, Hardware Implementation, Decision making.**

I. Introduction

Humanoid robotics always remains a major interesting field in the scientific community. Ideally, a humanoid robot should be able to perform different cooperative tasks with a human [1] or work in dangerous areas instead of a human. However, most studies of humanoid robots today focus only on simple whole-body motion such as walking [2], [3] and [4].

In order to enable a humanoid robot to perform useful work for a human, it is necessary that it can perform some task using the arms as well as walk around freely. Therefore, evolution of robotic arms is very much necessary to widen the applications of humanoid robots. It is an important topic in research related to humanoid robots.

A robotic arm is a robot manipulator, usually programmable, which can perform similar functions to a human arm. The parts of the manipulators are connected by joints allowing either rotational motion or translation. There are many different types of robotic arms made for different purposes having different degrees of freedom, architectures and applications. But many of them are manufactured to fulfill one particular purpose in Industry level applications. The procurement and establishment of such different robotic arms for different purposes is usually a big headache and time taking process. To minimize the efforts, often different modifications and improvements are made by manufacturers to increase the domain of its applicability. This also increases the cost and complexity of the system.

The present model is a novel implementation of self-learning and mutual-learning based on Cognitive system in a Robotic arm, which has total seven degrees of freedom very much similar to a human hand. The micro-controller which acts as the main controller guides all the movements of the robotic arm and acts as the brain of the system. There are various sensors embedded with the on-board micro-controller to acquire the data from the environment. The product is the high-tech industrial level application leading to simplicity of many tasks. As the most important task of any robotic arm is gripping and picking objects from any location, the attempt is made in implementing cognitive learning in identifying different shapes of objects and picking them up. These results in the incremental information and ability to perform tasks autonomously based on acquired experience. A cognitive architecture specifies the underlying infrastructure for the proposed intelligent system.

The robotic arm has wide applications in many fields including the general industry level, precise medical treatments and also security level. The major demand of the proposed intelligent robotic arm can be expected from the Research fields, Security purposes (from personal to organizational level security), Health sector, Offices and Industries.

The organization of this paper is as follows. Section I served as an introduction. Section II sketches the literature survey. Section III discusses the functions of the proposed robotic arm and the working algorithm in detail. Hardware architecture is described in Section IV which mainly contains its mechanical structure, hardware and softwares. Section V gives the results of the hardware implementation in the task of grasping a cylindrical object, different states in different motions and the accuracy achieved in using low cost equipments. Section VI concludes the paper.

II. Literature Survey

There are many robotic arms made till now for different purposes. But they are manufactured for either heavy loading-unloading purposes or very specific purposes. Also many of them are manually controllable. These arms cost too much for the common purposes of picking up different objects. Many of them are routine modification on existing manually

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controlled robotic arms.

One of the robotic arms with the learning algorithm is developed in the Integrative Neuroscience Department, Stem Cell & Brain Research Institute, France. The project involved development of a spoken language based posture and behavior editor for Lynx two-arm system, with autonomous sequence learning [5]. Also a robotic arm with a specific purpose of human respiratory recording mechanism is manufactured in Institute for Robotics and Cognitive Systems, University of Lübeck, Germany [6].

A robotic arm with similar purpose of object picking is publicized by LEGO as ProChallenge. It involves sensors and robust mechanical structure for manual control [7]. Also, a "pick and place" robotic system is being developed at the University of Pisa, which involves motion planning and distance learning and very much different than the proposed arm [8].

F. Larsson, E. Jonsson and M. Felsberg present a visual servoing method based on a learned mapping between feature space and control space using Lynx Robotic arm [9] while G. Massera, S. Nolfi and A. Cangelosi describe the learning of robotic arm using neural network, but in simulations [10]. Similarly R. Bianco and S. Nolfi describe the neural learning of robotic arm for grasping purpose on the basis of tactile sensors [11].

Many attempts had been made to provide a suitable prosthetic device to be used as a mechanical artificial hand. Because of the unique movements possible of the human hand, it has proven to be very difficult to emulate with the use of such prosthesis. None of the references shown in the prior art truly depict the application of decision making for the purpose of picking up objects. Further, they are characterized by complexity in construction and operation, and also include cost limitation.

III. FUNCTIONALITY

The robotic arms perform usually perform movements looped by feedback mechanism. Often this leads to cumbersome user controls, making it difficult to operate. This problem inspired us to go for a using a virtual arm, an exact replica of robotic hand. The virtual arm operates like an actual human hand with joint by joint replication.

A. *Functions*

Gripping and picking the objects is the primary task for many of the robotic arms. When we consider these tasks, it is very much necessary to achieve the relative motions smoothly without much vibration. Also these must be completely controlled in closed loop to get complete information of the position of arm at any moment. To consider all the aspects, information from different types of sensors like camera, encoders, Infrared sensors, potentiometers is collected and actuators are synchronized accordingly in the model.

The arm has total seven degrees of freedom including two degrees of freedom for the movement of the base on which the whole system is mounted. The five degrees of freedom include the elbow rotation with respect to vertical axis, pitch motion to lift objects, roll motion with respect to the axis passing through the hand, wrist motion and gripping action similar to the human hand. Also the palm of the arm has the Pent-Dactyl structure similar to the human palm with five fingers. Thus the arm can grip and lift objects of different shapes in its capacity using its fingers.

The main function of the arm can be stated in two different environments –Mutual learning and Self learning.

In both cases, the arm can recognize the shape and size of the objects in front of it to make consequent decisions. In mutual or supervisory learning aspect, the arm first identifies the shape of the object and correlates with the past motions which it already learned through grasping objects of different shapes. Depending on the comparison, the stipulated task of grasping the object is performed. On the other hand, the self learning or unsupervised learning involves complete process of grasping the objects autonomously through feedback by camera and Infrared sensors. The details of the functions of the arm are explained in the algorithm section.

B. *Working Algorithm*

As mentioned before, the arm can be utilized in supervisory (mutual learning) modes unsupervised and (self learning).The supervisory mode contains the movement of each limb under the supervision of the similar virtual arm or master arm. In this mode, the virtual arm controls the main hand. The virtual arm is designed to have same seven degrees of freedom as the main arm also including the base movement with joystick control. One can easily guide the arm using virtual arm with communication channel in between. Thus, the virtual arm provides simplicity and user-friendliness at its limit for the manual control.

The tendency of human arm to approach the object for picking task changes according to the shape of the object. For example, the horizontal object is normally gripped from top, while vertical object is normally gripped from sideways. Similar to this, many objects for their particular purposes have specific shapes. These objects can be easily identified depending on their shapes.

When the robotic arm encounters any type of object in front of it to grip, it detects the shape of the object using camera feedback and image processing. For the precise determination of dimensions of object, image enhancing techniques, Sobel edge detection, image filtering techniques and noise removal algorithm is used. The resulting data from the image processing algorithm is transmitted to the micro-controller through parallel port communication.

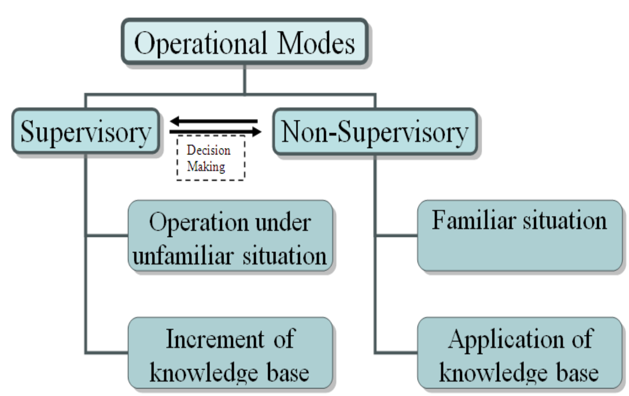

Fig.1. Functions of the Robotic Arm

Briefly, the architecture includes those aspects of a cognitive agent that are constant over time and across different application domains which are expressed in Fig.2. [12]. These are typically given as follows.

• The short-term and long-term memories that store content about the agent's beliefs, goals, and knowledge;

• The representation of elements that are contained in these memories and their organization into larger-scale mental structures; and

• The functional processes that operate on these structures, including the performance mechanisms that utilize them and the learning mechanisms that alter them.

In the cognitive system implemented in the robotic arm, the scene is captured using camera sensor and output is being fed to the micro-controller which interprets the situation. The feedback from camera provides the information about the shape of the object in front of it or pattern. On the other hand, goal is decided by the user, which defines the task which is to be completed.

From the situation interpretation and the goal defined by the user, the decisions are taken based on the knowledge base which is defined by the supervision of virtual arm at different situations. The planning and decisions define the exact motions of actuators and they are fed to the actuators through basic P-control algorithm using micro-controller programming.

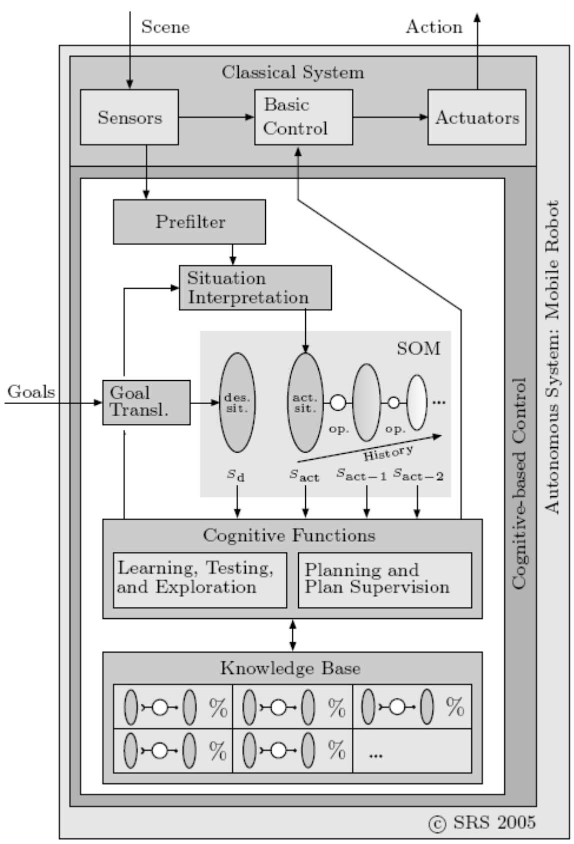

Fig.2. Architecture of a knowledge based autonomous system

All the motion during supervisory learning is stored in the memory of the micro-controller. Thus whenever the arm encounters different situation which is not included in its knowledge base, the supervisory mode controls the motion of the hand using virtual arm. When the arm encounters similar situation to one of the previously stored history, then unsupervised control controls the motions of the arm with continuous feedback from the sensors. Thus the arm is able to pick horizontal and vertical objects in different manners. Continuous learning and different goals increases the knowledge base of the arm in large extent.

IV. Design and Hardware Implementation

The most important aspect behind the design is the biologically inspired geometry of the natural human hand. The design of the model is completely new with relatively cheaper manufacturing requirements. The developed model is a mechatronical design mounted on a differential drive which mainly contains a Pent-dactyl gripping mechanism, all possible rotations along three axes, sensor-camera for shape detection and a reprogrammable circuit for automation and learning. Detailed description of the prototype construction can be given as follows.

A. *Mechanical Structure*

The innovative gripping mechanism consists of five strings through five fingers and a DC geared motor, which can pull or release the fingers. The fingers of the palm are made up of Balsa wood which has high strength to weight ratio. This minimizes the weight of the palm, resulting in less power requirements.

Since the motion of the wrist of human hand is restricted to a certain angles, the wrist movement in the robotic arm is achieved using four-bar mechanism. This mechanism appropriately restricts the wrist motion and provides a parabolic path. Another innovative design is a servo mounting system at the elbow joint of the robotic arm. This is shown in the AUTOCAD model (Fig.3 and 4).

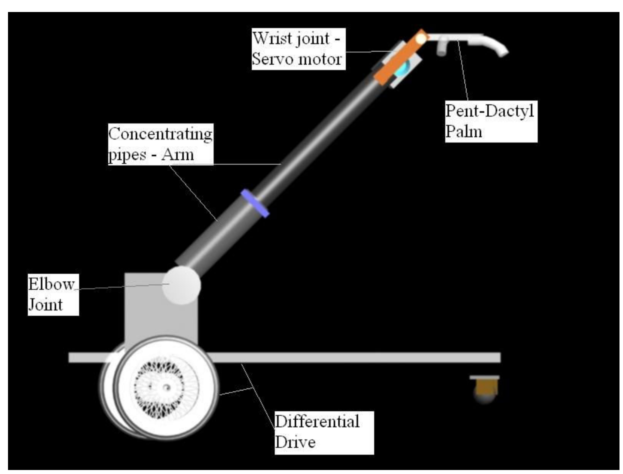

Fig.3. Side view of the CAD model of proposed robotic arm

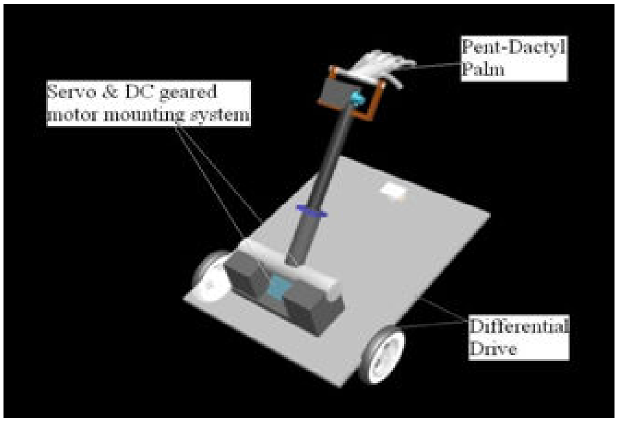

Fig.4. Isometric view of the CAD model of proposed robotic arm

The mechanical structure of the hand is a complete innovation from its gripping mechanism to its three axis motion. For the requirement of less power and low torque in our prototype, light weight servo motors are used at appropriate places. The mechanical model is built from scratch integrating counter balances and a stiff structure. The initial stage palm of the hand is shown in figures.

B. Software and Hardware

The camera sensor provides an image of the object which is analyzed to get the shape. The camera used for this process is Logitech webcam C120, although any type of webcam with USB connection can be used as it can be easily operated using MATLAB. The pixels are processed in a computer by a MATLAB program which gives the information about the orientation of the object. The output is fed to the Atmega32 AVR microcontroller via parallel port. Atmega32 is a high-performance; low power AVR 8-bit micro-controller with advanced RISC structure, convenient facilities like 10-bit ADC, USART serial communication channel, Timers and 2 kB internal Static RAM with 16 MHz clock speed provided.

Among various sensors, the TSOP-1738 Infrared sensors are used as proximity sensors, while precise potentiometers with different resistances are used for deflection measurement. The corresponding analog voltage is digitalized using 10-bit ADC n micro-controller. The microcontroller is programmed to control the servo-motors and high torque DC-geared motors in order to get the desired arm movement and thereby picking up the object. Image processing is done in MATLAB and AVR is used for microcontroller programming.

V. RESULTS

The prototype after first stage is shown in Fig.5 with the virtual master arm. Different motions at different degrees of freedom are shown in the subsequent figures. Dimensions of the prototype model exactly matches with that of an adult human arm. All the arm motions have been successfully implemented. These motions include

a) Elbow movements.
b) Wrist movements.
c) Finger movements.

Initially the prototype was implemented without the feedback of the angles of rotations of different joints. Also the feedback with improper proportional parameters had led to the unstable output. At one of the testing phase, the uncontrollable motion had resulted into a breaking of gears of DC-geared motor at the crucial moment. This event taught us the importance of saturation limit at the starting of any type of control system.

The results of the image processing include dimensions and shape of the object – horizontal, vertical, square or circular. The manual control can grasp the object of comparable size perfectly using virtual (master) arm. The supervised mode is able to store subsequent learned data at its limit due to limitation of memory of microcontroller and retrace any of the learned motions with continuous feedback from Infrared proximity sensors.

Mutual learning has been successfully implemented. It can mutually learn from a virtual arm (attached to a human arm) and duplicate all of its motions up to a precision level of 2 degrees. It is also able to learn in unsupervised conditions, where it prepares a knowledge base from a past experience in supervisory mode and based on the continuous sensor inputs (proximity sensors and visual sensors), it decides the motion of the joints. Using this, the prototype can exactly grip and pick certain objects having size approximately equal to the palm and move from one place to another carrying the objects using joystick control.

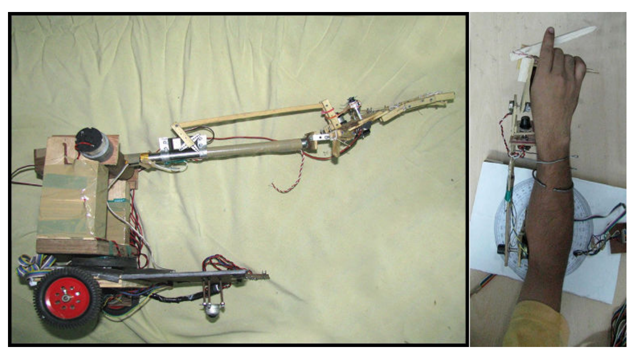

Fig.5. Prototype (Mechanical Structure) after the first stage of Robotic Arm

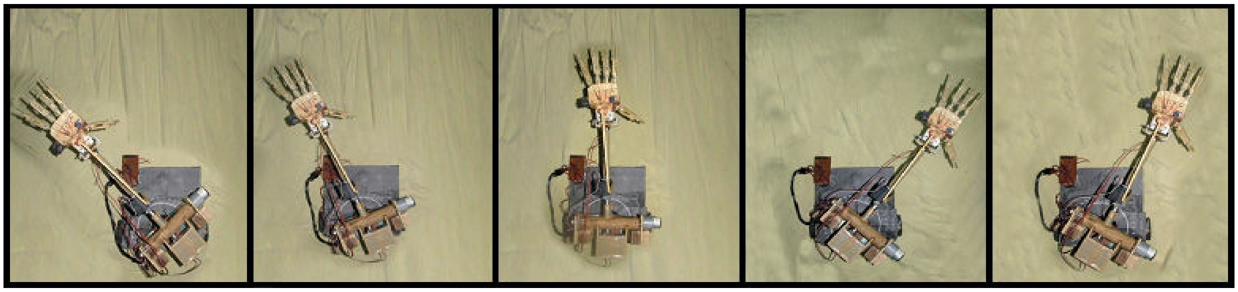

Fig.6. Elbow movement about vertical Axis

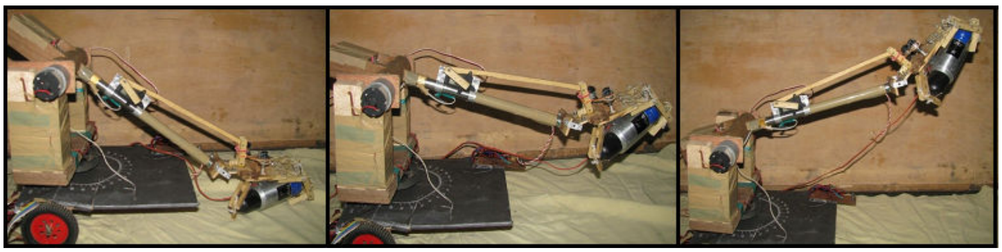

Fig.7. Pitch motion to lift objects

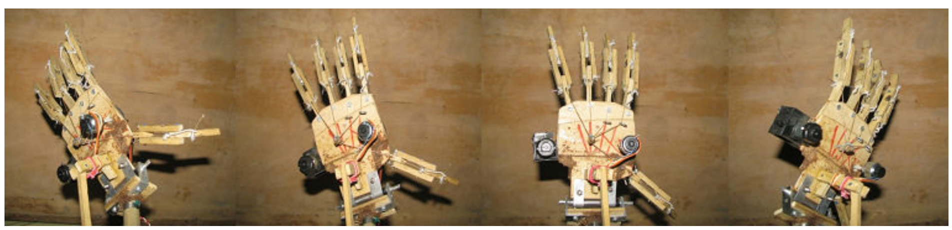

Fig.8. Roll motion about Longitudinal Axis (to adjust gripping position)

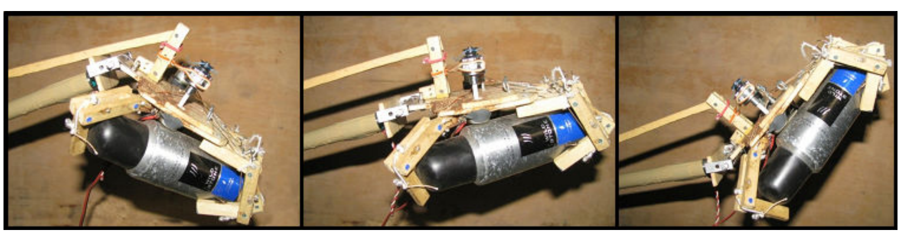

Fig.9. Wrist movement

I. CONCLUSION

The implemented model of the robotic arm shows that cognitive system is the efficient way of teaching the machines particular tasks. Using simple sensors, the accuracy up to 2 degrees can be easily achieved. Combination of the learning approach and appropriate sensors results in development of effective operational modes for a robotic arm at much lesser cost in different applications.

The supervised mode is made user-friendly through the use of a virtual arm which greatly brings down the level of skill required to handle the main robotic arm without compromising its accuracy. The optimal power usage can provide mobility to the battery driven movable platform for longer duration. The less memory of microcontrollers is a limitation to store and increase the knowledge base although enough for normal applications. For complicated systems, microprocessors chips can also be used which will also provide suitable user interface platform.

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