Design of Imitative Control Modalities for a 3 Degree of Freedom Robotic Arm

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Abstract

This research article focuses on enabling human-computer interaction (HCI) with two input control modalities designed to control a robotic arm. The robotic arm comprises of 3 Degrees of Freedom (DOF) and is controlled using the following 2 strategies : Inertial Sensor-glove and Attribute based motion tracking. The Mathematical model of the given 3 DOF robotic arm was derived and the two proposed methods were designed specifically for same. The inertial sensor-glove, worn by the user, is embedded with inertial sensors that provide data to track the motion of the user's arm. The Attribute based motion tracking strategy is a computer vision based approach which tracks the motion of a target object held by user using a camera and operates similar to a mouse-pointer but in 3 dimensions, enabled by a novel idea proposed in this paper. Fitts's Targeting tasks were performed to analyse the performance of these Human Computer Interactive input modalities.

Keywords— Human computer interaction, robotic arm, sensors, image processing, Fitts's law.

0.1 Introduction

Robotic arms have always been of fascination to engineers worldwide and are used in many industrial manufacturing and assembly plants. Usual implementation of these robotic arms are in welding, parts rotation and placement in automotive assembly lines, where close emulation of a human arm and its dexterity are desired. These robotic arms perform highly repetitive actions in a fixed environment where the robotic arm is affirmed in a defined position and modelled to smoothly access the target location. On the other hand, some applications require the actuation of a robotic arm flexible to operate in a dynamic environment involving human intervention, which primarily requires some input control modality to actuate mechanical arms like in the case of a crane. A dynamic environment in the sense, applications of the robotic arm which are not carried out in a contained industrial space. Automation is not the key aspect in such applications which are usually non-repetitive. For instance, welding and maintenance tasks in skyscraper construction sites are still being done manually by workers. There is heavy risk for life being involved in such construction sites when working at high altitudes.

According to United States Department of Labor's statistics, about 971 construction workers died in the year 2017 alone and 39.2% of them died from falls in the US [1]. In such hostile environments, it is safer to implement mechanical systems like robotic arms to prevent fatal injuries and loss of life. Apart from this, underwater construction sites, space stations, nuclear power plants application, manual scavenging application, rescue from bore-well application etc can also require such mechanical systems replacing manual human intervention.

In these applications, the robotic arm needs to be versatile, portable and should be sufficient enough to act based on the engineer's command from a control room. This input command can be provided using input devices or input modalities specifically designed for that mechanical arm's design. Input modalities like digital joysticks and paddle joysticks are few conventional systems used in robotic arms. These human computer interactive user input modalities need to be easy to handle and smoothly operatable. Therefore, it is more suitable to manipulate the robotic arm based on the user's arm movements. This idea of imitative controlling requires sensing human arm movements and gestures. Such gesture recognition systems usually involve three major approaches. The *wearable sensor* based approach, the *vision* based approach, which involves cameras and image processing techniques and the *depth* approach, which utilizes depth sensors like Time of Flight or Ultrasonic sensors to capture depth information [2]. In this research article the first two approaches were explored and two input modalities were designed. One is the *Inertial Sensor glove* and the other is the *Attribute based motion tracking*, a computer vision based approach. A performance measure on these Human Computer Interactive user input modalities was determined with the experiments suggested in the research based on how faster and easier the user handled the device during the course of the experiments.

0.2 Literature Review

In the last few decades, several prototypes were designed for robotic arm control using various sensors and computer vision based techniques.

Sulabh Kumra et.al[3], have used flex sensors to obtain data from the user's hand to actuate the robotic arm which was interfaced through man machine interface. Flex sensors lack robustness and are expensive. The inertial sensors used with the glove are lesser in number, more robust and relatively economical compared to flex sensors.

Roland Szabo et.al[4], have utilized 2 cameras to detect robotic arm movement in space using stereo vision. The cameras were placed orthogonal with each other so that the 3 dimensional information of the robotic arm movement can be obtained easily. In our research, the proposed novel method of *attribute based motion tracking* uses only one camera to monitor the user's arm movements in 3 dimensions.

Mahidzal Dahari et.al[5], have worked on the mathematical modeling and inverse kinematics of a 6 DOF robotic arm. In our research, the mathematical modeling of the 3 DOF robotic arm was done.

Hairong Jiang et.al[6], have measured the performance of their proposed input modality, a 3D joystick for a robotic arm for quadriplegics, to operate them as an assistive device, using Fitts's targeting law test and a pouring test. Similar Fitts's targeting law test experiments were done to evaluate the performance of the HCI input modalities proposed for our 3 DOF robotic arm model.

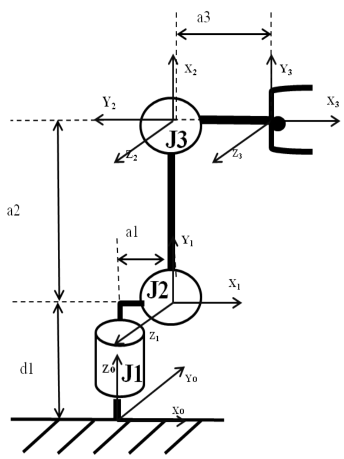
0.3 Problem Statement

Several industrial applications like welding in high-rise construction sites,still involve human intervention posing the heavy risk of injuries and fatalities. A robotic arm manipulable with some input modality can be used to perform such dexterous tasks with same or even better level of accuracy, also ensuring human safety.

This research proposes two such HCI input modalities namely, *Attribute based motion tracking* and *Inertial sensor based glove* for the actuation of a Robotic arm with three degrees of freedom (DOF). These two control modalities are designed for better handling compared to a conventional joystick.

0.4 Mathematical Representation of Robotic Arm

An articulated robotic arm with revolute joints, comprising 3 degrees of freedom was used in this research. The kinematic diagram of the 3 DOF Robotic arm and its Denavit-Hartenberg (DH) parameters are shown in Fig. 1



DH Parameters

i	Θ_i	a_i	α_i	d
1	Θ_1	a_1	90	d_1
2	Θ_2	a_2	0	0
3	Θ_3	a_3	0	0

Figure 1: 3DOF Robotic Arm and its Denavit-Hartenberg (DH) Parameters

where Θ_1, Θ_2, Θ_3, are the angles corresponding to joints J1, J2, J3 of the robotic arm respectively. In the DH parameter table in Fig. 1, a_i correspond to the link lengths, α_i are the link twists and d_i are the link offsets. The two imitative control modalities need to be designed for the same.

0.5 Inertial sensor-glove

The robotic arm acts as the output unit of the system has 3 joints J1, J2, J3 . Each of these joints can move freely through an angle of 0-180 degrees. Moreover, the position of these joints resemble the joints in a human arm. It was observed that the manipulation could be best realized when the robotic arm mimics the motion of the users arm. The joints J1 and J2 can be actuated by tracking the movement of the human elbow. The joint J3 can be actuated by tracking the movement of the human hand. Since the dynamics of the robotic arm as well as the human arm are angular in nature, it is appropriate to record this angular motion of the human arm with the help of a sensor capable of detecting the angle of a body.

0.5.1 Inertial Sensor

The Inertial sensor, commonly known as Inertial Measurement Unit (IMU) is used in measuring angular motion in bodies. An inertial sensor comprises of an inbuilt gyroscope, accelerometer and magnetometer. The Euler angles namely roll, pitch and yaw corresponding to x,y and z axes respectively can be calculated from the inertial sensor's data.

0.5.2 Circuit Design

The MPU9250 inertial measurement units (MPU1 and MPU2) used in this system are interfaced to an ATMega328 microcontroller by the i2c serial communication protocol. The sensors act as the slaves connected to the micro-controller which acts as a master , in this Master- Slave configuration.The connection diagram is shown in Fig 2.

The +5V pin provides 5V supply from the ATmega328 microcontroller based board (Arduino Nano) to power the sensors. In sensor MPU1, the +5V from Arduino is connected to Vcc. This assigns the default i2c address of

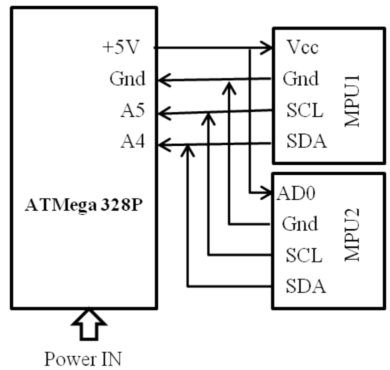


Figure 2: Circuit connection Diagram

MPU1 as 0x68. In the sensor MPU2, the +5V is connected to AD0 pin which fixes its i2c address as 0x69. For both the inertial sensors, the pins A4 and A5 are connected to SDA (DataLine) and SCL (Clock) respectively. This connection shown in Fig 2 enables the microcontroller to fetch the data from sensors to a corresponding address at a time.

0.5.3 Sensor Placement

Upon observing the design of the robotic arm, the joints J1 and J2 can be actuated by tracking the ***yaw* and *pitch* movements of the forearm about the elbow joint**. The joint J3 can be actuated by tracking the ***pitch* movement of the hand about the wrist joint**.

As shown in Fig 3a, the sensors are placed in two regions, i) *the hand* (extending from the fingers to dotted line ***a***) and ii) *the forearm* (extending from the dotted line a to dotted line b). The angular motion of *the hand* which is fixed to the wrist joint, is tracked by the inertial sensor (MPU2), placed at the tip of the index finger. It provides data to calculate pitch angle movement of that region (*p2*). To track the motion of *the forearm* region which is fixed to the elbow joint, an inertial sensor (MPU1) is placed at the topmost part of the forearm. This provides data to calculate the angles, yaw (*y1*) and pitch (*p1*). These sensor positions are illustrated in Fig 3b.

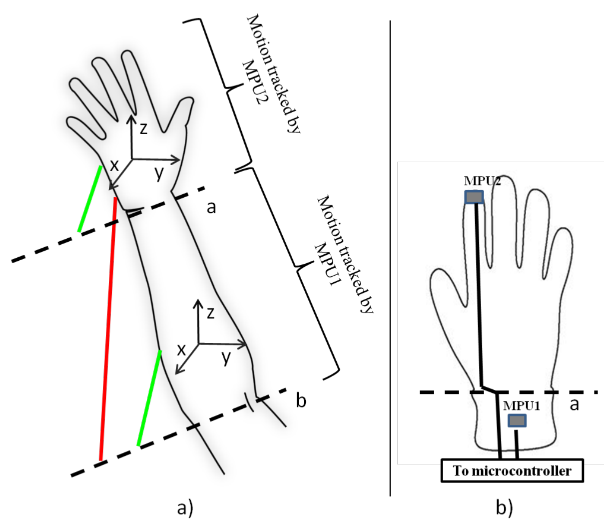


Figure 3: a) Assigning Reference Frame for Inertial Sensors b) Sensor Placement in the Glove.

The sensors are calibrated such that the dotted lines ***a*** and ***b*** act as the reference levels for the sensors MPU2 and MPU1 respectively, as denoted by green lines. The elbow of the user needs to be rested upon a horizontally flat surface during this calibration making line b as the horizontal bottom reference. The red line denotes the improper default assignment of reference line to both sensors.

This placement of the sensors in a wearable glove enabled to cover all the 3 degrees of freedom of the robotic arm by tracking the movement about the human wrist and elbow. This data from glove is utilised to control the robotic arm.

0.5.4 Translating data from Glove to Robotic Arm

As mentioned in the above section, the required euler angles were calculated from the sensor data. This angle data is used to provide the pulse width modulation (PWM) control signal to actuate the servo motors in the 3 joints of the robotic arm. The direct relationship between the degrees of freedom of the robotic arm and the angles calculated from Inertial sensor glove is expressed as,

$$(\theta_1, \theta_2, \theta_3)_{arm} = (y1, p1, p2)_{glove} \tag{1}$$

Hence, a wearable sensor based glove was designed as an input unit to track these arm movements.

0.6 Attribute based motion tracking.

Attribute based motion tracking is a computer vision based approach where certain attributes of a target object, held by a user before a camera, is recognized and its motion is tracked. The three joints of the robotic arm are controlled such that the movement of its end effector is based on the direction of motion of the target object held by the user . In this research, the attributes of the target are red colour and spherical shape. Thus, the system needs to recognize the target's colour and the shape initially, in order to track the target's motion.

0.6.1 Colour recognition

To perform the colour recognition, an image frame from the camera is taken as a live signal in real-time and a set of following tasks are performed.

The image frame is sharpened in order to obtain a proper colour gradient. This colour gradient of each pixel is in the Red Green Blue (RGB) format. The pixel colour gradient is converted to Hue Saturation Value (HSV) format since the HSV format is easier and more effective to choose the target's colour compared to the RGB format [7]. The HSV format values for the red coloured target held by the user is predetermined. A mask is applied in this image frame to filter out other coloured pixels in it, except red. Unwanted grains and noisy spots are removed by dilation and erosion. Thus, red coloured pixels in an image frame is detected.

0.6.2 Shape recognition

The system detects the region distributed with maximum red pixel density in the image frame while rest of the sparsely distributed red pixels are ignored. Since the red-spherical shaped target object appears circular in the 2D image frame, a circular contour is obtained from this region of red pixels. Thus, the contour of the red-spherical object is recognized. A well-defined outlining circle can be drawn over this contour. The x,y coordinates of the center of this circle located in the frame and its radius are obtained.

0.6.3 Motion tracking and Translation

The colour and shape recognition process performed over the image is repeated in the subsequent frames of the live stream capture. By comparing the *x,y* co-ordinates of circle's center with the subsequent frames, the 2 dimensional motion of the target can be tracked. These 2D coordinates are denoted as x and y, which are crucial in controlling the robotic arm.

In order to track the 3rd dimensional motion, the *radius* of the outlining circle is considered. The *radius* appears to increase when the target is brought closer while it decreases when moved farther. This *radius* variable is denoted as *z*. This novel method enables the system to track the motion of the target in all 3 dimensions. The 3 dimensional position data *(x,y,z)* obtained from the system needs mapped to the joint angles (θ_1,θ_2, θ_3).

$$(\theta_1, \theta_2, \theta_3)_{arm} = inv\_kn(x, y, z) \tag{2}$$

This $inv\_kn()$ function performs the inverse kinematics process of converting data corresponding to 3D coordinates into input joint angles such that the end effector of the robotic arm tracks the motion of the hand-held red spherical target, thereby imitatively controlled. The inverse kinematics process is explained in the next subsection.

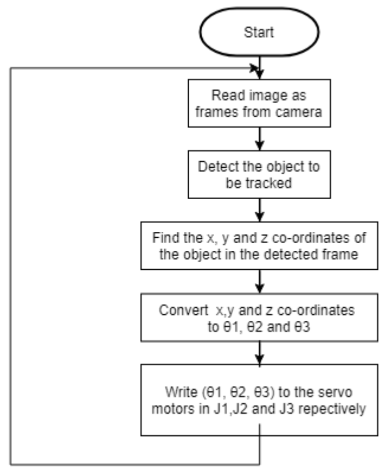


Figure 4: Flowchart of Attribute based motion tracking

0.6.4 Inverse kinematics

Inverse kinematics of robotic arm the mathematical process of estimating the robotic arm's joint angles are based on the data representing the desired position of the end effector of the robotic arm. Fig 5 geometrically represents the 3 DOF of robotic arm used in this research.

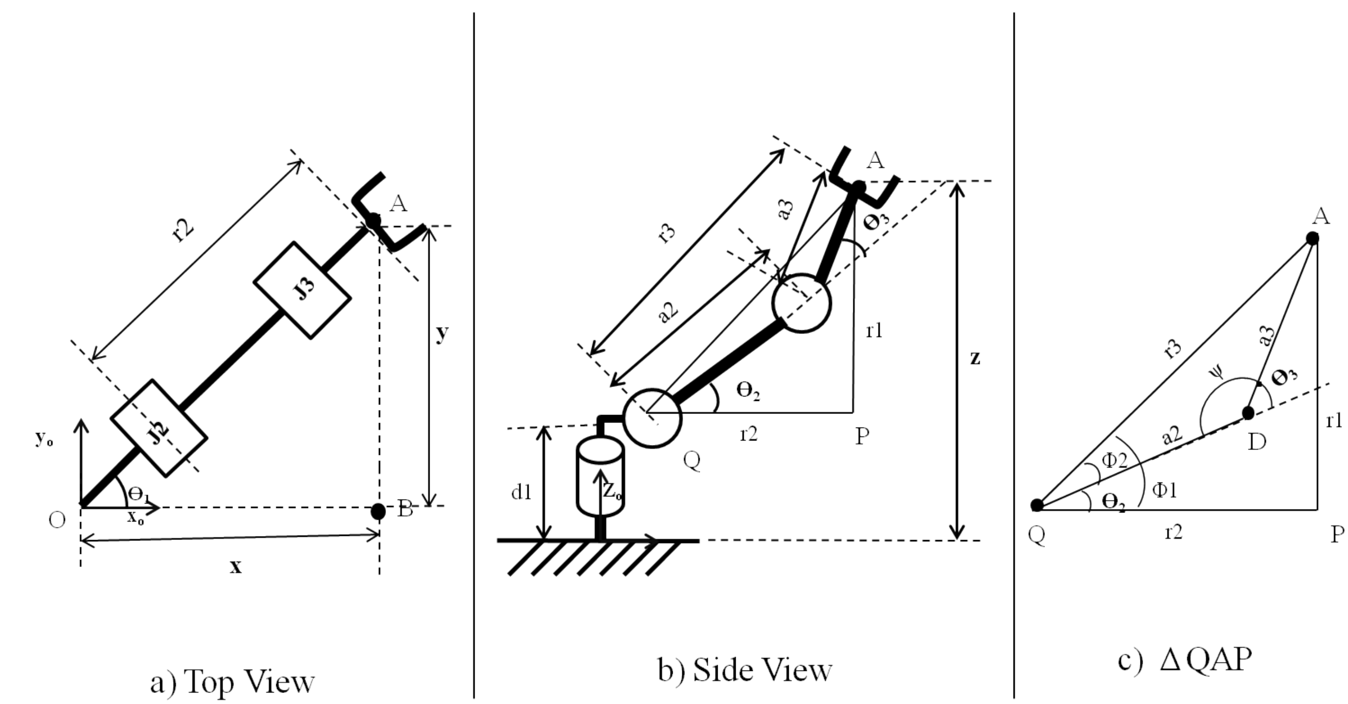


Figure 5: Geometric Model of the Robotic Arm for Inverse Kinematics

Consider x,y,z as the 3D real world co-ordinates that represent the end effector's desired position. The joint angles θ_1,θ_2, θ_3 are to be calculated. a1,a2,a3 are arm link lengths given in the DH parameter table mentioned in Fig. 1.

From triangle AOB,in Fig 5a,

$$\theta_1 = \tan^{-1}[\frac{y}{x}] \tag{3}$$

$$r2 = \sqrt{x^2 + y^2} - a1 \tag{4}$$

From Fig. 5b,

$$r1 = z - d1 \tag{5}$$

$$r3 = \sqrt{r1^2 + r2^2} \tag{6}$$

In triangle QAD,

$$a3^2 = a2^2 + r3^2 - 2 \cdot a2 \cdot r3 \cdot cos\phi 2 \tag{7}$$

From triangle QAP in Fig 5c,

$$\Phi 1 = \tan^{-1}[\frac{r1}{r2}] \tag{8}$$

$$\Phi 2 = \cos^{-1}[\frac{a2^2 + r3^2 - a3^2}{2 \cdot a2 \cdot r3}] \tag{9}$$

$$\theta_2 = \Phi 1 - \Phi 2 \tag{10}$$

$$r3^2 = a2^2 + a3^2 - 2 \cdot a2 \cdot a3 \cdot \cos\psi \tag{11}$$

$$\psi = \cos^{-1}[\frac{a2^2 + a3^2 - r3^2}{2 \cdot a2 \cdot a3}] \tag{12}$$

$$\psi + \theta_3 = 180^\circ \tag{13}$$

$$\theta_3 = 180^\circ - \psi \tag{14}$$

Equations (3),(10),(14) result in the joint angles θ_1,θ_2, θ_3 that are needed to be calculated in order to control the joints J1,J2 and J3 respectively. The process flow for the Attribute based motion tracking is represented in Fig. 4. Thereby, the two input modalities were designed to imitatively control the robotic arm. An experimental approach was taken to test the user's affinity and ease towards handling these two modalities in the Experiments and Results section.

0.7 Experiments and Results

Fitts's law is a predictive model of human movements and responses which is used in human computer interaction and user interface design. The performance index of an HCI input modality reflects the human rate of information processing when operating it. High performance index suggests faster and better ease of handling of an input modality[8]. Fitts's law is usually applied in 2D virtual pointing tasks in computer screens, where the target is bounded in both dimensions. Two experiments based on the Fitts's targeting law were conducted to analyse the performance of the input modalities proposed in this research .

0.7.1 2D test

The first experiment is the *2D test* where a screen with square gridlines is placed in front of the robotic arm with a pen tip attached to its end effector. For each input modality, the time taken by the user to mark all the squares in the grid with the robotic arm is recorded. This experiment was done by 3 users (U1,U2,U3) with two grids of different sizes(4×4 grid with $3cm \times 3cm$ per square and 3×3 grid with $5cm \times 5cm$ per square). Table I shows the time taken corresponding to each input modality for marking all squares in each grid.

In Fig. 6, which represents Table I, it is seen that the Attribute Based Motion tracking (mentioned as Vision method) enabled the users to complete the 2D targeting task quicker than with the inertial sensor glove (mentioned as Sensor method).

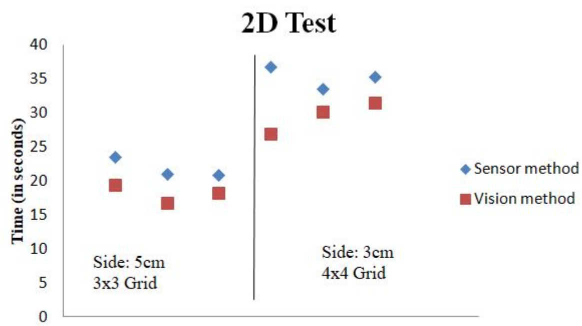


Figure 6: Scatter Plot representation of 2D test for 3 users for both grid sizes

Table 1: Time taken (in seconds) for both input modalities across 3 users -2D test

	5cm-3x3			3cm-4x4		
Modality	**U1**	**U2**	**U3**	**U1**	**U2**	**U3**
Sensor Method	23.68	21.19	20.92	36.9	33.68	35.4
Vision method	19.53	16.96	18.34	27.15	30.39	31.65

0.7.2 3D test

The second experiment is the *3D test* where 2 objects of sizes (W) $3.5cm \times 3.5cm$ and $8cm \times 8cm$ are kept alternatively at locations (D) 10 cms , and 18 cms away from the base of the robotic arm and within its reach. The index of difficulty(ID) is calculated for all 4 combinations as

$$ID = \log_2[\frac{2D}{W}] \tag{15}$$

Fig. 7 shows the average time taken by every user to control the robotic arm to touch the surface of the object recorded for all 4 combinations of targeting tasks. The solid trendline represents the time taken by the user U1 with *inertial sensor glove* to perform the tasks across various difficulty indices. The dotted trendline represents the time taken by the same user U1 with *Attribute based motion tracking* modality to perform the tasks across various difficulty indices. For U1, the slopes are found to be 1.22 and 1.56 for inertial sensor glove and attribute based motion tracking respectively. The reciprocal of this slope is the performance index. In this 3D test, Inertial sensor glove had smaller slope or better performance index, indicating a better human rate of information processing during the targeting task.

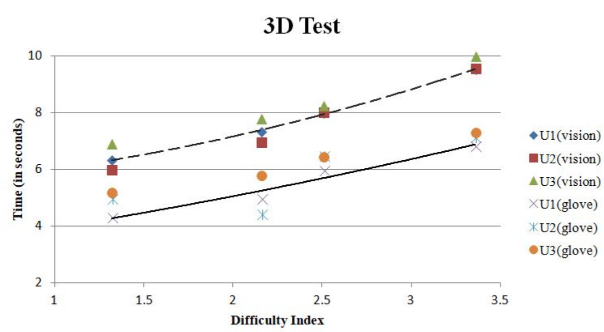


Figure 7: Scatter Plot representation of 3D test for 3 users for both control modalities.

The results of 3D test favouring Inertial sensor glove, accounts to the flexibility provided by imitating the user's arm in 3 dimensions directly with help of sensors, while the 2D test results favouring Attribute based motion tracking gives an idea about the ease of handling of the robotic arm in 2 dimensional pointing tasks offered by this modality.

0.8 Conclusion

Concluding this paper, it was observed that the Inertial sensor glove is more appropriate for applications requiring 3 dimensional motion than Attribute based motion tracking, whereas the latter is more convenient to use in applications involving 2 dimensional pointing tasks, as described in the previous section .

Despite the Inertial sensor glove costing copiously lesser than Attribute based motion tracking method, it cannot be easily adapted to any robotic arm system with a different number of degrees of freedom. This might require hardware changes like more number of sensors required to be positioned in different places of the user's arm in order to adapt it to the chosen robotic arm. This method might not even be possible if the robotic arm model does not match a normal human arm. Meanwhile, this is not a drawback for Attribute based motion tracking as it needs only the inverse kinematics model to be done specific to that robotic arm and doesn't affect the hardware configuration of the modality, hence providing a more generic design. Moreover, the proposed computer vision approach of tracking motion in 3 dimensions enabled with single camera optimizes the hardware requirements necessary for this input modality .

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