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Accurate Estimation of Robotic Arm Movements for Effective Motion Control: Utilizing Multiple Sensors and Data Fusion

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Abstract:

The robotic manipulators are highly complex coupling dynamic systems, which require a mathematical model for planning and controlling the robotic motions. It is imperative to calculate the kinematic parameters such as rotational matrix, joint angles, angular velocity, and angular acceleration, which determines the control performance of the models. For this purpose, a multiple-sensor-based Mathematical approach that utilizes inertial measurement unit (IMU) and triple-axis accelerometer is presented in this paper. A combination of one IMU and three triple-axis accelerometers is affixed to each of the two rigid bodies for real-time determination of parameters and the robotic arm orientation. Additionally, the model incorporates an Extended Kalman filter (EKF) fusion technique to combine data from various sensors, mitigate measurement noise, and adapt in real-time to changing environments. To implement this approach, a MATLAB code is developed to read, preprocess sensors data, and simulation of the proposed model. All the results are presented graphically and indicate that the motion parameters and pose measurements are calculated accurately and effectively.

Introduction

In the recent past, there has been a remarkable evolution of innovation in the field of robotics, where robots are now extensively deployed for multiple operations such as painting, prototyping spot welding, spraying etc. (Murray et al., 2017). To understand the intricacy of robots and functionality of their applications, it is crucial to acquire knowledge about electrical and mechanical engineering, computer science, mathematics and economics (Spong *et al*., 2006). Robotic automation has witnessed immense opportunities for growth in the spectra concerned with hazardous environments, space, entertainment, micro-electro-mechanical mechanisms, and medical surgeries. To be able to function appropriately in these fields, the robotic arms demand innovative characteristics as opposed to conventional robots, such as high rigidity, flexibility and motion control (Kim *et al.*, 2015). Considering the functionality of a robotic arm, it operates in a similar fashion as that of a human arm while depending on its liberty to move (Kinjal *et al*., 2015). A multiple-axis motion control is required for providing flexibility to the robots in performing intricate tasks with ease and accuracy. Accuracy in robotics refers to a robot's capability to reach its designated target, hit a mark or acquire an optimal answer. Therefore, a motion control system is an integral component in the robotic arm manipulator as it affects the performance and accuracy of the robots (Kang *et al*., 2009). Kinematics, motion control systems, accuracy and arm controller are highly challenging aspects in the field of robotics, for which, several researches have been conducted in the past (Thomas and Rajasekaran, 2014).

The robotic manipulators are highly complex coupling dynamic systems, non-linear, and highly coupled dynamic systems which requires a mathematical model for planning and controlling robotic motions (Tusset *et al.* 2023). For the same, it is imperative to know the exact parameters that affects motions in the robotic arm. A robot has several measurable entities that has a substantial impact on the effectiveness of the robot when performing a specified task. However, due to the coupling dynamic system ingrained in the robotic manipulators, developing an accurate mathematical model for better control is a challenging task. Furthermore, the control performance of these models are dependent on certain parameters such as angular velocity, orientation, rotational matrix, acceleration etc. As mentioned above, there are certain kinematic errors that are encountered and moreover, the estimation of such parameters is rather difficult through CAD software tools, where the results lack accuracy. A fine accuracy in robotic motions is required in recent industrial applications (Liu *et al*., 2015). Accuracy plays a critical role in the manipulators, as the effective control of the robotic motion path ensures high productivity and cost efficiency. The effective measurement of these parameters, therefore, offers autonomous, efficient and accurate robot processing. Therefore, there is a need of fine accuracy in calculating the robot parameters, so as to develop models for planning and controlling robotic motions. In the current research, therefore, the major aim is to design a mathematical model for determining the performance parameters such as angular velocity, rotational matrix, joint angle and angular acceleration between two rigid bodies for effective motion control in robots. In particular, the research aims at developing methods for presenting geometric and dynamic characteristics of robotic manipulation, and the various sensors used in the present research context.

Over the past few years, there has been a significant advancement Inertial Measurement Units (IMUs). These IMUs have become increasingly compact, lightweight, and cost-effective. As a result, they have found applications in various domains such as sports, gait analysis, and rehabilitation monitoring (Laidig *et al.*, 2021). IMUs are utilized in these applications to estimate motion variables, including orientations, velocities, and positions. This estimation can be performed in real-time or through post-processing of recorded data. The combination of multi-sensors will increase the accuracy in estimating the parameters (Dler *et al.*,2019). Further, the study offers certain basic concepts that can be used in developing mathematical models for robot manipulators, kinematics, planning and controlling, computer vision, and dynamics.

The objective of this work is to develop a mathematical model that efficiently estimates the kinematic parameters and orientation of a robotic manipulator using a multi-sensor-based approach. The proposed model integrates data from a 9-axis IMU and three triple-axis accelerometers attached to each rigid body of the manipulator, allowing for comprehensive motion analysis. By employing the Extended Kalman Filters (EKF) algorithm, the sensor measurements are combined effectively, leading to accurate parameter estimation. The researchers validated the model through MATLAB implementation with real-world data, generating graphs of Euler angles, angular acceleration, and angular velocity, as well as visualizing the robot's position. The results demonstrate the model's capability to accurately estimate motion parameters and effectively track the manipulator's pose. This approach holds promise in enhancing the efficiency, safety, and reliability of robot arms through improved mathematical modeling and accurate motion control.

2. RELATED STUDIES

In a study conducted by (Du and Zhang, 2014) sensors and data fusion mechanisms are used to develop a mathematical model for estimating the accuracy of robotic pose measurements. The proposed method is a self-calibration method that is formulated by inculcating a position sensor and an inertial measurement unit (IMU). These are attached to the robot arm, and the sensor extracts the position of the robotic manipulator from the IMU. For determining the orientation and position of the manipulator, Kalman, and particle filters are used, which assists in improving the reliability and accuracy of the robot arm. The filter is also used for estimating the errors in parameters, and therefore, better accuracy is obtained.

A mathematical model is developed by (Van Heerden, 2017) for higher control, a trajectory planner for humanoid robots. A model predictive control approach was used to create trajectories in real-time while comprehending the different mass heights and foot positions. The approach reduces the gradient computation time, and for validating the performance of the proposed approach, a robot is allowed to walk on a terrain where the placement of the foot is at two different heights. The results have revealed that the mechanism is effective in improving the disturbance recovery capacity by 7%.

(McLean, 2018) present a research paper that introduces a robotic joint sensor unit that incorporates an incremental encoder and additional accelerometer to estimate relative angular acceleration, velocity, and position of hinged robotic links. Two cascaded Unscented Kalman Filters are employed to separately estimate the IMU and relative components. Simulation results demonstrate accurate state estimation during various dynamic motions.

(Lapusan *et al*., 2022) propose a new approach for shape sensing of hyper-redundant robots using an AHRS IMU sensor network integrated into the robot's structure. The method enables real-time feedback systems by directly calculating kinematic parameters in the modules' operational space, reducing computational time. The approach is validated on a hyper-redundant robot with articulated joints and identical 2-DoF modules, and experimental results demonstrate the feasibility and effectiveness of the proposed sensor network and shape-sensing approach.

(Cvitanic *et al*., 2022) address the need for accurate real-time state estimation of flexible manipulators in the aerospace industry. It investigates the benefits of incorporating acceleration and angular velocity measurements from an inertial measurement unit (IMU) alongside high-end position and orientation sensors. The sensor fusion is achieved using a Kalman Filter and Particle Filter for different types of motion. Simulation results show significant improvements in velocity estimation (up to 95%) and angular acceleration estimation (up to 45%) when fusing IMU data with laser tracker data.

(Rahman *et al*., 2023) conducted a study that focuses on the development of a 3D rigid body as a substitute for a human arm in physical therapy. The objective is to estimate the elbow joint angle using three inertial measurement units (IMUs) and a two-stage algorithm incorporating the Madgwick filter. The accuracy and stability of the algorithm were validated using two electro-goniometers (EGs) attached to the rigid body. The proposed algorithm outperformed the IMU manufacturer's algorithm, achieving a maximum root mean square error (RMSE) of 0.46° compared to 1.97°. Even in the presence of external acceleration, the algorithm demonstrated stability, producing an RMSE of 0.996°. The estimated joint angles consistently fell within therapeutic limits.

Neurauter and Gerstmayr (2023) published an article that specifically addresses motion reconstruction challenges using IMUs for rigid bodies and proposes a novel method that incorporates optimization and correction polynomials to minimize motion deviation. Experimental results with an industrial manipulator demonstrate substantial reductions in position errors, achieving a 95% decrease in maximum error and an average reduction of nearly 90% throughout the measurement duration. The proposed method is suitable for experiments with constraints on velocity, position, and orientation, beginning and ending at standstill.

3. KINEMATIC MODELLING

Kinematics and dynamic mathematical models are the basic entities for adjusting a robot's controllers. The joint coordinate of the robot corresponds to the robot pose in the kinematic model. The sensors and manipulators of a robot must be attenuated in robotic manipulations such as sensor fusion or vision-based manipulation i.e., their inter-relationships must be well-characterized. This calibration is extremely important for complex robots, with many sensors and degrees of freedom that perform tasks in an unstructured environment. Various performance parameters like orientation, angular velocity etc. of rigid bodies has to be determined accurately in order to make a proper moment of these rigid bodies.

A model has been proposed that is effective in calculating the parameters (rotational matrix, joint angles, angular velocity and angular acceleration) of two rigid bodies. The two bodies are connected with each other in a form of a robotic arm (forearm and upper arm), where the bodies are attached to a socket (elbow). The bodies are moving continuously, and the purpose here is to ensure they do not touch each other or move apart. One IMU and 3 triple-axis accelerometers are attached to each of the bodies for calculating the aforementioned parameters. The IMU unit comprises of two sensors namely, magnetometer, and gyroscopes. While these sensors are used to monitor and process the data collected, the triple-axis accelerometer is used for measuring the parameters. Instantaneous sensor measurements are used so as to avoid the accumulation of errors over time. The data is stored in the IMU and then passed through the extended Kalman filter (EKF) to improve the accuracy and estimation of the parameters, as the sensors generate a redundant amount of data, which is reduced through filtering. Below **figure** 1 determines the block diagram of the proposed model.

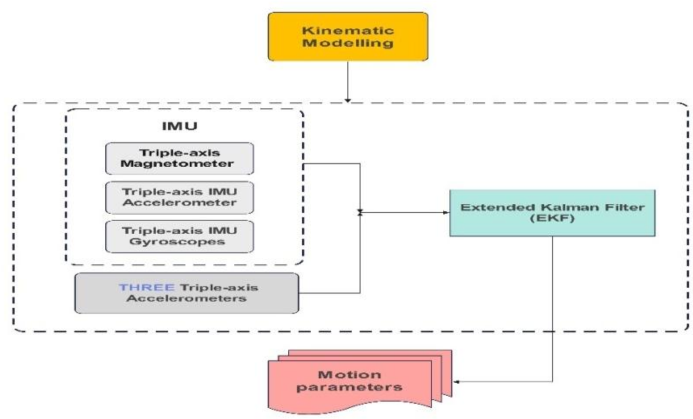

Figure 1: Outline of the proposed mechanism

4. PARAMETER IDENTIFICATION

The present study is focused on two links/bodies (universal joint used between links and in the ground). The sensors that are used here are: Six Adafruit ADXL345 (triple-axis accelerometer)–Three in each link/body and Two Adafruit 9-DOF IMU Breakout (L3GD20H + LSM303) –One in each link/body.

Figure 2: Adafruit ADXL345 Accelerometer

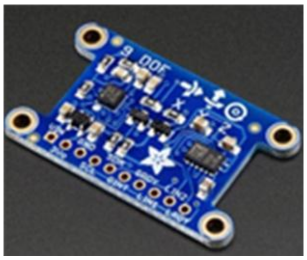

Figure 3: 9DOF IMU

The sensors are placed in a circular pattern, as seen in **Figure** 4. Here, A1, A2, A3 and A4 are 3 accelerometers and one IMU attached to body A respectively and B1, B2, B3 and B4 are 3 accelerometers and one IMU attached to body B. The requirements of the mathematical model are:

1. Find the joint angle in the x, y and z-direction
2. Rotational direction and relative orientation
3. Angular Velocity and Angular Acceleration in 3 direction
4. Error accumulation
5. Modeling and simulation of the links

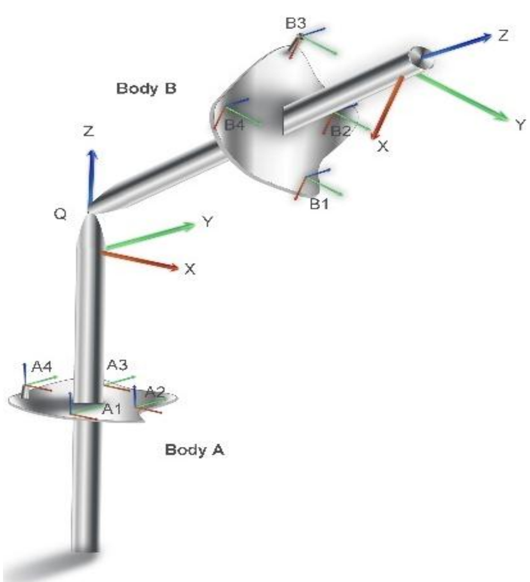

Figure 4: Three 3-Axis Accelerometers and one IMU Attached to Each Body

Among these sensors, the accelerometer is used to monitor the angular acceleration or the speed of the two rigid bodies, the gyroscope monitors the relative orientation and direction, and lastly, the magnetometer is used as a compass to determine the absolute orientation without the accumulation of errors. The quaternion algorithm as presented in (Xiaoping *et al*., 2008) is used for the estimation of the orientation of the rigid bodies. The triple-axis accelerometer measures the variations and parameters. This information is then passed to the Extended Kalman Filters (EKF), as the bodies are moving continuously and with EKF fusion algorithm, the angular information assists in the estimation of the orientation of dynamic bodies.

5. RECOVERY MOTION OF 2-D LINKED ROBOTS

5.1 Initial data

The initial robot pose is measured by the sensors. 2 samples of the data are obtained from acceleration sensors from each link, where the links correspond to the two rigid bodies. The initial position velocity is zero for both the links.

Initial position of link1 (body A) pose as expressed in Euler sequential angles rotations is X = 178 degree, Y = -38.96 degree, Z = -144.15 degree

Initial position of link2 (body B) pose as expressed in Euler sequential angles rotations is X = -90.50 degree, Y = 63.73 degree, Z = -99.97 degree

Here, three different coordinate systems are used, which are connected by pure rigid rotation to each other. They are:

1. Base coordinate system (denoted with lower index $_B$, for instance P_B)
2. Coordinate system, referenced with Link 1 (Body A) and denoted as $_{L1}$, for instanceP_{L1}
3. Coordinate system, referenced with Link 2 (Body B) and denoted as $_{L2}$, for instanceP_{L2}

Coordinates of link 1 sensor point/position in link1 coordinate frame is:

$P_{S\,L1} = [0.2 \quad 0 \quad 0]$
Coordinates of link 1 end point in link1 coordinate frame is:
$P_{L1} = [0.4 \quad 0 \quad 0]$
Coordinates of link 2 sensor point in link2 coordinate frame is:
$P_{S\,L2} = [0.2 \quad 0 \quad 0]$
Coordinates of link 2 end point in link2 coordinate frame is:
$P_{L2} = [0.4 \quad 0 \quad 0]$
Timestamp dt = 0.01 seconds

The motion for both the bodies are estimated, including:

1. Link1 position angles, angular velocities, angular accelerations in reference to base
2. Link2 position angles, angular velocities, angular accelerations in reference to link1 frame
3. Link2 position angles and rotation matrix in reference to base frame

The motion recovery in numerical form is then executed with MATLAB software.

5,2 Mathematical model

As mentioned above, the present study is focused on two links (universal joint used between links and in the ground). The ground point in the mathematical model describes the angle rotation of the links with each other and the base. At one hand, the general case of this description requires the use of rotation matrix, however, the numerical integration with rotation matrix is not a trivial task and further requires the mathematical apparatus like Jacobians to integrate all the three angles at once. Also, the use of Euclidian angles to describe the increment of angles is infeasible as they are applied in a sequence and not in one instance. Besides operation with Euclidian angles can cause well-known problems as gimbal lock. Here, the angle rotation has been manually kept in the frame of 0-360 degrees. Using quaternions is an efficient means to avoid the aforementioned problems. Also, quaternions are supported in MATLAB with a number of functions as it is rendered as a complicated mathematics.
Here, the total amount of rotation is donated by quaternion Q, where quaternion Q_{L1} describes the total amount of link1 from zero position to currently described position in base coordinate frame, and Q_{L2} contains total amount of rotation of link 2 from its zero position to current position in reference to Link 1. For description of position of link 2 point in base coordinate frame, the quaternions Q_{L1L2} is used.
Having a point position in local frame P_{L1} and knowing the rotation from base zero position to current position Q_{L1}, it is implied that for rotation at quaternion to obtain point actual position in base frame (Craig, 2005):

$$P_B = Q_{L1} * P_{L1} \tag{1}$$

For estimating the coordinates of link 2 point P_{L2} in link 1 reference frame, then:

$$P_{L1} = Q_{L2} * P_{L2} \tag{2}$$

It is essential to note that operation * here is not dot multiplication but special operation in hyperspace and introduced for simplicity, but in full case for quaternions **q** and original point **v** it is:

$$q = q_0 + iq_1 + jq_2 + kq_3$$
$$v = iv_1 + jv_2 + kv_3$$

$$v' = \begin{bmatrix} v_1 \\ v_2{}' \\ v_3{}' \end{bmatrix} = \begin{bmatrix} (1-2q_2^2-2q_3^2) & 2(q_1q_2+q_0q_3) & 2(q_1q_3-q_0q_2) \\ 2(q_1q_2-q_0q_3) & (1-2q_1^2-2q_3^2) & 2(q_2q_3+q_0q_1) \\ 2(q_1q_2+q_0q_2) & 2(q_2q_3-q_0q_1) & (1-2q_1^2-2q_2^2) \end{bmatrix}$$

Having known coordinate of link 1 in base coordinate frame, its linear velocity is defined through vector multiplication of angular velocity of link 1 in base frame ω_{L1} (Craig, 2005):

$$V_B = \omega_{L1} \times P_B \tag{3}$$

The same is applied for link1 and link 2, respectively:

$$V_{L1} = \omega_{L2} \times P_{L1} \tag{4}$$

Quaternion increment can be obtained from angular velocity numerical integration, as demonstrated below. In the general case, the angular velocity is derivative on angle vector α change:

$$\omega = \frac{d\alpha}{dt} \tag{5}$$

Linear acceleration of these point (P_B and P_{L1})

will be (Xiaoping *et al.,* 2008):

$$a_B = \mathcal{E}_{L1} \times P_B + \omega_{L1} \times (\omega_{L1} \times P_B) \quad (6)$$

$$a_{L1} = \mathcal{E}_{L2} \times P_{L1} + \omega_{L2} \times (\omega_{L2} \times P_{L1}) \quad (7)$$

Where $\mathcal{E}_{L1}$ is the angular acceleration of link 1 in base frame. Substituting (3) in (5) and (4) in (6), the following is obtained:

$$a_B = \mathcal{E}_{L1} \times P_B + \omega_{L1} \times V_B \quad (8)$$

$$a_{L1} = \mathcal{E}_{L2} \times P_{L1} + \omega_{L2} \times V_{L1} \quad (9)$$

Also, linear acceleration is the derivative of the linear velocity on time:

$$a_B = \frac{dV_B}{dt} \quad (10)$$

$$a_{L1} = \frac{dV_{L1}}{dt} \quad (11)$$

This is the basic mathematical apparatus required for executing the task of recovery of robot motion. However, the motion is an acceleration of link middle point, and therefore, the recovery of motion is started at this point. Obtained acceleration from link1 sensors is the sum of motion of link1 and the gravity acceleration, which is:

$$a_{BS} = a_B + a_g$$

Therefore, the link1 motion in base coordinate frame is obtained through sensors acceleration minus gravity acceleration, which is supposed to be constant

$$a_B = a_{BS} - a_g \quad (12)$$

From (10) the increment of velocity is obtained as:

$$dV_B = a_B * dt$$

This increment on k-th step is added to the previous step velocity to obtain the actual velocity value:

$$V_{SL1} = V_{Sk} = V_{Sk-1} + dV_B$$

After obtaining the actual velocity of sensor point of link 1, it is numerically integrated to obtain the shift of physical angle. For this purpose, the properties of the quaternions are used. As far as link 1 is connected to the base allowing only link1 rotation, all of the V_s can be expressed as angular rotation, and this will be the angular rotation for the whole link in global/base frame. From (3), the velocity is obtained to be:

$$\omega_{L1} = \frac{P_B \times V_{SL1}}{\|P_B\|^2} \quad (13)$$

To apply quaternion paradigm of numerical integration, the actual (on the current step *k*) angular velocity ω_{L1loc} in local link1 frame, sensor point position P_{Bkloc} and sensor point velocityV_{SL1loc} are used. The mathematical operation is identical to equation (11), and the local velocity is obtained by inverse rotation on the quaternion by:

$$V_{SL1loc} = Q_{L1}^{-1} V_{SL1}$$

On the next step, this local ω_{L1loc} is integrated to obtain addition to rotation (angles shift). By using equation (5), this addition is expressed in quaternion in the following way:

$$d\alpha = \omega \, dt$$

$$d\alpha_q = \sqrt{d\alpha_x^2 + d\alpha_y^2 + d\alpha_z^2} \quad (14)$$

$$dQ_{L1} = \begin{bmatrix} \alpha_x \cdot \sin(0.5 \cdot d\alpha_q)/d\alpha_q \\ \alpha_y \cdot \sin(0.5 \cdot d\alpha_q)/d\alpha_q \\ \alpha_z \cdot \sin(0.5 \cdot d\alpha_q)/d\alpha_q \\ \cos(0.5 \cdot d\alpha_q) \end{bmatrix}$$

After this addition in rotation, the addition of angle shift is implemented and expressed in dQ_{L1} to total accumulated amount of rotation expressed byQ_{L1}as:

$$Q_{L1k} = Q_{L1k-1} * dQ_{L1k-1}$$

Initial sensor data, obtained from 4 accelerometers have to be put together and aligned with link direction. As mentioned before, the sensors are placed in a circular manner as demonstrated below:

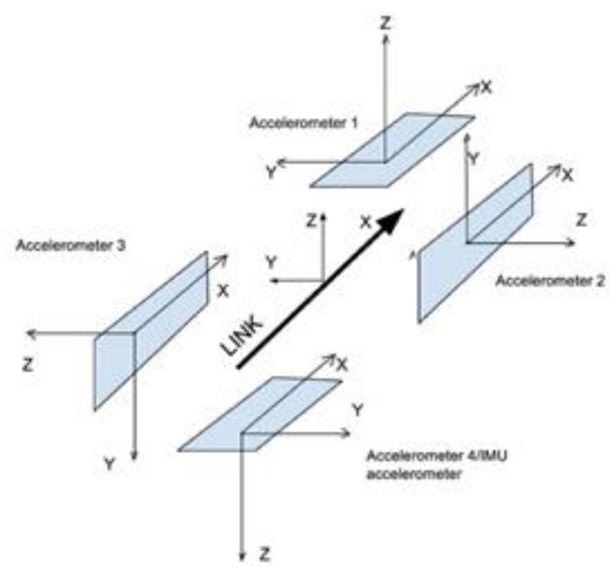

Figure 5: Sensor location scheme on the link1

Accelerometer 1 is located in the top and it is already aligned to link 1 coordinate frame. Accelerometer 2 is on the right side and its measurement vector is to be rotated at -90 degrees. Accelerometer 3 is located at the left side and is to be rotated at -270degrees (or 90 degrees). Bottom Accelerometer 4 on IMU is to be rotated at 180 degrees. All these operations are implemented for link 1 and link 2.

$$a_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{bmatrix} \quad a_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \quad a_4 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix}$$

The similar operation on motion recovery is executed for link 2 by considering that link 1 is stationary. Acceleration of link 2 is the sum of link 1 induced motion and gravity. So link 2 motion in link 1 frame is obtained by:

$$a_{L1} = a_{L1S} - a_g - a_B$$

a_B can be found from equation (9). The rotation of the required point is obtained with equation (2). Integration of acceleration to linear velocity, linear velocity to angular velocity, and angular velocity integration to quaternion are performed by using the formulae explained above.

6. IMPLIMENTAION AND EXPERIMENTAL RESULTS

MATLAB code is developed which effectively read the data from sensors and synchronizing the data from different sensors, state initialize, the code integrates the sensor data using the EKF to perform data fusion, estimates all the relevant parameters using the derived mathematical model, validate and analyze the results

Two rigid bodies (referred to as links) are used in this experiment to verify the proposed method. Here, these bodies are representing a robotic arm and are connected with each other via a socket. Simulation of the proposed mechanism is executed in the MATLAB software. The links of size 40 cm each are moving continuously in space 3D direction. The motion is estimated for 2 sec for each of the moving bodies. The placement of the sensors have been explained in the previous section, where the accelerometer is attached to the middle of each link. The distance between each sensor is 4.5 cm. With set initial vales, the initial pose for link 1 is demonstrated in **Figure** 6.

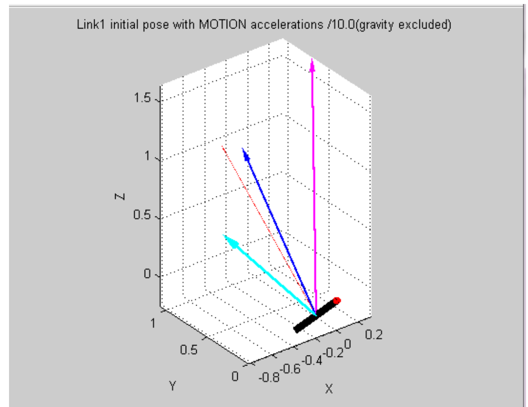

Figure 6: Link 1 initial pose with motion accelerations

The sensors monitor the motion, collect the relevant information and send it to the triple-axis accelerometer, which then estimates the values of the parameters. After this, the data is passed through the extended Kalman filter, and the accurate parameters are obtained. With the movement of the rigid bodies, which is monitored by the sensors, the angles at X, Y and Z axis are obtained for link 1. **Figure** 7 corresponds to the same.

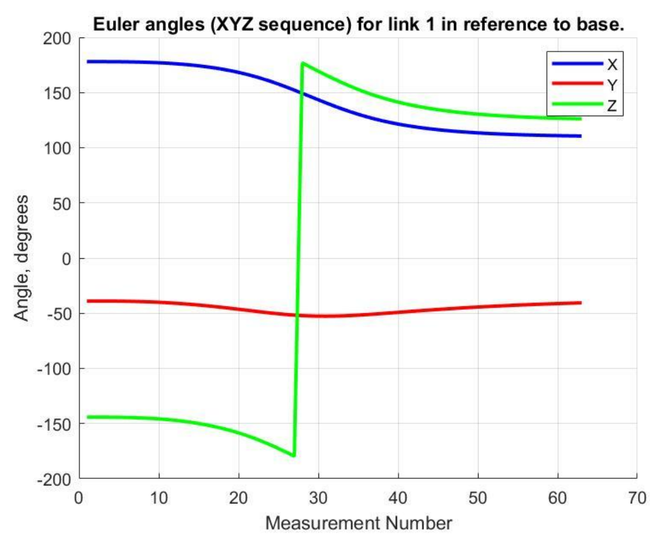

Figure 7: Euler angles for link 1

The below **Figure** 8 and 9 corresponds to the angular velocity and angular acceleration, respectively, of link 1, which relates to the speed with which the body moves.

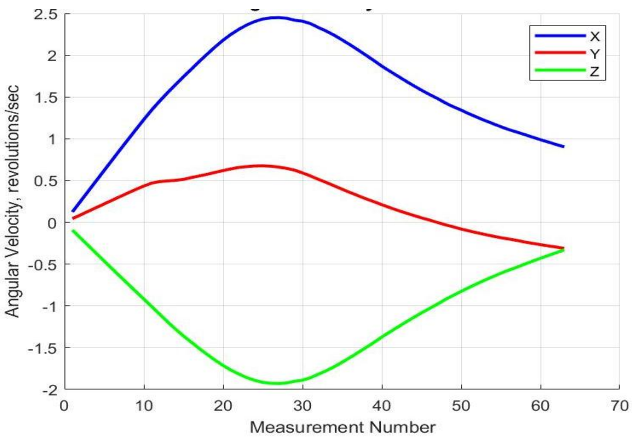

Figure 8: Angular Velocity for link 1

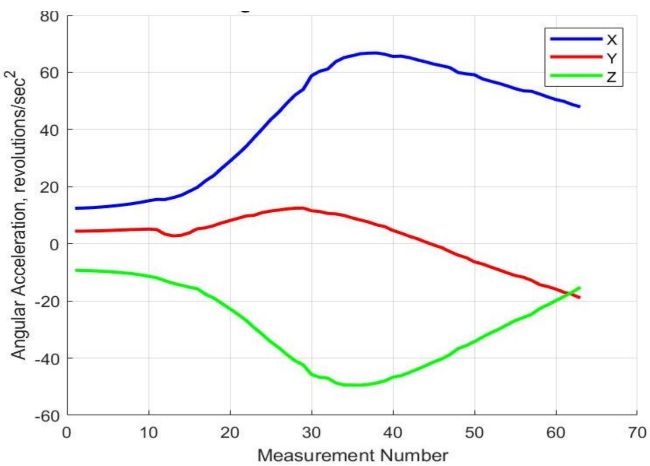

Figure 9: Angular velocity for link 1

After 360 iterations, the final pose of the link 1 is obtained, which is presented in **Figure** 10.

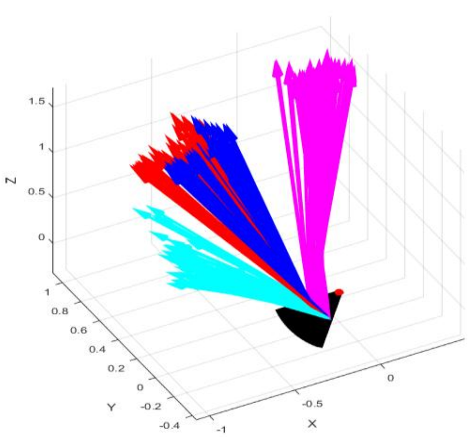

Figure 10: Link 1 final pose with motion accelerations

For link 2, the similar mathematical model is applied, as explained in the previous section. While the angular acceleration and angular velocity of link 2 are same as that of link 1, its rotational angle is different. As shown in **Figure** 11, it is evident that the joints have different rotational angles, and therefore, the objective is fulfilled, where the two bodies should be placed together but not touch each other.

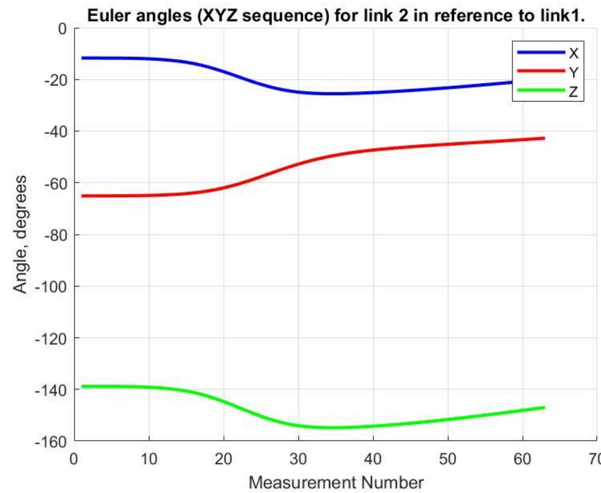

Figure 11: Euler angles for link 2

Considering the socket, which is attached to both the rigid bodies, if the two links are separated then **Figure** 12 shows the pose of the robot socket.

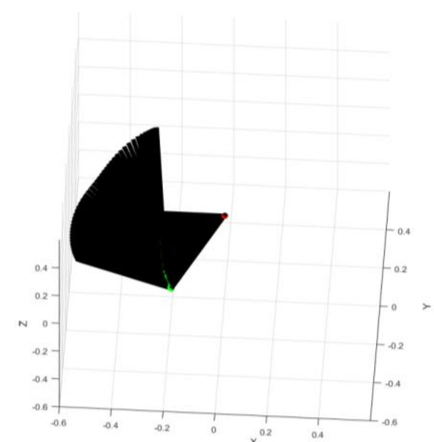

Figure 12: Robot pose without the links

7. DISCUSSION

The proposed mathematical model integrates the data from the 9-axis IMU and the accelerometers using the EKF algorithm which effectively combines the sensor measurements to estimate the kinematic parameters and determine the orientation of the robotic manipulator accurately. With three accelerometers placed on each link, they capture acceleration in three perpendicular axes, allowing for a more comprehensive understanding of the link's movement.

To validate the effectiveness of the model, the researchers programmed it using MATLAB. They implemented the model using real-world data and obtained graphs illustrating the Euler angles, angular acceleration, and angular velocity for both links provide insights into the manipulator's movement characteristics. Additionally, the position of the robot was visualized.

The results obtained from the implementation demonstrate the model's capability to accurately estimate motion parameters and track the pose of the manipulator. provide insights into the manipulator's movement characteristics.

8. CONCLUSION

The paper introduces a method that utilizes sensors to estimate the kinematic parameters of a robotic arm, for precise motion control. By equipping each body with an IMU and three triple axis accelerometers the proposed approach successfully determines the positions of the bodies during manipulation. Developing a novel mathematical model that combines data from multiple sensors is crucial for achieving improved precision, and reliability in estimating the parameters of a robot arm.

Moreover, the integration of multiple sensors ensures greater reliability in the estimation process, offering inherent fault tolerance. In cases of sensor failures or errors, redundant data sources allow the robotic system to maintain its functionality and operate safely, especially in safety-critical applications.

The advantages of this approach have reaching implications across industries enabling the creation of more advanced, efficient and adaptable robotic systems, with broader applications. The integration of the EKF algorithm also improves the accuracy of parameter estimation. Real world data implemented in MATLAB validates the effectiveness of this model in estimating motion parameters and visualizing the robots position. The experimental results demonstrate that the proposed mathematical model is both accurate and efficient. Utilizing position and orientation information has also contributed to pose estimation. It is important to note that creating models for robot arms remains a challenging task. However employing models brings benefits leading to the development of more efficient, safer and reliable robot arms.

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