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Accuracy Assessment of Demonstrative-Kinesthetic Teaching of Robotic Manipulators to Acquire the Desired Position

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ABSTRACT

Industrial robots have been integrated into manufacturing activities to meet the dynamic nature of customer needs. As a solution to keeping a competitive edge on the competition, it has necessitated the adoption of newer and improved manufacturing practices. The technological advancement brought about by the overall development of cyber-physical systems has dramatically facilitated the needed technological growth. The adoption of robotics has led to smart manufacturing and encouraged the establishment of a collaborative work environment. The study aimed to program a robotic manipulator using demonstrative-kinesthetic teaching, assessing its accuracy to acquire desired target positions and validating using a palletising experiment. Using structured texts to perform the same experiment serves as a control experiment, and the demonstrative-kinesthetic teaching approach is compared against it in terms of joint values acquired while using both methods. The Dobot Magician robot manipulator was programmed with both approaches for the experimental tasks. The results showed a more accessible programming approach, especially considering workforces not accustomed to robotic programming and robot manipulator learning of demonstrated tasks. The high level of joint accuracy demonstrated the high flexibility the demonstrative-kinesthetic teaching offers as a programming method, especially in programming and re-programming in factory set-ups due to the fluctuating manufacturing demands.

Keywords: Accuracy assessment; demonstrative-kinesthetic teaching; desired position; robotic manipulator; palletising; structured-texts.

INTRODUCTION

The manufacturing world is quickly evolving to cope with consumer demands' dynamic yet complex nature. Smart manufacturing is the way forward in response to the needs that traditional manufacturing practices are no longer practical to achieve. The onset of the fourth industrial revolution (4IR) has necessitated overhauling conventional manufacturing practices with the adoption of newer, cost-effective, and efficient strategies. These strategies include using robotics and automation and applying innovative technologies such as artificial intelligence and machine learning (Kwanya, 2023) in manufacturing processes.

Robotic manipulators play a crucial role in achieving smart manufacturing, thus bringing about the rise of smart factories. A robotic manipulator is a unique robot employed mainly in industries for specialised task execution with re-programmability possibilities (Arteaga et al., 2022). Jahnavi and Sivraj (2017) describe a robotic manipulator as an electromechanical device consisting of kinematic joints and links driven by motors or other actuators. Repetitive tasks are carried out accurately and precisely due to the automatic control alongside the mechanical structure. Robots were initially programmed using traditional methods such as teaching pendants, structured texts, and graphical interfaces (Amar et al., 2020). The methods proved to be quite non-intuitive, tedious, and time-consuming (Zhou et al., 2020).

Newer programming methods such as programming by demonstration (PbD) or learning from demonstration (LfD), use of augmented and virtual reality (AVR), machine learning (ML) technologies

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(Mosavi & Varkonyi, 2017; Orendt et al., 2016), kinesthetic teaching (KT), and one-shot kinesthetic(Müller et al., 2020) are being employed with improvements in technologies. KT programming is an approach where the programmer shows new behaviours via learner robot body manipulation as it records through its sensors (proprioception) (Calinon, 2018; Villani et al., 2018). The techniques employed are physical manipulation, demonstrative-kinesthetic teaching (DKT), and robot movement control through interfaces, such as teleoperation or tele-kinesthetic teaching (TKT).

TKT technique offers an opportunity for remote programming, especially for dangerous areas like nuclear plants (Si et al., 2021). Still, it faces the limitations of additional lengthy user training on the interfaces, availability of the chosen input hardware, and additional effort required to develop the selected interface (Ravichandar et al., 2020). The DKT allows for natural programming. The onboard sensors record the robot's state during the interaction, provisioning an intuitive approach with minimal training requirements (Eiband et al., 2023; Tykal et al., 2016) as it does not burden the programmer with the requirement of knowledge of programming languages such as Python (Heimann & Guhl, 2020) or robotics (Tykal et al., 2016). It provides an avenue for exploring the physical human-robot interaction (pHRI) (Landi et al., 2017).

The use of vibrotactile feedback for the comprehension of specified kinematic constraints by operators was explored by Ruffaldi et al. (2017) as KT task enhancement, considering the challenges posed by redundant designs from human poses. The DKT approach was used by Capurso et al. (2017) as the lead-through programming (LTP) as a means of fast trajectory teaching of redundant robots to eliminate the expensive torque/force sensors. Automatic trajectory generation by non-expert users from single kinesthetic guidance was carried out by Müller et al. (2020) as a means of reducing costs. The costs were associated with robot integration in production lines.

The KT provides avenue for the non-skilled shop-floor operators to program the robots in line with the assigned tasks. DKT provides an intuitive avenue for programming robots, especially in incorporating robots and humans within the same workspace, thus the collaborative technology (Cobot). The study aimed at programming a robotic manipulator using the DKT, creating a platform to facilitate the DKT programming, and assessing the accuracy in acquiring desired target positions using DKT. Structured texts (Control) were used as a control experiment, and the palletising experiment was done using DKT and Control to validate the experiment.

MATERIALS AND METHODS

Description of Robotic Manipulator

The robot manipulator used in this study was the Dobot Magician. It has three stepper motors and one servo motor. The manipulator has four axes, with an end-effector having a payload of 500g. The robot manipulator's joint range of motion is in Table 1.

Table 1: Joint Range of Motion (Shenzhen Yuejiang Technology Co., 2017)

Axis Movement	
Axis	Range
Joint 1	-135^{o} to $+135^{o}$
Joint 2	0^{o} to $+85^{o}$
Joint 3	-10^{o} to $+95^{o}$
Joint 4	$+90^{o}$ to -90^{o}

The joint and cartesian configurations of the Dobot magician are shown in Figure 1.

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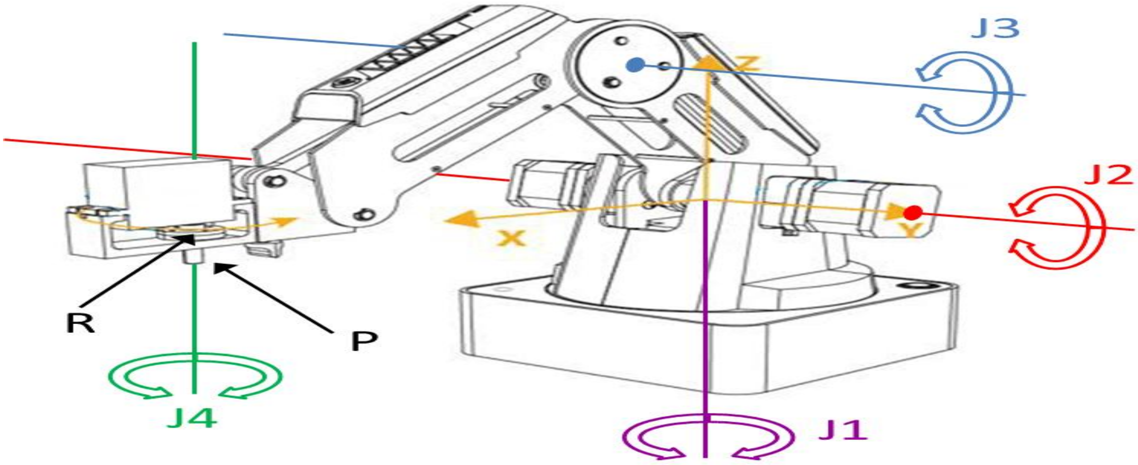

Figure 1: Joint and Cartesian Configurations of Dobot Magician (Adapted from Shenzhen Yuejiang Technology Co. (2017))

Experimental Set-up and Procedure

The materials for the experiment were a laptop, robotic manipulator (Dobot Magician), wooden block, USB connection cable, power source, pneumatic pump, and pneumatic gripper (end-effector). The experiment was set up as shown in Figure 2.

To determine the accuracy of DKT, a control platform (Figure 3) based on Python language was created using Visual Studio IDE to control the robot demonstratively (DKT) by using the lock button on the forearm to capture the positions of the end-effector(Hand-held Trigger (HHT)) and tabulate the joint values in a pose.csv file. For the control experiment, the same effector positions were captured using structured texts (Control), and the joint positions were saved on the pose1.csv file using the ***getpose ()*** command in the code.

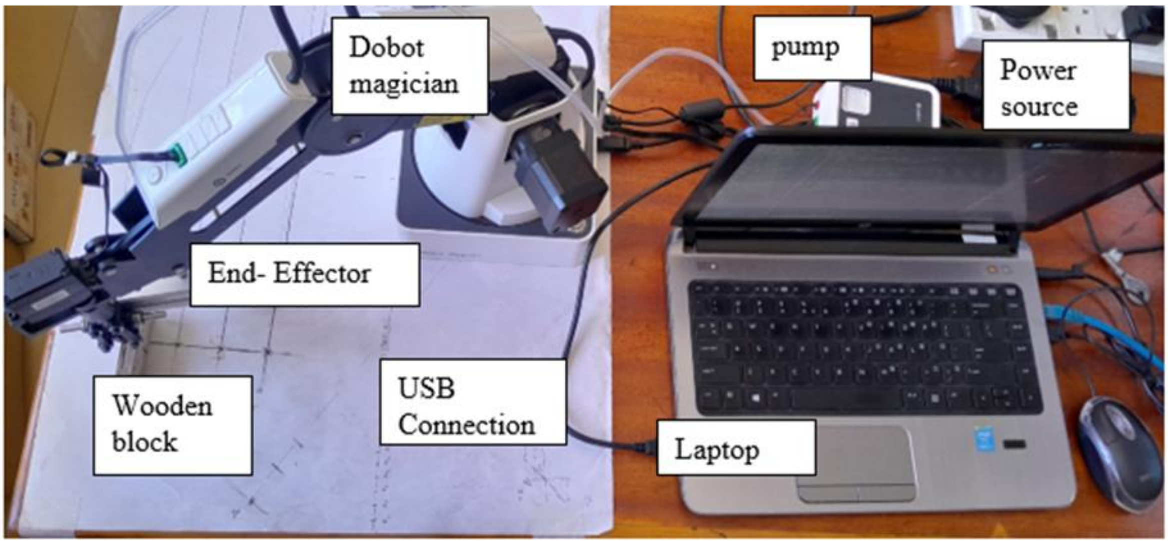

Figure 2: Experimental Set-up

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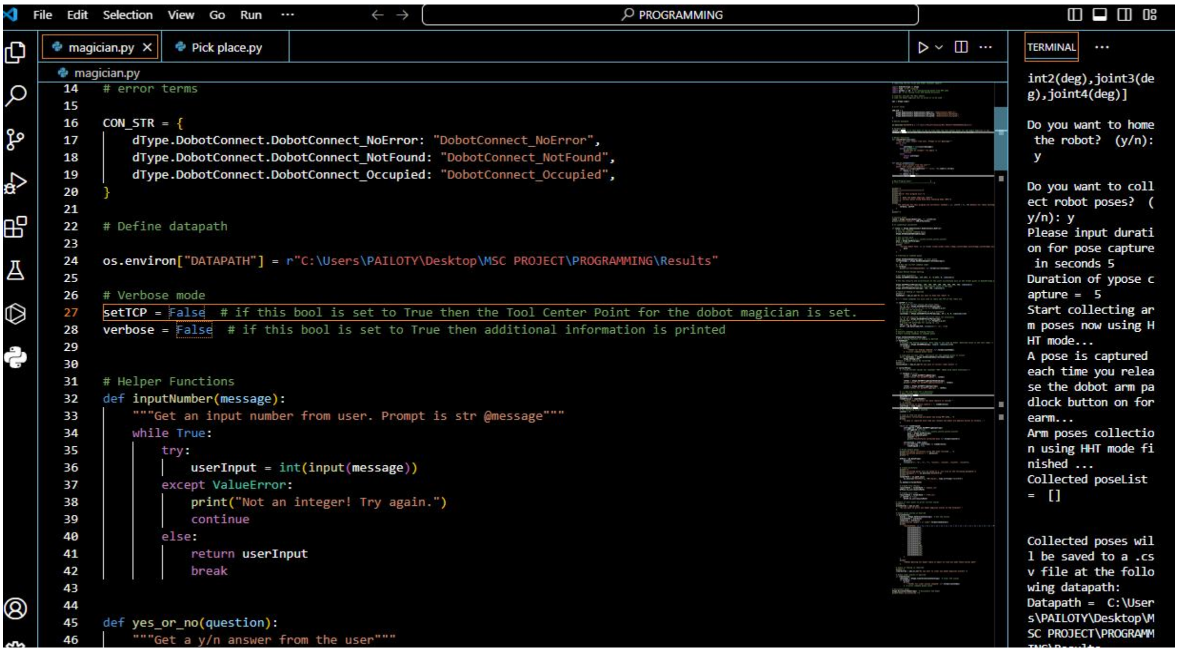

Figure 3: Control Platform in MS Visual Studio.

The palletising experiment involved picking the wooden block from the start to the stop position over four levels. The position of points A and B were determined for distances 25mm, 40mm, and 55mm apart from the initial position of A_1 (Start) and B_1 (Stop) on a straight line as the stop points of the experiment in Figure 4 and Figure 5.

The experiment was replicated for each level (A_2, B_2, A_3, B3, A_4, B_4). The joint values were recorded and stored in the CSV file for each replication and level.

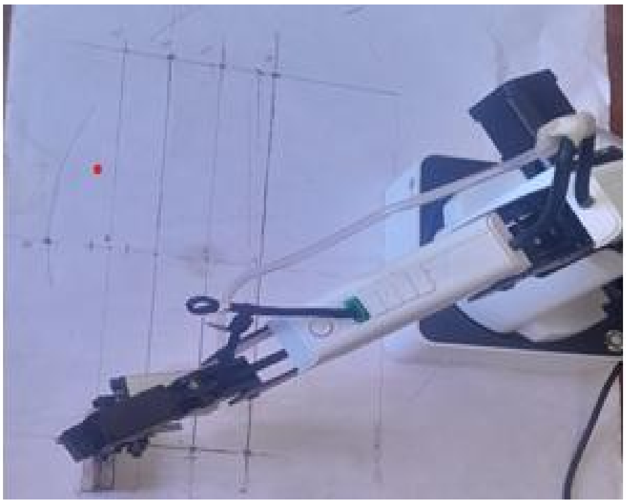

Figure 4: The start position A_1

Figure 5: The stop position B_1

RESULTS AND DISCUSSION

The accuracy of the target position was determined using the joint values obtained during the palletising task. End effector positions were determined using structured texts (Control) and DKT techniques for the joint configurations. A comparison of the joint values for the structured text (Control) with the DKT was as shown in Figure 6 - 8.

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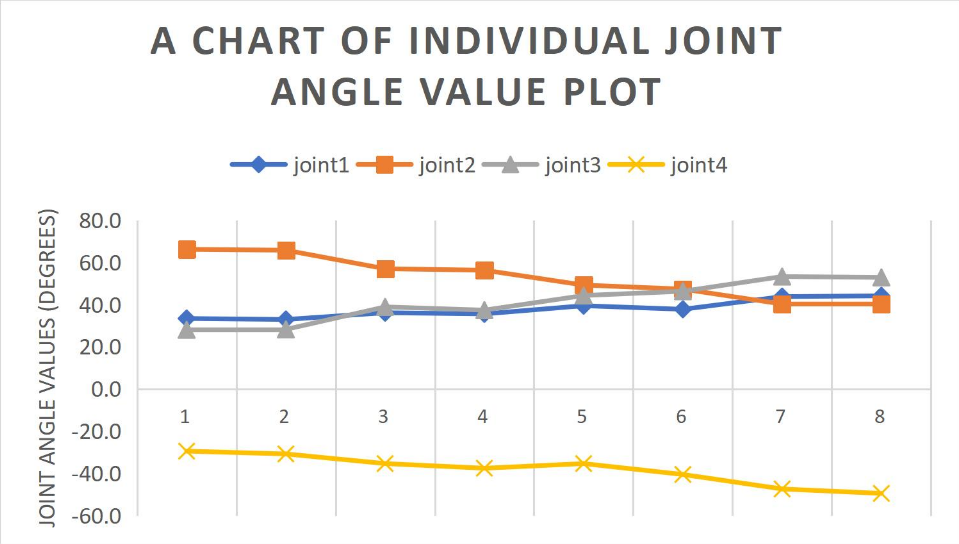

Figure 6: Individual Joint Angle Value Plot

The joint value absolute and percentage errors were calculated using Equation (3-1and Equation (3-2).

$$Absolute\ Error = Control - DKT \qquad \text{Equation (3-1)}$$

$$Percentage\ Error = \frac{Absolute\ Error}{Control} * 100\% \qquad \text{Equation (3-2)}$$

The percentage errors of the joints were as plotted in Figure 3-2, and overall joint mean percentage errors, as shown in Table 3-1.

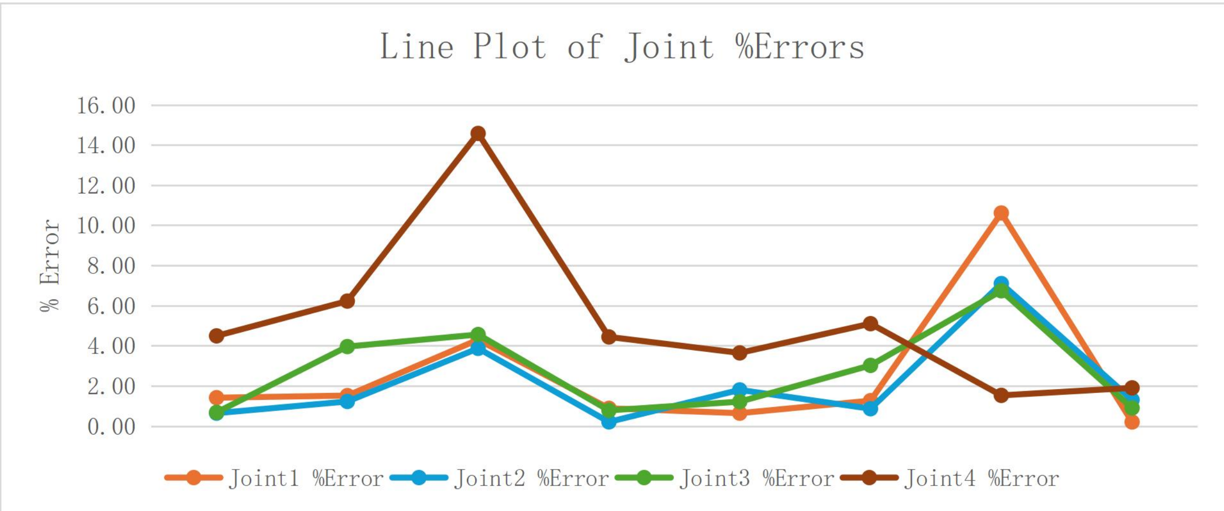

Figure 7: Joint Percentage Errors

Table 2: Joint Mean Percentage Errors

Joint1	Joint2	Joint3	Joint4
2.60	2.12	2.73	5.24

From Figure 7-8 and Table 2, it was determined that joint 4 had the highest mean percentage error of 5.24%, while joint 2 had the lowest mean percentage error of 2.12%.

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The low mean percentage error on joint 2 was due to the possible least number of sources of inaccuracies in comparison to the high value on joint 4, which may have been contributed by user-related inaccuracies, especially in placing the end-effector in the desired position demonstratively, computational errors, computer-control algorithms and, link bending due to gravity and loads.

From the palletising task, in this case, pick and place, the robotic arm could pick the wooden box from the start positions of A and place it at place B as required. Pick and place points A and B were chosen using the Control program, which provided the basis for determining accuracy.

CONCLUSION

The robotic arm was programmed to carry out palletising tasks as programmed with the demonstrative-kinesthetic teaching (DKT) and compared with the use of structured text (Control) to assess the accuracy of DKT in acquiring a desired position. The robotic arm could pick items at set pick points and move them to the place points, and the points' accuracy level was determined by the joint angle values obtained using the DKT and compared against those obtained by the Control method. It was determined that joint 4 had the highest mean percentage error of 5.24% while joint 2 had the lowest mean percentage error of 2.12%. The significant percentage of error in joint four was attributed to the user's accuracy level while selecting the target points using the robotic arm kinesthetically, joint value rounding off errors by the computer, and link bends due to gravity.

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