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Neural Learning enhanced Teleoperation Control of Baxter Robot using IMU based Motion Capture

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Abstract—In this paper, we have developed a neural network (NN) control enhanced teleoperation strategy which has been implemented on the Baxter robot. The upper limb motion of the human operator is captured by the inertial measurement unit (IMU) embedded in a pair of MYO armbands which are worn on the operator’s forearm and upper arm, respectively. They are used to detect and to reconstruct the physical motion of shoulder and elbow joints of the operator. Given human operator’s motion as reference trajectories, the robot is controlled using NN technique to compensate for its unknown dynamics. Adaptive law has been synthesized based on Lyapunov theory to enable effective NN learning. Preliminary experiments have been carried out to test the proposed method, which results in satisfactory performance on the Baxter robot teleoperation.

I. INTRODUCTION

The robotic technologies have been well developed recently that the robots now have various of abilities to finish different tasks, e.g. medical robot, industrial robot and space probe. Automatic robot technology now is well developed, but there is still a lot of challenges for robot to deal with uncertain environment by itself. The current artificial intelligence (AI) technology does not support robot to fulfill tasks without human guidance.

Thus, a telebot that is controlled remotely by a human operator from a distance is desired in many scenarios, as called teleoperation. And it is an important and useful tool in the research fields. There are many teleoperation applications have been advanced in recent years. In [1], a shared control method of baxter robot manipulator has been developed. While the user teleoperating the motion of the end-effector of the manipulator, the robot manipulator can avoid obstacle automatically with the original performance of the end effector motion. A method for imitating human writing skills to a baxter robot manipulator has been present in [2]. By using electromyography (EMG) signals and a haptic device, human operators can teleoperate a robot manipulator doing a fine calligraphy. In [3], a surface electromyography (sEMG) signals enhanced teleoperation strategy has been presented. The human operators are able to sense the circumstance in a haptic manner and to adapt muscle contraction subconsciously as if they are directly interacting with the environment. [4] describes the development of a virtual robot teleoperation platform based on hand gesture recognition using visual information.

Motion capture system is one of the teleoperation method. Motion capture system mainly includes two interfaces, vision system based sensing interface and wearable device/joystick remotely input interface. There are several sensors have been used for the vision based system such as Kinect and Leap Motion. In [5], human motions is captured by Kinect sensor and the joint angles of Baxter robot has been calculated to teleoperate the robot based on vector approach and inverse kinematics approach. In [6], human welder movement is captured by the Leap Motion sensor, and then the learnt skill has been transferred to a welding robot via a teleoperation system. For the remote input interface, wearable devices such as exoskeleton [7] or joystick such as Omni haptic device [8] are commonly used. In this paper, we adapted a new generation wearable device, MYO Armband (Sec. II-A), into a motion capture system to teleoperate Baxter robot manipulator.

However, there are always uncertainties of the robot model existing during teleoperation, especially the dynamic uncertainties, which will affect the result of teleoperation. There are many tools have been proved useful for control design of robotic system to deal with the dynamic uncertainties, such as neural network (NN) and Fuzzy Logic. The NN control has been extensively studied not only in the discrete-time system [9], [10], but also in the continuous-time system [11]–[14] control system design. And it also been used in various robotic applications such as Wheeled Inverted Pendulum [15] or Marine Surface Vessels [16].

In this paper, we have successfully applied the neural learning enhanced control techniques to teleoperate the Baxter robot manipulator. A pair of MYO armbands worn on the operator’s forearm and upper arm are used to teleoperate the robot manipulator. Preliminary experiments are carried out to test the desire performance and the results are given.

II. PRELIMINARIES

A. MYO Armband

MYO armband is a wearable device developed by the Thalmic Labs company. By wearing MYO on the arm, it can interact with system via Bluetooth. A MYO armband has 8 built-in EMG sensors, along with 9-axis IMU sensor, so that can recognise the hand gesture and arm movement. The 8 EMG sensors are able to identify hand gesture by moving the arm muscles. The sensors generate data by electrical impulses from arm muscles, and each user has different type of skin, muscle size and etc. It is important to calibrate for
Fig. 1. MYO armband is a wireless device [17]

Fig. 2. Kinematic model of Baxter arm. Only the joints highlighted in red circle are used, modified from [19].

each user before using the device. So that the MYO armband can recognise the gesture performance more accuracy.

B. Baxter Robot

Baxter® robot is an humanoid robot with two 7 degree of freedom (DOF) manipulators installed on the right/left arm bases respectively. Each arm contains 7 joints and 8 links with an interchangeable gripper attached on the end-effector. The kinematics model of Baxter robot has been carried out in our previous work [18], based on Denavit-Hartenberg (DH) parameters. The robot can perform under three different types of control modes, position control mode, torque control mode and velocity control mode.

C. RBF Neural Networks [15]

A linear-in-the-parameter RBF NN can be used to approximate a continuous function, i.e., \( \phi(z) : R^m \rightarrow R \), over a compact set \( \Omega_z \subset R^m \), can be emulated as

\[
\phi(z) = W^{*T}S(z) + \epsilon(z) \quad \forall z \in \Omega_z
\]

where \( W^* = [w_1, w_2, \ldots, w_l]^T \in R^l \) is the weight vector, \( z \in \Omega_z \) is the input vector with \( \Omega_z \subset R^m \) being a compact set, \( l \) is the NN node number, and \( \epsilon(z) \) is the approximation error. \( S(z) = [S_1(\|z - \mu_1\|), \ldots, S_l(\|z - \mu_l\|)]^T \), is the regressor vector, with \( S_i(\cdot) \) being a radial basis function, and \( \mu_i (i = 1, \ldots, l) \) being the centre. The Gaussian functions choose as

\[
S_i(\|z - \mu_i\|) = \exp \left[ \frac{-(z - \mu_i)^T(z - \mu_i)}{\varsigma^2} \right] \quad (2)
\]

where \( \mu_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{im}]^T \in R^m \) represents the center of each receptive field and \( \varsigma \) is the variance.

For a large enough number of neurons, having a weight matrix \( W^* \) such that

\[
F(z) = W^{*T}S(z) + \epsilon(z) \quad (3)
\]

where \( W^* = [W_1^*, W_2^*, \ldots, W_*^*] \in R^{N \times n} \) is the weight matrix of RBFNN. The estimated weight \( \hat{W} \) will be used in practice to replace \( W^* \) for the approximation of a continuous function in this manner \( F(z) = \hat{W}S(z) \), where \( \hat{W} \) is the learning law which will be specified later.

III. MOTION CAPTURE

A. Human Arm Motion Capture by the Method of X-Y-Z Fixed Angles

As shown in Fig. 3, the global coordinate frame \((x_G, y_G, z_G)\) is defined as: x-axis points to the side; y-axis points forwards, z-axis pointing upwards. For the easy calculation of the shoulder joint angles, the local frame of humerus \((x_H, y_H, z_H)\) and forearm frame \((x_F, y_F, z_F)\) coincides with the global frame.

The rotation matrices of the orientations of the humerus frame and forearm frame under the global frame can be obtained as below:

\[
\mathcal{R}^i_{GH} = \begin{bmatrix} X^i_{GH} & Y^i_{GH} & Z^i_{GH} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (4)
\]

\[
\mathcal{R}^i_{GF} = \begin{bmatrix} X^i_{GF} & Y^i_{GF} & Z^i_{GF} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (5)
\]
where $R \in \mathbb{R}^{3 \times 3}$ is the rotation matrix, $i$ is the initial position, “C”, “H” and “F” denote the global, humerus and forearm frame respectively. The rotation matrix $R_{YX}$ represent the orientation of the frame “X” with respect to frame “Y”. The column vector $X_{MN}$, $Y_{MN}$ and $Z_{MN}$ denote unit vectors describing the principal directions of the frame “N” in terms of frame “M”, and $X_{MN}$, $Y_{MN}$, $Z_{MN} \in \mathbb{R}^{3 \times 1}$.

The local frame of humerus and forearm are not stationary and the orientation of the humerus frame with respect to the first MYO armband frame and the forearm frame with respect to the second MYO armband frame are constant matrix, given as

$$R_{UH}^f = (R_{GU}^f)^T R_{UH}^f$$
$$R_{LF}^f = (R_{GL}^f)^T R_{GF}^f$$

where “f” represents the frame of the first MYO armband worn on the upper arm, and “L” represents the frame of the second MYO armband worn on the lower arm.

The orientations of the humerus and forearm under the global frame while operator moving his/her arm can be described as:

$$R_{GH}^f = R_{GU}^f R_{UH}$$
$$R_{GF}^f = R_{GL}^f R_{LF}$$

where $f$ denotes the current arm position.

A quaternion $q_1 = [x, y, z, w]^T$ can be obtained from the first MYO’s gyroscope, where $(x, y, z)$ is a vector and $w$ is a scalar quantity.

$$q_1 = xi + yj + zk + w$$

Then we can obtain the orientations of the humerus under the global frame from the quaternion, as follows:

$$
R_{GH}^f = \begin{bmatrix}
    r_{11} & r_{12} & r_{13} \\
    r_{21} & r_{22} & r_{23} \\
    r_{31} & r_{32} & r_{33}
\end{bmatrix} = \begin{bmatrix}
    1 - 2(y^2 + z^2) & 2(xy - wz) & 2(wy + xz) \\
    2(xy + wz) & 1 - 2(x^2 + z^2) & 2(yz - wx) \\
    2(xz - wy) & 2(wx + yz) & 1 - 2(x^2 + y^2)
\end{bmatrix}
$$

Acknowledgement of describing the frame $\{B\}$ in frame $\{A\}$ is as follows: $\{B\}$ is coincident with frame $\{A\}$. First, rotate frame $\{B\}$ about $X_A$ by an angle $\gamma$, then about $Y_A$ by an angle $\beta$, finally, about $Z_A$ by an angle $\alpha$ [20]. The angles $\gamma$, $\beta$, $\alpha$ are the roll, pitch and yaw respectively.

$$R_{GH}^f = R_z(\alpha)R_y(\beta)R_x(\gamma)$$

With two MYO armbands, we can measure the five joint angles of the operator’s arm. From (10) and (11), the three shoulder joint angles (shoulder flexion/extension, abduction/adduction and internal/external rotation) are calculated.

Through the data collected from two MYO armbands, we can calculate these two elbow joint angles (elbow flexion/extension and pronation/supination).

$$q_{d1} = \arctan\left(\sqrt{\frac{t_{11}^2 + t_{12}^2}{t_{13}^2}}\right)$$
$$q_{d2} = \arctan\left(\frac{t_{23}}{t_{13}}\right)$$
$$q_{d3} = \arctan\left(\frac{t_{32}}{t_{31}}\right)$$

where the $q_{d3}$, $q_{d2}$ and $q_{d1}$ represent the joint angles of shoulder roll, shoulder yaw and shoulder pitch, respectively.

$$q_{d4} = \arccos\left(\frac{O_e \hat{A} \cdot O_e \hat{A}^T}{O_e \hat{A} \cdot O_e \hat{A}^T}ight)$$
$$q_{d5} = \arccos\left(\frac{O_e B \cdot (O_e \hat{A} \times O_e \hat{A}^T)}{O_e \hat{A} \cdot O_e \hat{A}^T}ight)$$

where the $q_{d4}$ and $q_{d5}$ represent the joint angles of elbow flex and elbow roll respectively. The $O^2 \hat{A}$ is the unit vector along the y-axis of the forearm frame. The $O^2 \hat{B}$ is the unit vector along the x-axis of the forearm frame. The $O^2 \hat{O}^1$ is the unit vector along the z-axis of the humerus frame.

B. Neural Networks Control

Let us define the desired joint space trajectory $q_d$ as

$$q_d = [q_{d1}, q_{d2}, q_{d3}, q_{d4}, q_{d5}]^T \in \mathbb{R}^5$$

Now, let us consider apply NN control technique based to achieve the following control of the joint space trajectory. The output signal of the system is required to follow the expected input signal. So design of the controller should enable the system to be quick, accurate, and stable. The angle matrix $q_d \in \mathbb{R}^5$ exported by the MYO is regarded as the reference signal, and the angle matrix $q \in \mathbb{R}^{6}$ returned by the robot are the actual angles. The dynamic equation of the manipulator is shown in (18).

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + N(q) = \tau,$$

where $M(q) \in \mathbb{R}^{5 \times 5}$ is the manipulator inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^{5 \times 5}$ is the Coriolis matrix for the manipulator, $G(q) \in \mathbb{R}^{5 \times 1}$ is the gravity terms and $N(q) \in \mathbb{R}^{5 \times 1}$ is unmodeled dynamics caused by exchangeable robot gripper and system uncertainties.

Define $z = \ddot{q} + \Lambda e_\theta$, $q_r = \dot{q}_d - \Lambda e_\theta$, where $e_\theta = q - q_d$, $\Lambda = diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$. Then the dynamic equation (18) can be rewritten as (19).

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + M(q)\ddot{q}_r + C(q, \dot{q})\dot{q}_r = \tau - N(q),$$

Design the adaptive controller as (20).

$$\tau = \hat{H}(q) + \hat{M}(q)\dot{q}_r + \hat{C}(q, \dot{q})\dot{q}_r - K_z,$$

where $\hat{H}(q)$, $\hat{M}(q)$ and $\hat{C}(q, \dot{q})$ are the estimates of $G(q) + N(q)$, $M(q)$ and $C(q, \dot{q})$, respectively.

Then the closed-loop system dynamic can be written as (21).

$$\dot{M}Z + CZ + K_z = (M - \hat{M})\dot{q}_r + (C - \hat{C})\dot{q}_r + (\hat{H} + H)$$
The following function approximation method is used.

\[
M(q) = W_M^T S_M(q) + \epsilon_M
\]

\[
C(q, \dot{q}) = W_C^T S_C(q, \dot{q}) + \epsilon_C
\]  

(22)

\[
H(q) = W_H^T S_H(q) + \epsilon_H(z),
\]

where \(W_M, W_C,\) and \(W_H\) are the weight matrices; \(S_M(z),\) \(S_C(z),\) and \(S_H(z)\) are the basis function matrices, and \(\epsilon_M(z),\) \(\epsilon_C(z),\) and \(\epsilon_H(z)\) are the approximation errors.

The basis function matrices are designed as follow.

\[
S_M(q) = \text{diag}(S_q, \ldots, S_q)
\]

\[
S_C(q, \dot{q}) = \text{diag}
\left(\begin{bmatrix} S_q & \ldots & S_q \end{bmatrix}\right)
\]

\[
S_H(q) = \begin{bmatrix} S_q^T \ldots S_q^T \end{bmatrix}^T,
\]

where

\[
S_q = \left[\phi(||q - q||), \phi(||q - q_n||), \ldots, \phi(||q - q_n||)\right]^T
\]

\[
S_q = \left[\phi(||\dot{q} - \dot{q}_r||), \phi(||\dot{q} - \dot{q}_l||), \ldots, \phi(||\dot{q} - \dot{q}_l||)\right]^T
\]

(23)

\[
\phi(r) = e^{-r^2}
\]

The estimates of \(M(q), C(q, \dot{q}),\) and \(H(q)\) can be written as (25).

\[
\hat{M}(q) = \hat{W}_M^T S_M(q)
\]

\[
\hat{C}(q, \dot{q}) = \hat{W}_C^T S_C(q, \dot{q})
\]

(25)

\[
\hat{H}(q) = \hat{W}_H^T S_H(q),
\]

By substituting (25) into (21), we have

\[
M \ddot{z} + Cz + Kz = \hat{W}_M^T S_M(q)q_r + \hat{W}_C^T S_C(q, \dot{q})q_r + \hat{W}_H^T S_H(q)
\]

(26)

where \(\hat{W}_M^T = \hat{W}_M^T - W_M^T, \hat{W}_C = \hat{W}_C^T - W_C^T\) and \(\hat{W}_H^T = \hat{W}_H^T - W_H^T\).

Choose the following Lyapunov function.

\[
V = \frac{1}{2} z^T M z
\]

\[
+ \frac{1}{2} tr \left( \hat{W}_M^T Q_M \hat{W}_M + \hat{W}_C^T Q_C \hat{W}_C + \hat{W}_H^T Q_H \hat{W}_H \right),
\]

(27)

where \(Q_M, Q_C,\) and \(Q_H\) are positive definite weight matrices. And the derivative of \(V\) is

\[
\dot{V} = -z^T K z
\]

\[
+ tr \left[ \hat{W}_M^T \left( S_M(q)q_r z^T + Q_M \hat{W}_M \right) \right] +
\]

\[
+ tr \left[ \hat{W}_C^T \left( S_C(q, \dot{q})q_r z^T + Q_C \hat{W}_C \right) \right] +
\]

\[
+ tr \left[ \hat{W}_H^T \left( S_H(q)z^T + Q_H \hat{W}_H \right) \right]
\]

(28)

The update law is designed as follow.

\[
\hat{W}_M = -Q_M^{-1}(S_M(q)q_r z^T + \sigma_M \hat{W}_M)
\]

\[
\hat{W}_C = -Q_C^{-1}(S_C(q, \dot{q})q_r z^T + \sigma_C \hat{W}_C)
\]

\[
\hat{W}_H = -Q_H^{-1}(S_H(q)z^T + \sigma_H \hat{W}_H)
\]

(29)

where \(\sigma_M, \sigma_C, \sigma_H\) are prespecified positive constants.

Substituting (29) into (28), we have

\[
\dot{V} = -z^T K z - \sigma_M tr \left( \hat{W}_M^T \hat{W}_M \right) - \sigma_C tr \left( \hat{W}_C^T \hat{W}_C \right)
\]

\[
- \sigma_H tr \left( \hat{W}_H^T \hat{W}_H \right)
\]

(30)
Using Young’s inequality, (30) can be further relaxed as
\[
\dot{V} = -z^T K z + \frac{\sigma_M^2 tr(W_M^T W_M^*)}{2} - \frac{\sigma_M^2 tr(\tilde{W}_M^T \tilde{W}_M^*)}{2} - \frac{\sigma_C^2 tr(W_C^T W_C^*)}{2} - \frac{\sigma_C^2 tr(\tilde{W}_C^T \tilde{W}_C^*)}{2} + \frac{\sigma_H tr(W_H^T W_H^*)}{2} - \frac{\sigma_H tr(\tilde{W}_H^T \tilde{W}_H^*)}{2}
\]
\[
= -z^T K z + \frac{\sigma_M^2 tr(W_M^* W_M^*)}{2} - \frac{\sigma_M^2 tr(\tilde{W}_M^* \tilde{W}_M^*)}{2} + \frac{\sigma_C^2 tr(W_C^* W_C^*)}{2} + \frac{\sigma_C^2 tr(\tilde{W}_C^* \tilde{W}_C^*)}{2} - \frac{\sigma_H tr(W_H^* W_H^*)}{2} - \frac{\sigma_H tr(\tilde{W}_H^* \tilde{W}_H^*)}{2}
\]
(31)

So that we have
\[
\dot{V} \leq -\eta V + \kappa
\]
where \(\eta = \min\{2K, \sigma_M/(\lambda_{\text{max}}(Q_M)), \sigma_C/(\lambda_{\text{max}}(Q_C))\}\), \(\kappa = \frac{1}{2} tr(\sigma_M W_M^* W_M^* + \sigma_C W_C^* W_C^* + \sigma_H W_H^* W_H^*)\). Since \(V > 0\) and \(\kappa\) is the product of the predesigned constants and weight matrices that we given, as long as \(\kappa \leq \eta\), we can have \(\dot{V} \leq 0\). According to Lyapunov theory, the system is stable.

IV. EXPERIMENTAL RESULTS

A. Experimental Set-up

An operator stands up right with two MYO armbands on the same arm in the lab. The first MYO armband is worn near the centre of the upper arm and it can measure the orientation of the upper arm. The second MYO armband is worn near the centre of the forearm and it is used to estimate the orientation of the forearm by gyroscope and calculate the wrist joint angles by eight bioelectrical sensors. Before the operator controls the virtual robot arm, the MYO armband must be calibrated and the EMG sensors must be warm up, so that the MYO armband can discern different hand poses. The operator must not move position so that only both arms can freely, and the arm must not at a fast speed through the course of the experiment.

![Fig. 5. The experiment setup with the initial pose of the robot.](image)

B. Results of Experiment

The Fig. 7 represents the position difference of the five joints respectively. The position difference is between robot trajectory and the reference point given by Myo armband. The left row of Fig. 7 was generated without NN learning, while the NN enhanced controller was applied in the right row of Fig. 7. It the can be seen that the tracking performance of the manipulator’s joints have been improved after adopting the NN learning control. And the NN learning weights for each single joint are given as shown in Fig. 6.

The model of using Myo armband to control Baxter robot arm was design and tested. The proposed NN learning controller was also tested and the results show its effectiveness of countering the unknown dynamics during teleoperation.

V. CONCLUSION

In this paper, a NN learning enhanced teleoperation control of Baxter robot is developed. The motion of human operator’s arm can be detected and reconstructed by using physical IMU signals, provided by a pair of MYO armbands worn on the operator’s arm. Then the data will be applied to Baxter robot’s joints respectively for teleoperation. The advantages of using the MYO armband are that MYO armband is portable and the calculated angles of shoulder joint and elbow joint are accuracy. NN learning based compensation mechanism for the controller helps user to overcome the effect of the uncertainties associated with the telerobot model and environment while teleoperating. The proposed controller guaranteed the system output tracking errors satisfied the prescribed transient and steady-state control behaviour bounds. Experimental tests studies have demonstrated the effectiveness of the proposed design techniques.

REFERENCES

Fig. 7. Robot trajectory compared with MYO reference point. Left: Without NN, Right: With NN.


