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Grasping Force Prediction for Underactuated Multi-Fingered Hand by Using Artificial Neural Network

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Abstract

In this paper, the feedforward neural network with Levenberg-Marquardt backpropagation training algorithm is used to predict the grasping forces according to the multisensory signals as training samples for specific design of underactuated multifingered hand to avoid the complexity of calculating the inverse kinematics which is appeared through the dynamic modeling of the robotic hand and preparing this network to be used as part of a control system.

Keywords: Grasping force, underactuated, prediction, Neural network

1. Nomenclature

(f_{t1_i}, f_{t2_i}) tangential components of the contact forces
(f_{n_i}) normal component of the contact forces.
$M_i(\theta)$ inertia matrix of the finger
$C_i(\theta,\dot{\theta})$ coriolis and centrifugal effects
$g_i(\theta)$ gravitational torques
τ_i vector of the joint torques
τ_i^f vector of joint friction torque
$\tau_i^r(\theta)$ torsional spring torque at the joints of the finger
J_i jacobian matrix of the finger
R_c^f rotation matrix for contact frame w.r.t fingertip coordinate frame
F_{t_i} vector of the tendon force of the finger
H_c coupling matrix between the vector of the joint angles (θ) and thevector of tendon displacements (l)
T applied torque from the main actuator
R regression values measure the correlation between outputs (Y) and targets (T)
μi coefficient of friction at fingertip (i)

2. Introduction

The robotic multi-fingered hand control problem can be divided into two main areas, kinematics control (the coordination of the phalanx of kinematics chain to produce the desired grasping posture of the robotic hand), and dynamic control (driving the actuators of the hand to provide the optimal grasping forces).

In general the control strategies used in robotic hand must involve the transformation between Cartesian space and Joint space through direct or indirect kinematics methods.

Inverse kinematics comprises the computation which is needed to find the fingertip force (contact force) for a given joint torque, this computation is fundamental to control the robotic hand but it is very difficult to calculate an inverse kinematic solution, especially if the actuator mechanism of the hand was underactuated mechanism, in addition to these difficulties, there is no unique solution for the inverse kinematic problem. That represents the main reason to apply an artificial neural network model (Sagiroglu. 1998), since ANN has been used for approximating the mapping between (object posture, desired contact force) and the corresponding (joint displacement, torque).

In this area, Khoogar *et al.*(2010) presented a dual neural network for kinematic control of robotic manipulator, the first network was a static multilayer perceptron, it's trained to simulate the jacobian of the manipulator and the second network is a recurrent neural network, it's used to determine the inverse kinematics solution of the manipulator. This network was used to avoid most of complexity present in the classical –trigonometric- based methods. Khalil *et al.*(2010) proposed an integrated multisensory feedback system which was developed around the Barrett hand with neural network to acquire (off-line) and then predict in real-time (on-line) the complex relationship that exists between the deformation of the grasped object and the interaction parameters resulting from the manipulation with a robot hand. Jha. (2009) used two types of artificial neural network models, MLP (multilayer perceptrons) model and PPN (polynomial poly-processor neural network) to simulate the complex behavior of inverse kinematics for robotic manipulator.E.A. Al-Gallaf. (2008) employed of ANN for multifingered robot hand manipulation in which the grasped object motion is defined in workspace with respect to six Cartesian based coordinates. Rahatabadet *et al.* (2007) designed a controller for artificial hand in flexion and extension motion based on neural network. Carenzi *et al.* (2005) developed a neural network model to learn the kinematics of object-dependent reach and grasp tasks with a simulated anthropomorphic arm-hand system. Rezzoug *et al.* (2002) proposed a multistage network architecture which was learned by different grasping postures of various types of objects with different number of fingers involved and different contacts configurations. Shanjun *et al.* (2011) presented a multifingered robot hand with Underactuated mechanism with ability to self-adaptive enveloping grasp and using for uncertainty task to grasp unknown object, this hand controlled by using rough set mixed neural networks which was learned based on human experience and knowledge.

Al-Gallaf. (2010) presented an intelligent fuzzy rule-based approach for computing optimal set of joints torques, for manipulating grasped object by dexterous multifingered robotic hand. Xia *et al*. (2004) presented a novel recurrent neural network for real-time dexterous hand grasping force optimization. Fok *et al*. (2002) developed two recurrent neural network to solve two problems, linearization of the friction cone constraint and minimization of the grasping force. Tang *et al*. (2002) developed a lagrangian network from lagrange multiplayer method and taking into account the nonlinearity of the friction constraint between contacts, by feeding the external load and the joint torque limits of the fingers to the network for generating the optimal contact forces. Galan *et al*. (2001) presented a novel adaptive critic-based neural network controller for controlling the fingers to follow a trajectory, this network trained on-line based on a critic signal for object contact control while it applies a desired force on the object for grasping task.

From previous literature, it can be concluded that most of them dealt with the dexterous robotic hand (fully actuated hand), but in this paper, the feedforward neural network with Levenberg-Marquardt backpropagation training algorithm is used to predict grasping forces according to the multisensory signals as training samples for specific design of underactuated multifingered hand (based on pulleys-tendon mechanism with flexible elements), to avoid the complexity of calculating the inverse kinematics and prepare this network to be used as part of the control system for the mentioned robotic hand.

3. Modeling of the Underactuated Three-Fingered Hand

Consider a grasp of a rigid object with three-fingered underactuated robotic hand as shown in figure.1. Contact type at each finger is a point contact with Coulomb friction and friction coefficient at fingers tip, such that:

$$\sqrt{\left(f_{t1_i}^2 + f_{t2_i}^2\right)} \le \mu_i f_{n_i} \tag{1}$$

Each finger is modeled as a serial link manipulator and governed by the classical Lagrange formulation as follows:

$$M_i(\theta)\ddot{\theta} + C_i\big(\theta,\dot{\theta}\big)\dot{\theta} + g_i(\theta) = \tau_i - \tau_i^f - \tau_i^r(\theta) - J_i^T R_c^f F_c \tag{2}$$

And (τ_i) is coupled to (F_{t_i}) as follows:

$$\tau_i = H_c^T F_{t_i} \tag{3}$$

Since (H_c) represent the relation between the vector of the joint angles (θ) and the vector of tendon displacements (l), it can be considered linear after neglecting the tendon friction and elasticity (Ficuciello. 2010), namely:-

$$l = H_c\theta \tag{4}$$

And the derivation of the coupling matrix (H_c) depends on the particular design of the hand.

The fingers of the robotic hand are actuated by a single geared DC motor with group of tendons-pulleys mechanism to drive the fingers, the tendon tension (F_{t_i}) is derived with respect to the applied torque (T) from the main actuator as:

$$T = \sigma\,\check{F}_t \tag{5}$$

Where (σ) represent the parameter matrix to connect between the actuator torque and the tendon tension vector ($\check{F}_t = [F_{t_1} \quad F_{t_2} \quad F_{t_3}]^T$), this matrix depends on the mechanical design of the robotic hand.

For statically speaking (neglecting $\dot{\theta}$ and $\ddot{\theta}$), the relation between the actuator torque and the grasping force $\mathrm{F_c}$ can be formulated from equations (2),(3) and (5) to produce:

$$F_c = R_f^c J_h^{-T}\left(H_c^T \sigma^{-1} T - \tau_h^f - \tau_h^r(\theta) - g_h(\theta)\right) \tag{6}$$

The above equation declares the difficulties to be faced for predicting the contact forces from the actuator torque, such as the inverse of the jacobian matrix (J_h^{-T}) and investigating the stable quantities of joints friction torque (τ_h^f), in addition to that, the parameter matrix (σ) gives more than one grasping force vector for the same actuator torque quantity, this is related to the grasping configuration. From this fact, the artificial neural network is used to solve this problem.

4. Hand Mechanisms and Sensory System Description

4.1. Artificial Hand Mechanism

The mechanism of the adopted artificial hand (semi-section) as shown in figure.2, is composed of power screw which is coupled to a DC geared motor to convert the rotational power from the motor (actuator) to linear motion, thus moving the group of nut and pulleys, and pull the tendon to close the fingers on the grasped object, if the pull is to continue after grasping, the springs are expanded to increase the contact forces. The fingertip is designed, as clarified in figure.2, to have the ability to measure both components of contact force (normal & tangential) and to satisfy the conditions of sensor mounting (Force sensor user manual 2012).

4.2. Sensory system description

Two flexiforce sensors, shown in figure.3, is used to measure normal and tangential components of the contact force together with the actuator torque through special purpose additional mechanism, designed for compensating between the real measured quantity (force) and the desired quantity (torque) ,as shown in figure.2. The actuator torque measurement was achieved through measuring the axial load on the power screw and applying the well-known mathematical relation to convert this axial load to applied torque on the power screw.

5. Grasp Modeling Based on Artificial Neural Networks

5.1. Artificial Neural Network Architecture

The feedforward neural network applied, has single hidden layer with (15) neurons of tan-sigmoid transfer function, the input layer has one neuron representing the actuator torque and the output layer has three neurons representing the grasping force. Each neuron receives its inputs directly from the previous layer (except for input neurons) and sends its output directly to neurons in the next layer, as shown in figure.4.

5.2. Artificial Neural Network Training and Test

The Levenberg-Marquardt backpropagation training algorithm is selected for its efficiency among other techniques and it is often the fastest algorithm (Hagan *et al.* 1994). The training and test procedures are done by the aid of Matlab7. Neural Network Toolbox (Neural Fitting Tool) with using the sensors reading data for actuator torque (input) and grasping force (output) as a training data as depicted in figure.5. Since the number of samples for training was (2599) samples for different durations of grasping under static conditions. These samples are taken by considering firstly that the robotic hand is at correct position and orientation around the specific object (polyhedral shaped object) before making contact with this object. After that the hand closed the fingers on the object to reach maximum contact force and then release this force gradually until fingers are separated from the object and the grasped object stand on the base of apparatus to neglect the effect of objects weight this for measure only normal component of contact force. This procedure was repeated for more than one cycle and for different durations with using the mean square error as an objective function for training algorithm.

6. Results and Discussion

For the training procedure, figure.6 to figure.8 show the training performance, since the experimental data is divided randomly to three portions, namely, (70% Training) are presented to the network during training, (15% Validation) are used to measure network generalization and to halt training when generalization stops improving, and (15% Testing) are represent the measure of network performance during and after training. The minimum reached mean squared error was ($2x10^{-2}$) during several minutes as a training time as shown in these figures.

Figure.9 shows multi samples of experimental data for testing the neural network. These results show good convergence except for those at high quantities of the actuator torque, since the scattering of the experimental data increased proportionally with the actuator torque. This is due to the operation parameters for the force sensor, such as sensitivity to applied load, linearity, durability and drift action in addition to faults of installation (Force sensor user manual 2012). However, these results show the same behavior between experimental and neural network results and this difference can be formulated statistically to correct this error. Also the reason of using this technique can aid to measure the tangential component of contact force and then detect slippage between finger tips and grasped object by comparing the results of the ANN and the forces obtained from the sensor as the real conditions of grasping, namely grasping with effect of object weight.

7. Conclusion

In this paper, the feedforward neural network with Levenberg-Marquardt backpropagation training algorithm is used to predict the grasping forces according to the multisensory signals as training samples for specific design of underactuated multifingered hand to avoid the complexity of calculating the inverse kinematics and prepare this network to be used as part of the control system for the mentioned robotic hand. This network shows good convergence to the experimental results except some of the results need to be treated statistically to reduce error effect.

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Notes:

Note 1. The (Target) represent the experimental contact force data which is implemented to train the ANN, and the (Output) represent the results of ANN simulation for the same (Input) data which is used for training process.

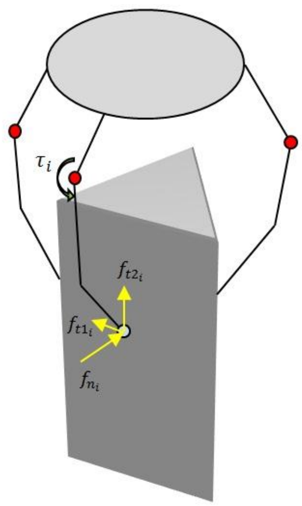


Figure1.The model of the robotic hand with grasped object

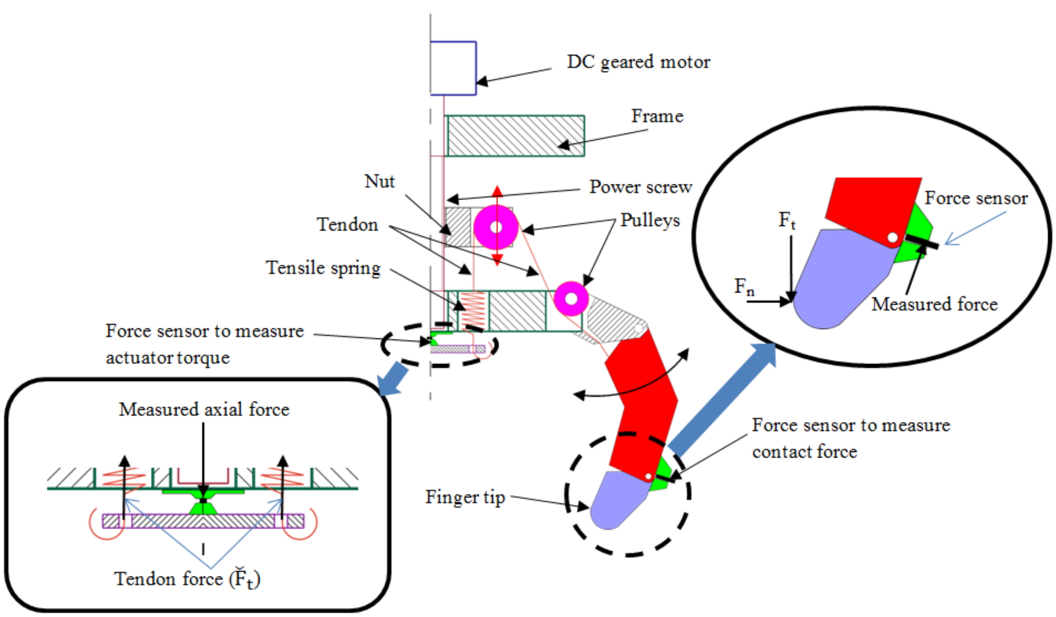


Figure2.The semi-section of the artificial hand mechanism

Figure3.The FlexiForce sensor

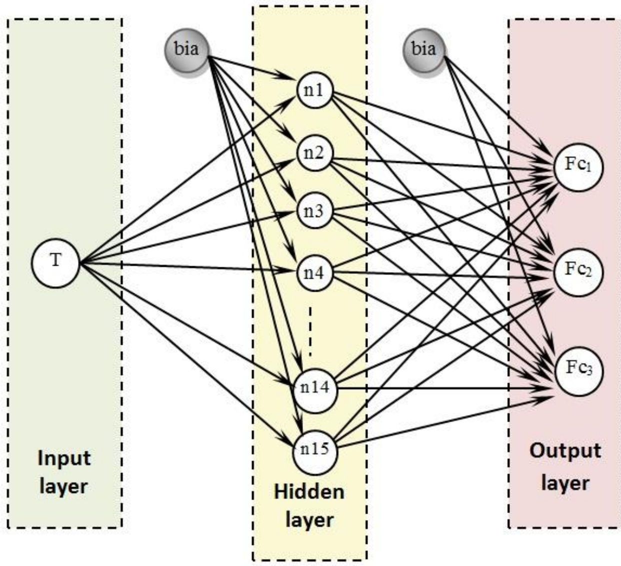


Figure4.The architecture of the ANN

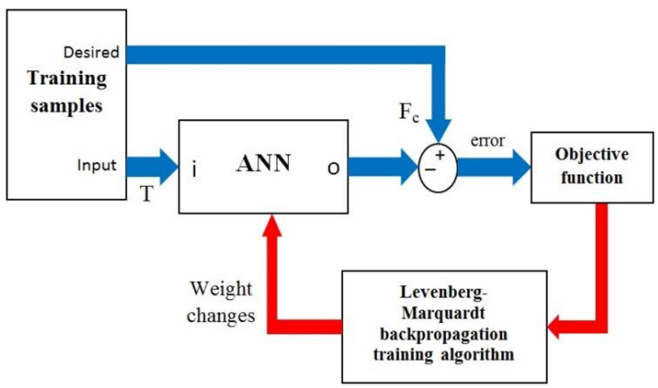


Figure5. The supervised training model

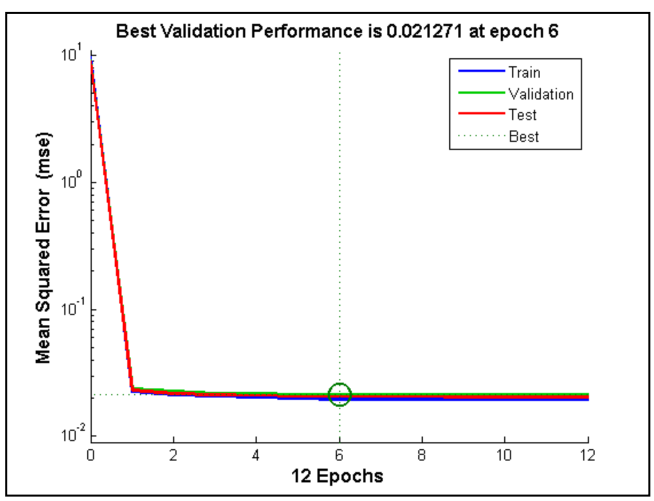


Figure6. The training performance

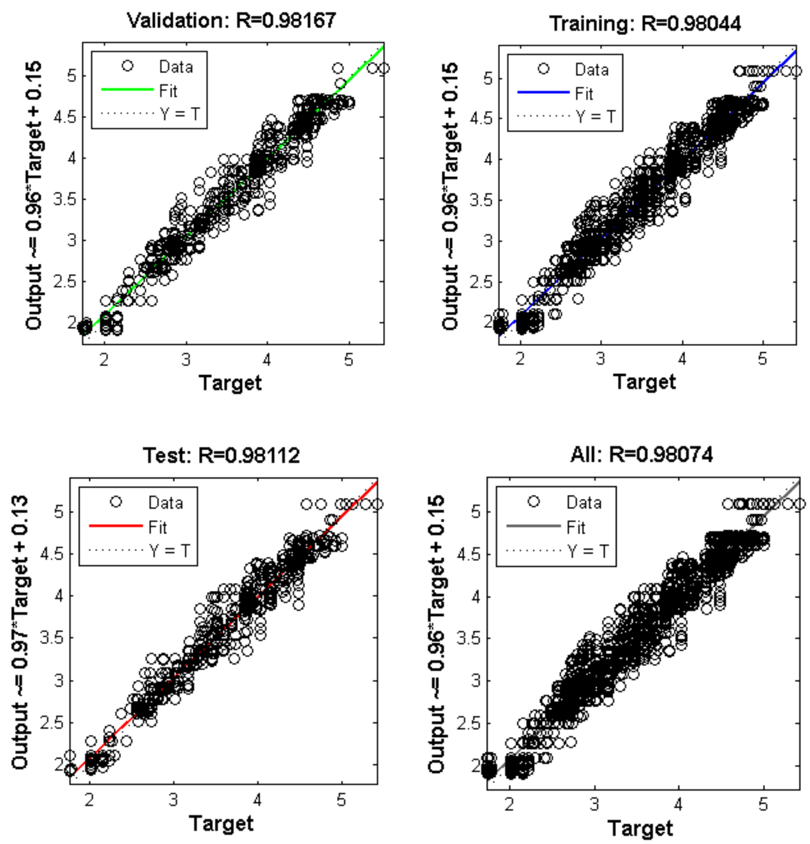


Figure7. The regression diagrams for output and target results

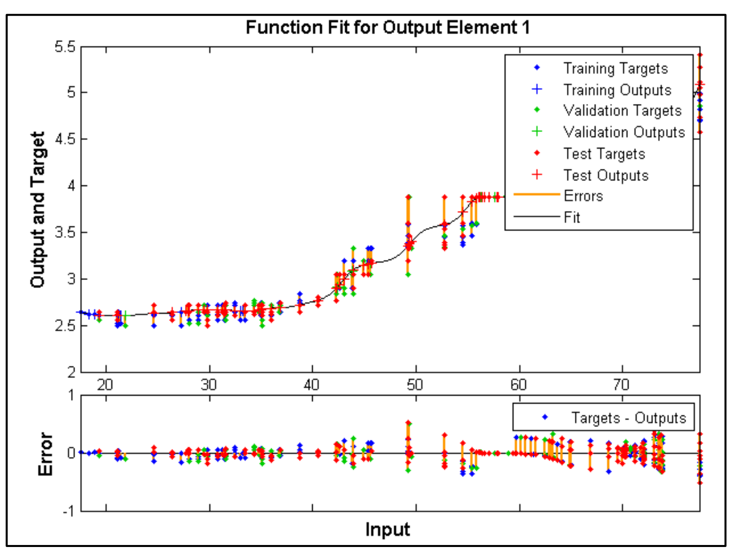
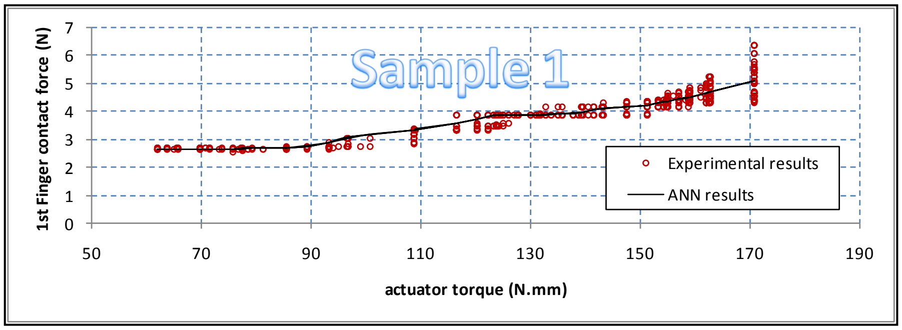
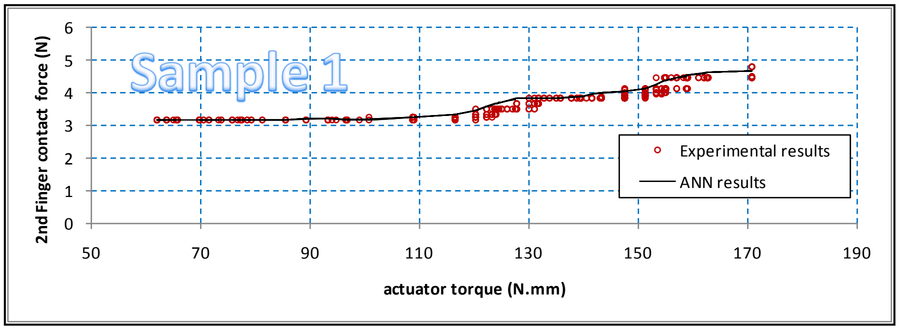
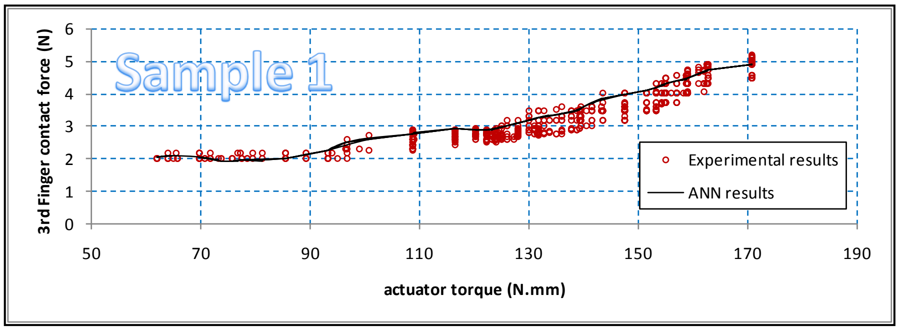
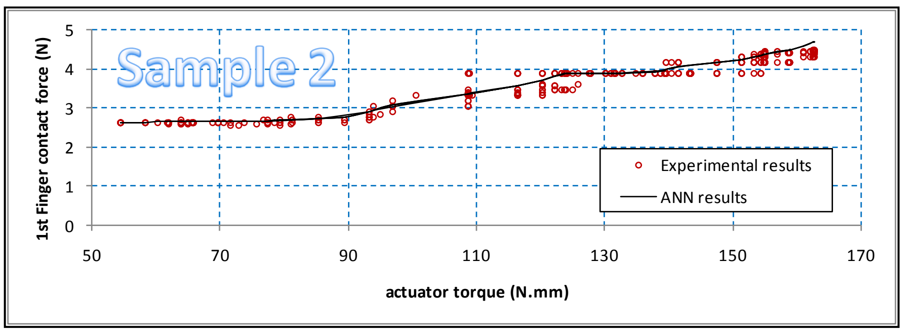


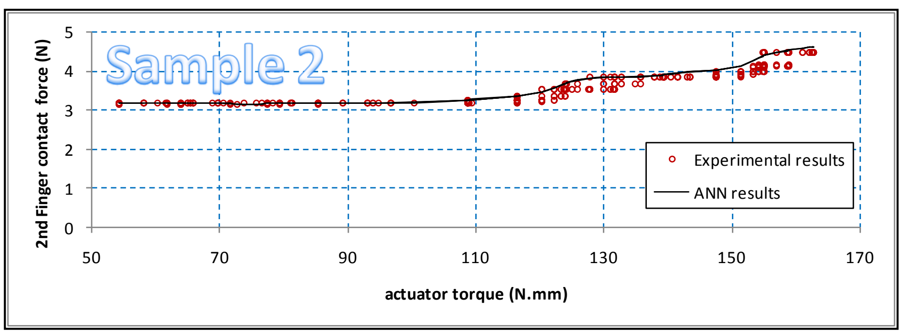
Figure8. The function fit for output and target results (Note 1)


Sample 1
1st Finger contact force (N)
actuator torque (N.mm)
Experimental results
ANN results


Sample 1
2nd Finger contact force (N)
actuator torque (N.mm)
Experimental results
ANN results


Sample 1
3rd Finger contact force (N)
actuator torque (N.mm)
Experimental results
ANN results


Sample 2
1st Finger contact force (N)
actuator torque (N.mm)
Experimental results
ANN results


Sample 2
2nd Finger contact force (N)
actuator torque (N.mm)
Experimental results
ANN results

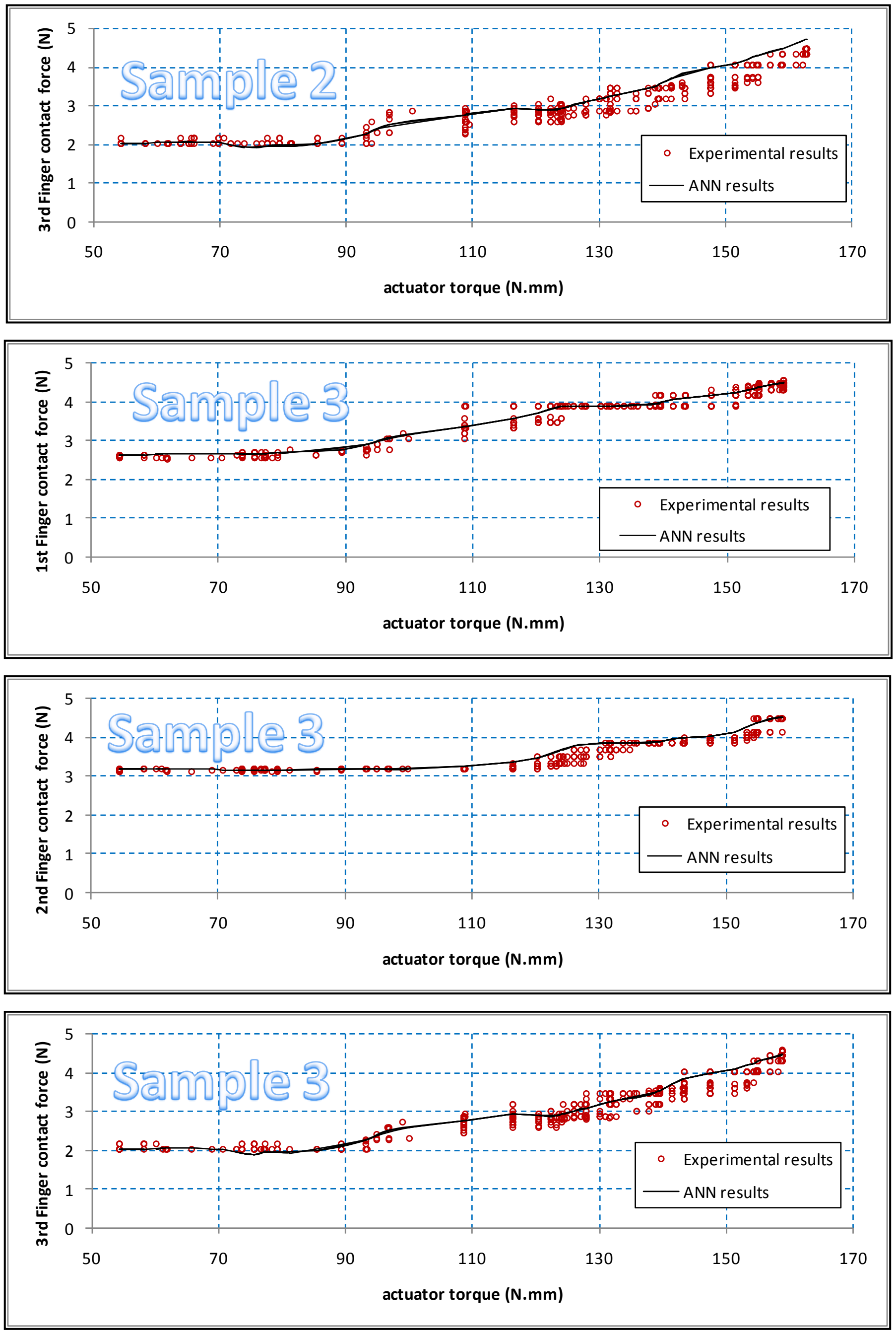


Figure9. The prediction of contact forces as compared to measured values.