Grasping Force Estimation Recognizing Object Slippage by Tactile Data Using Neural Network

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***Abstract* - Hierarchical and wider applications of robots, manipulators, and pick and place machines are facing challenges in industrial environments due to their insufficient intelligence for appropriately recognizing objects for grasping and handling purposes. Since robots do not posses self-consciousness, estimation of adequate grasping force for individual objects by robots or manipulators is another challenge for wider applications of robots and manipulators.**

This article suggests a mathematical model, recently developed, for computation of scattered energy of vibrations sensed by the stylus during an object slippage in robot grippers. The model includes in it dynamic parameters like trial grasping force, object falling velocity, and geometry of object surface irregularities. It is envisaged that using the said mathematical model, with the help of robust decision making capabilities of artificial neural network (NN), a robot memory could be able to estimate appropriate/optimal grasping force for an object considering its physiomechanical properties.

On the basis of above mentioned mathematical model, this article demonstrates an experimental methodology of estimating adequate grasping forces of an object by robot grippers using Backpropagation (BP) neural networks. Four different algorithms have been explored to experiment the optimal grasping force estimation.

Keywords – robot, object grasping, slip detection, grasping force, scattered energy of vibration, Backpropagation, neural networks.

I. INTRODUCTION AND PROBLEM ORIENTATION

Robots, and pick and place machines are designed and manufactured as non-compliant systems. By virtue of their stiff joints, actuators and flexible control systems, robots, and pick and place machines can be used to perform repetitive superhuman-like operations. Examples of these operations are very wide spread starting from diversified materials handling in manufacturing sectors to fruit and vegetable harvesting. Another special purpose application of robots is performing humanlike operations at hazardous environment including remote and inaccessible area operations. Collecting the right samples of right materials or minerals from space locations as well as underwater and mining areas is a group of problems requiring humanlike intelligence for robots. Participation in surgical operations in human organisms is another splendid activity of robot technology. The end-effectors of robots are the most responsible unit in all these operations. This decides how to grasp the object, from which direction and how much force to be applied in grasping and how to incur motions. The safe and non-dependable handling of unknown objects, including delicate objects, is a challenge in the field of robot technology. Intelligent grasping devices are used to handle unknown objects.

Estimation of adequate grasping force, by a robot itself, is essential for grasping an object properly, neither dropping the object due to inadequate grasping force nor smashing it applying overestimated force by the robot grippers.

It is anticipated that in object sensing activities the following main problems may arise and need to be solved:

- Object recognition
- Shape, size and mass estimation
- Status of environment of the object
- Object slippage during grasping
- Determination of necessary grasping force
- Determination of handling motions.

The information quality needed to perform certain robotic manipulation and grasping tasks still remains unknown. Neither it is known how exactly human manipulate objects [1]. First of all it is essential that a robot can recognize that it is using appropriate force during grasping so that the object attempted to grasp is not slipped down. At the same time the robot does not imply excessive force that can damage the object. In this article an attempt has been made to recognize object slippage during grasping by robot end-effectors using a tactile and to estimate necessary grasping forces using tactile data by the help of artificial Neural Network (NN) computational technique.

II. LITERATURE PREVIEW

Many robot tasks require contact between the robot and its environment. Such tasks include object manipulation by a robot hand – in an assembly operation, and probing an unknown environment through the robot end-effectors. Physical contact between a robot and its rigid environment requires the robot to be mechanically compliant, in order to avoid excessive contact force control based on force sensing.

Literature study shows that control of contact has been studied largely in the context of robot force control based on force sensing. A number of control schemes have been successfully developed.

The concept of the generalized surface is essential to all of the force control schemes. In this case motion is possible along the directions tangential to the surface, and force is possible along the directions normal to the surface. The knowledge of the generalized surface allows one to define the constraint coordinate, and a force control scheme can then be formulated by regulating the behavior of the robot end-effectors along the axes of constraint coordinate.

There are three methods [2] of detection of displacement of object due to slip during grasping:

A. Detection from an oscillation at the slip

This method is based on the detection of surface roughness on the object as an oscillation and its principle is analogous to that of a record player. In Reference [2] the authors used a Rochelle salt crystal supported by a rubber damper and a sapphire needle attached to the point. The sapphire needle, while slides on an object surface, the surface texture make the needle to oscillate which indicates the object slippage.

B. Detection from a moved distance by transforming a linear slip displacement into rolling motion

In this method the detection of a rolling displacement by a roller covered by an elastic body with a large coefficient of friction so that it rolls with the moving object surface. The authors [2] used a magnetic type A-D converter and in separate example used a photoelectric type A-D converter to detect slip signal without touching the object.

C. Detection from a change in grasping pressure or pressure distribution of fingers.

This method is based on physiological phenomenon of human skin sensation [2]. In this method pressure sensors act as neurons surrounded as on human body. It is assumed that bumps/ridges on our hands, along with other sensing elements, are used in most of the cases to recognize object surfaces. Changes of pressure in any of the sensors of arrays of pressure sensors witness the object slippage during grasping by robot end-effectors.

However, inabilities of sensors to differentiate between pressure changes caused by object slippage or pressure changes caused by operational vibrations appear to be the main disadvantages of this method.

III. SLIPPAGE RECOGNITION BY SCATTERED ENERGY OF VIBRATION

Robots, and pick and place machines are not capable by themselves of recognizing objects nor can they take an intelligent decision for grasping objects. For grasping purposes robots need to learn the nature and type of the object to be grasped, as well as robot must be able to determine the grasping force/s necessary and suitable for the object to be grasped and manipulated.

During grasping of unknown non-fluidic objects it is vital to avoid the object slippage from the fingers of the grippers due to inadequate grasping force. It is also essential not to damage the object by over-estimated grasping force applied. For intelligent machines, it is a factor that they demonstrate human-like performances while grasping and/or handling an object. In these cases a human, after recognizing an object, uses test and trial method to estimate the necessary grasping force to avoid slippage. One option for an intelligent machine may be to use test and trial approach during grasping as an object by sensing its surfaces, mass, and other required factors.

Solid object surfaces, even machined surfaces have varying degrees of irregularities. As in Figure 1, irregularities of surfaces are explained [3] by surface texture, which is again explained by surface waviness and surface roughness. Surface roughness has peaks and valleys. Surfaces of almost all metal objects particularly pins, shafts, axles, bushes, bolts, levers, or any metal blocks surrounding us can be modeled as shown in Figure 1.

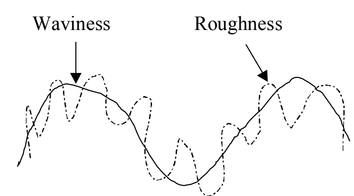

Figure 1. Nature of object surface texture

The tactile / stylus method is a recognized and widely used method to determine the grade of surface texture in manufacturing industries. If a stylus slides across a surface it goes through the peaks and valleys of that surface. This across-surface motion of a stylus following peaks and valleys creates reciprocating vibratory motions of the stylus itself along its axis perpendicular to the nominal surface as depicted in Figure 2.

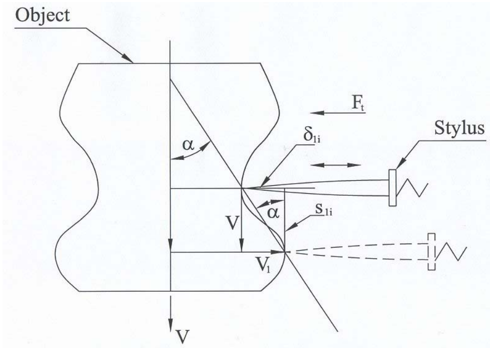

Figure 2. Sensing slippage by a stylus

Again surface roughness or waviness is characterized by the geometry of peaks and valleys of waviness. A tactile/stylus embedded into the gripper or fingers of a robot can sense any slippage of grasped object while the stylus slides across the peaks and valleys of surface irregularities or surface waviness. The linear reciprocating motion of a stylus can be modeled in the form of newly developed scattered energy of vibrations.

A. Scattered Energy of Vibration emanated during Object Slippage

A novel parameter, called scattered energy of vibration, is philosophically the energy that is emanated during vibration [4] by the motion of a body to a particular displacement due to a particular cause and instantly it is disbursed around in the environment or in the bodies in contact.

In this particular case, the Scattered Energy of Vibration (E_{sc}) is the amount of energy emanated, as well as instantly dissipated, due to vibrations of stylus, which could be determined [4] by a newly developed equation expressed as follows:

$$E_{sc} = n.F_{tr}.v.\tan \sum_{i=1}^{n} \left(\cot \frac{\delta_{1i}}{s_{1i}} \right) \quad (1)$$

Where,

E_{sc} - Total scattered energy of vibration;

F_{tr} - Trial-grasping force possible to manipulate by a control system;

n – Number of irregularities a stylus has sensed during an object slippage;

v – Falling velocity of the slipping object;

δ_{1i}, s_{1i} - Geometry of surface irregularities of the object.

Equation (1) demonstrates that, E_{sc} is directly proportional to the number of peaks and valleys, and their geometry sensed by the stylus during slippage, and also the falling velocity of the object.

Since it is a necessity to apply enough grasping force instantly, when the object demonstrates any incipient slip to stop slippage, the displacement travelled by a falling body can be considered as a micro-displacement. In cases of micro-displacement the falling velocity v of any body of any mass can be again considered to be the same and it is a constant vector.

IV. GRASPING FORCE ESTIMATION BY NEURAL NETWORK

In recently years, artificial neural networks (NNs) have drawn tremendous interest due to the demonstrated successful applications in process industry [5], financial modeling [6], biomedical engineering [7], manufacturing [8], and so on. Neural network soft computational techniques can be a convenient method to estimate the appropriate grasping force to grasp objects by robot end-effectors. Backpropagation (BP) algorithm to train neural networks has been used in a large number of problems dealing with class discrimination and pattern recognition. Some authors have used NN in solving tactile related problems [9], even in noisy environment. In this paper, a study has been carried out to assess the possibility of using neural networks to estimate optimal grasping force that can grasp an object without damaging it as well as without slippage. The NNs were trained using Backpropagation algorithms and tested and found reasonably good results as an introductory experiment.

A. Input Vector and Associated Output for Training Neural Networks

Data for training and testing the NNs are the input vectors consisting of two variables such as object falling velocity (x_1) and the scattered energy of vibrations (x_2) caused by surface roughness (Equation 1) and slippage of object touched by stylus. Calculation of these two input vector components (x_1, x_2) was determined using information of the surface roughness and frictional force of slipping objects. The associated force (f) required to hold the object adequately were determined using the Equation 1.

Numerical values of vector components (x_1, x_2) and their associated grasping force (f) as output forms the data sets to train and test NNs. NNs were trained using 100 numbers of data labeled as train data and tested by 60 numbers of data labeled as test data.

B. Backpropagation Learning Algorithm

In Backpropagation learning weights and biases of the neural network are updated in the direction to decrease the performance function most rapidly by using negative gradient. For one iteration, the simplest learning algorithm of Backpropagation is given as in Equation 2 as follows:

$$\hat{\mathbf{w}}_{t+1} = \hat{\mathbf{w}}_t - \alpha_t \mathbf{g}_t \quad (2)$$

Where,

$\hat{\mathbf{w}}_t$ - a vector of current weights and biases,

$\mathbf{g}_t$ - the current gradient, and

α_t - the learning rate.

There are many variations of Backpropagation (BP) algorithms; four of them have been used in these experiments, which are briefly described as follows.

Gradient Descent Algorithm: In gradient descent Backpropagation (BP), learning rate is simply multiplied with the negative of the gradient to determine the changes to the weights and biases. It needs a proper choice of learning rate [10] since larger learning rate may lead the algorithm to become unstable and smaller learning rate may take long time to converge. Despite the fact that the Backpropagation [11] has previous reports of successful implementation on various complex problems, the standard Backpropagation (BP) with the gradient descent learning algorithm is found to be too slow in the training phase [12, 13].

Gradient Descent with Momentum Algorithm: In this a momentum [10] is added to gradient descent Backpropagation learning that makes weight changes equal to the sum of a fraction of the last weight change and the new changes suggested by the gradient descent Backpropagation (BP) rule. Simple gradient descent algorithm network may stuck in a shallow local minimum which can be overcome by addition of a momentum that allows network to respond to recent trends in the error surface in addition to the local gradient. This way, gradient descent with momentum often provides faster convergence.

RPROP: The resilient Backpropagation (RPROP) training algorithm eliminates some harmful effects arises from the magnitudes of the partial derivatives using in gradient descent algorithm. In the RPROP the sign of the derivative is used to determine the direction of the weight update and the size of the weight change is determined by a separate update value instead of the magnitude of the derivative. The following update principles are considered in RPROP.

- If the derivative of the performance function with respect to the weight remains same sign for two successive iterations, the weight and bias is increased by a factor Δi.
- If the sign of the derivative of the performance function changes with respect to that of the previous iteration, the update value of weights and biases is decreased by a factor Δd.
- If the derivative is zero then the same update value of weights and biases is applicable.
- The weight change needs reduction if the weights oscillate.
- The weight change needs an increase in magnitude, if the weight continues to change in the same direction for several iterations.

RPROP generally converges much faster than the previous algorithms [14].

Scaled Conjugate Gradient Algorithm: In the training algorithms discussed in the previous sections, a learning rate is used to determine the change of the weight for update. This is actually termed as the step size in the weight surface. In the conjugate gradient algorithms [15, 16], a search is made along the conjugate gradient direction to find out the step size that minimizes the performance function along that line.

In literature there exist other methods to accelerate training (e.g. using variation of activation function [17]) as well as improving performance (e.g., using synthesis of multiple networks [18]) which can also be explored to address the current problem.

V. EXPERIMENTS USING NN

In these experiments, the Backpropagation (BP) algorithms stated in previous section were used to determine the optimal grasping force to hold objects by a robot. Input vectors (x_1, x_2) and the corresponding force (f) of the trained data set were used to train networks until it reaches a set value of minimum error or maximum epoch. Four nets M1, M2, M3, and M4 were trained using the algorithms as shown in Table 1.

Table 1. NN nets and the training algorithm

Nets	Backpropagation Training Algorithms
M1	Gradient Descent
M2	Gradient Descent with Momentum
M3	RPROP
M4	Scale Conjugate Gradient

Each of the learning process of the nets was repeated 20 times and the one that provides near to the average response was selected. Figures 3-6 show the Error versus Epoch curves for each of the nets before termination of the training process. The first three curves show that nets M1, M2 and M3 did not reach the minimum error settings and terminated the training process when reaches maximum epochs. The curve for M4 terminated the training process when reaches the minimum error settings.

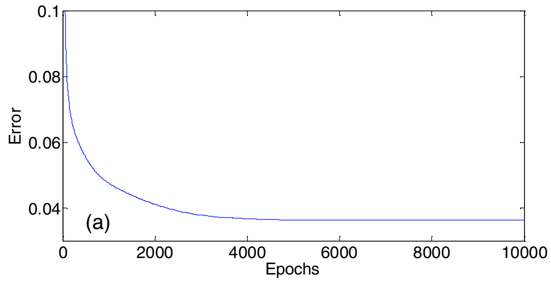

Figure 3. Typical learning characteristics by Gradient Descent Algorithm

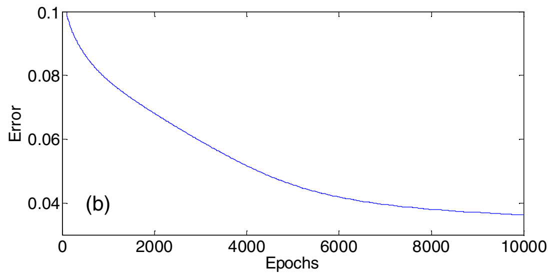

Figure 4. Typical learning characteristics by Gradient Descent with Momentum

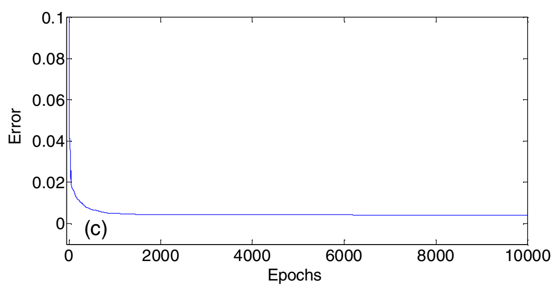

Figure 5. Typical learning characteristics by RPROP

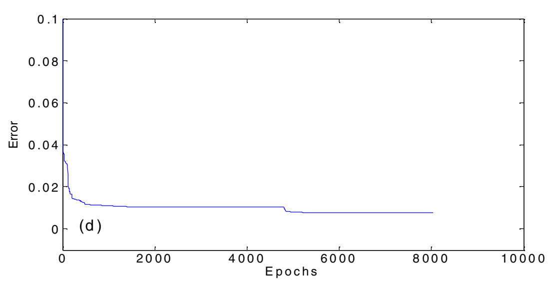

Figure 6. Typical learning characteristics by Scale Conjugate Gradient Algorithm

The mean square error (MSE) or the nets are shown in Fig 7. Net M3 has the minimum mean square error for train data but it is too high for the test data that indicates it has low generalization capacity than other nets. MSE for test data slightly varies for M1, M2, and M4 nets whereas for train data it is lower for M4. Variation of MSE between train and test data is similar for M1 and M2 nets.

Table 2 shows the correct responses of the nets in estimating the grasping force. The responses are satisfactory as a preliminary experiment. It needs to be explored more with other algorithms of NN or has to be developed a new algorithms for better performances.

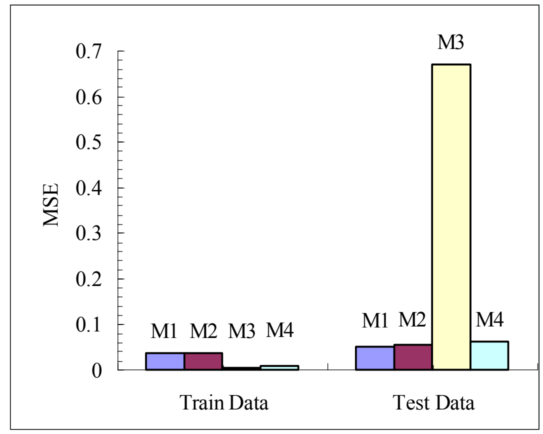

Figure 7. The MSE of the trained NNs to find out grasping forces required holding objects by robots

Table 2 Responses of NNs for train and test data

Nets	Correct Responses in Percent	
	Train Data	Test Data
M1	53	63.97
M2	51	58.92
M3	63	69.02
M4	56	67.34

VI. CONCLUSSIONS

Theoretical basis of a new methodology for slip detection, based on scattered energy of vibration, during grasping by robot end-effectors has been proposed.

Scattered energy of stylus vibration due to object surface texture has been modeled, and has been successfully used to detect object slippage using NN computational techniques. With the help of NN optimal grasping force estimation has been demonstrated with reasonable accuracy of operations and it has been proved that the methodology is capable to work in real life robotic applications.

The trained NN could correctly estimate the grasping force from trained objects with 51-63% accuracy, and testing objects they can estimate the grasping force with 60-70% accuracy. However, further improvement is expected when neural network architecture is optimized using genetic algorithm [19] or other machine learning algorithm, such as, support vector machine (SVM) is used [20]. Higher number of data may also yield better results.

The newly developed model and the methodology is a breakthrough scientific achievement in the areas of robotized manufacturing and assembly operations, and can be used in the robotic technology as well as in machine manufacturing industry.

This is a prototype work and the results of experiments have proved that further development may allow applying the methodology in real life robotic applications in industries.

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