Simulation of Human Tactile Perception using Neural Networks

Mihir Ganu
Dept. of Electronics and Telecom
Sardar Patel Institute of Technology,
University of Mumbai
mihirganu@gmail.com

Sanket Sharma
Dept. of Electronics and Telecom
Sardar Patel Institute of
Technology,
University of Mumbai
sanketonly@gmail.com

Moksharth Doshi
Dept. of Electronics and Telecom
Sardar Patel Institute of Technology,
University of Mumbai
moksharthdoshi@gmail.com

ABSTRACT

There is ample research present on haptics and thehaptic technology is actively applied in numerous engineering applications. However, little research is present in training machines the perception of human touch. We introduce a novel method for training machines the perception of hardness of the object being presented to the machine's surface. The machine simulates the sensory perception process in humans to perceive the hardness of the object. The simulation is done using neural networks. The training of the network is achieved using samples obtained from human subjects. Similar to humans, the trained network successfully rates the hardness of the object .

Keywords—tactile, pressure, hardness, haptics, sensing, neural network, humanoid

INTRODUCTION

The sensing area. The input is used to control movements of robots or for controlling other decisions. For this, various tactile sensors have been developed in different ranges of accuracy[1]. This is a straightforward method and does not involve converting the sensed physical parameters into verbally descriptive sensory perceptions. The other approach involves sensing applied pressure and processing these inputs with the help of soft computing techniques[4].Researchers have used Neural Network and Fuzzy Inference System (FIS)[2] to evaluate sensory attributes of fabrics. The results obtained by the two methods were successfully employed for predicting the tactile sensory attributes. A Neural Network model was found to give better results.

The project presents a novel method to train machines the human tactile perception using Neural Network. The objective is to train a system to perceive the hardness aspect of the object being presented, exactly as humans perceive the touch of an object. The hardness of an object is sensed as pressure by mechanoreceptors embedded in human skin and the human brain perceives the hardness/softness of the object according to sensed pressure strength[3]. In the project, the pressure sensor of the machine was given a touch of an object. The same was given to a human subject as well. The human subject was asked to rate the hardness of the object being presented. Using the methods in neural networks , the machine was trained with sensed pressure and associated human rating of the perceived pressure. These inputs form rule base used for training the

neural network. Ample number of such inputs were used to make the training more accurate. The approach of using input pressure and associated human ratings to train the computer network is aimed at making the machines tactile perception as close as possible to humans. Once trained, the system was able to recognize and perceive the hardness of an object on its own.

A. Related work

The basic approach in haptic technology involves use of tactile sensors to measure the pressure being applied by an object. The tactile sensors measure the pressure applied on

B. Contribution

The experiment successfully employs a novel approach to tactile sensing and perception. The method used eliminates the need of expensive tactile sensors The principle used in the method can be applied for evaluation and measurement tactile attributes such as texture, temperature of the object etc. The method described, provides an economical solution to the problem of tactile sensing, using which, humanoid robots capable of   tactile sensing and perception can be designed.

SYSTEM MODEL

A. Human Sensory Perception

When an object is applied to the surface of the human skin, the skin is deformed. The sensation of the pressure applied re-sults from deformation of tactile receptors (mechanoreceptors) lying under the skin[3]. The receptors generate voltage pulses when the stimulus strength is greater than threshold[1][3][6]. These pulses, pre-processed at receptor level, travel to Cerebral Cortex of the human brain through the nervous system. The cerebral cortex is an organizing computational map, in the human brain[3]. The interpretation of the generated stimulus strength is performed in cerebral cortex. The cortex associates the stimulus strength to the memory of the previous touch to interpret the hardness/softness of the object[3].A verbal
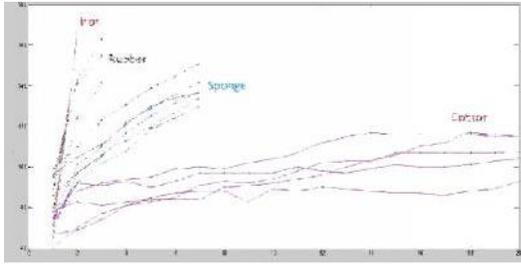
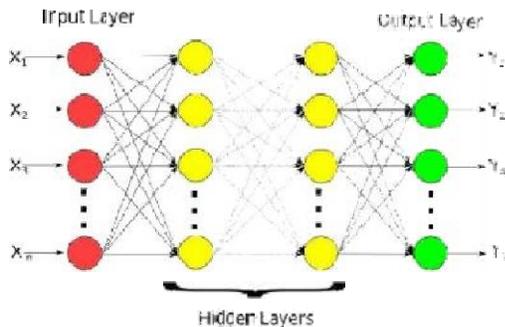**Fig.1 A Typical Multi-Layer Perceptron Configuration**

Fig.2 FSR output (on Y-axis) plotted as a function of Deformation Length (on X-Axis) for a few samples.

The above plot shows the difference in a given deformation length. The readings obtained are not consistent due to limited accuracy of the FSR. descriptor such as 'soft', 'slightly hard', 'very hard' is attached to the perceived value which represents stimulus strength.

B. Ratings by Humans

To obtain the ratings of various objects with respect to hard-ness perception, we used following objects: cotton, sponge, rubber, iron. All of these objects were applied to the fingertip of human subjects, with their eyes closed. In order to obtain readings purely based on the pressure applied to the skin and the memory of the touch of the object, the objects were not shown to the human subjects previously. The object was pressed on their fingertips till the object was completely deformed. The subjects were then asked to rate the hardness of the object on the scale of 1-10. Each of the object was applied randomly to the subjects, three times. This process was carried out with eight human subjects. Thus creating a total of 96 human ratings associated with the 4 objects.

INPUTS AND TRAINING

A. Neural Networks

Artificial Neural Networks (ANNs) are modelling tools, inspired by the functioning of the human brain. They attempt to simulate the way in which the human brain models the data it receives, and thus emulate the computing capability of the brain. ANNs consist of simple computing units called Neurons and synaptic weights or connections between them. Each neuron processes the information

applied to its inputs, to produce an output or activation, which is applied to neurons in the subsequent layers. The different configurations of these neurons and weights define the statistical abilities of the net-work. There are various configurations and learning algorithms used for various tasks, as elaborated in [8].

The network configuration used in this paper is the Multi-Layer Perceptron. A typical MLP model consists of multiple hidden layers, as given in Fig 3.1. The first layer (Input Layer) is where the raw inputs are connected. These inputs are multiplied with the synaptic connections or weights ,and are then applied to each neuron in the next layer. Each layer subsequent to this layer is a hidden layer. Each Neuron in these layer, sums up all of its inputs. These summations are sent through a non-linearity, usually a sigmoidal or hyperbolic tangent non-linearity. The activations or outputs of these neurons are applied to the next layer where a similar process takes place. Thus, the input signal is forward-propagated through to the final layer in the MLP. This Layer is the Output Layer of the MLP. The output of the network is taken from this layer. As we have used a non-linearity, the activations of this layer may be binary or bipolar, depending on the choice of non-linearity. The activations of this layer may be then converted to probability values by applying the softmax output function, which mathematically divides each neuron activation by the sum of all activations of that layer. Thus, all the output values now sum up to unity.

B. Input to the Network

We used a Force Sensitive Resistor (FSR) for detection of pressure. The FSR has diameter of 1 cm and pressure sensitivity range of 1.5psi-150 psi; which is suitable for tactile applications. To capture the variation in resistance of the FSR, a voltage divider circuit is implemented. The test objects were kept under the FSR, supported by a hard surface. Linearly increasing pressure was applied to the object through the FSR, leading to some deformation of the object. The FSR readings as obtained at the output of the voltage divider network were recorded for each mm increase in deformation length, till the extent that the objects could no longer be deformed. Maximum deformation for soft objects will be more than that for hard objects, as illustrated by the difference in the length of each segment in the Fig 3.2. The output of FSR and voltage divider circuit is a voltage that increases with increase in pressure as sensed by the FSR. This value of the output voltage is sent to the Neural Network through analog-to-digital converter for digital input to the neural network.

C. Training the network

A total of 96 readings were obtained from human subjects, of which 64 were used for training the network and 32 for the testing the model. Training the network involves applying the inputs and, the target output. And then mapping the various inputs from the input space to the output space, which in this case are respectively the sensor reading, compression length, and the human rating of the hardness of

the object. Due to the non-linearity used, ANNs have the ability to map highly non-linear functions. The predicted output is then compared to the human ratings, to generate an error signal. This error signal was used to train the network. The Net was trained using one of the most widely used training algorithms , the Back-propagation algorithm developed by Rumelhart et al.[9] . This involved propagating the error signal as generated in the final layer to the layers before it, through to the input layer. The synaptic weights are then adjusted according to the back-propagated error signal. This process is used iteratively to reduce the error signal.

OUTPUT AND TESTING

The inputs applied are the FSR readings and the compression length for each object. The output layer of the network has 10 neurons each for one human rating. The output of each of the final neurons represents how much the network is in favour of that particular human rating. So if the activation of the seventh neuron in the output layer is 0.8, while that for the sixth neuron is 0.1, then it implies that for the given inputs the network favours the seventh neuron to fire more than the sixth one. Thus the network predicts that the human rating of hardness for that particular input object would be Seven. Once the network was trained, the testing phase involved subjecting humans and the system to the touch of the same object.

RESULTS AND DISCUSSION

The system's accuracy was tested on a test set of 32 ratings, which were not shown to the network during training. The systems prediction was compared to the human ratings on the same objects and the system had predicted the correct results in 21 (65.6It must be noted that, a system which simulates the human touch 100

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We want to express acknowledgements to Prof. Dr. **D.** R. Kalbande for important intellectual contributions. implementing a touch sensitive humanoid robot at a very low cost. Our approach is different from others as it involves training the machines actual human perception, of detecting hardness of the object, with the training inputs from humans, instead of just sensing the pressure applied by the object. By the use of neural networks, we achieve better generalizations. As neural networks do not have to be explicitly programmed to model the data, they require little to no prior information about the task at hand. They learn directly from the data. Thus these networks are easier to implement and do not depend upon how well the underlying concepts have been understood, instead, these networks model the underlying statistics of the input data, themselves. Other applications of tactile sensing can be evaluation of fabrics in textile industry, purity checking of materials.

CONCLUSION

We have introduced a new approach to training machines the perception of human touch. The method can be used for evaluation and perception of other tactile attributes as well. The method uses a simple Force Sensitive Resistor,

eliminating requirement of expensive tactile sensors with high accuracy. These sensors can be embedded into humanoid robot gloves, combined with the economic computing power needed to run the network, this system can be used for implementing a touch sensitive humanoid robot at a very low cost. Our approach is different from others as it involves training the machines actual human perception, of detecting hardness of the object, with the training inputs from humans, instead of just sensing the pressure applied by the object. By the use of neural networks, we achieve better generalizations. As neural networks do not have to be explicitly programmed to model the data, they require little to no prior information about the task at hand. They learn directly from the data. Thus these networks are easier to implement and do not depend upon how well the underlying concepts have been understood, instead, these networks model the underlying statistics of the input data, themselves. Other applications of tactile sensing can be evaluation of fabrics in textile industry, purity checking of materials.

REFERENCES

[1] Dahiya, R.,Metta, G.,Vallio, M., 2008 - Tactile Sensing From Humans to Humanoids, IEEE Transactions on Robotics

[2] Jegurim,S.,Adolphe,D.,Sahanoun,M.,Douib,Schacher,L.,Chei khrouhou,M.,Intelligent Techniques for modeling the Relationships between Sensory Attributes and Instrumental Measurements of Knitted Fabrics, Journal of Engineered Fibers and Fabrics, Volume 7,Issue 3-2012

[3] Guyton, A. , Hall, J.,2006, Textbook of Medical Physiology, ELSEVIER SAUNDERS

[4] Meister , E., Kryvoukhov,2011,An Artificial Tactile Sensor Skin For Modular Robots

[6] Lederman. S, Browse R.,1988,The Physiology and Psychophysics of Touch

[7] Okomato, s.,Nagano,H.,Yamada, Y.,2012,Psychophysical Dimensions of Tactile Perception of Textures, Journal of IEEE Transactions on Hatics,Vol.X, NO.X,201x

[8] Haykin, S. 2000. Neural Networks: A Comprehensive Foundation, Prentice Hall, New Jersey, 2nd edition, 999. Presented at the ASME ICE Division Fall 2000 Technical Meeting September 25-27, Peoria

[9] Rumelhart, D. E., Hinton, G. E., Williams, R. J. 1986. Learning Representations by Backpropagating errors, Nature 323, 533536.

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