NEURAL NETWORKS FOR PNEUMATIC TACTILE PERCEPTION

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ABSTRACT

The neural network model as proposed by literature presents very interesting computational capabilities. We are interested in its application to the classification problem. It can be a general method for giving semantic meaning to row data captured from sensors.

Traditional techniques as discriminant and cluster analysis provide powerful tools for this labour but they lack the flexibility and adaptability offered by neural networks.

We are looking for a methodology that allow us to incrementally extract semantic information from a group of sensors endowed in an autonomous system. The first approach is an intent to clusterize row data captured by pressure sensors in a pneumatic skin and to obtain higher level information about the localization and intensity of the stimulus.

In this paper we present a real system based on a pneumatic skin designed to cover a robot manipulator arm. We show how a multicell surface coat can be configured in such a way that a few sensors can provide information enough for a categorization system to discriminate two features of an impact over the skin surface.

The skin is presented as a security device for a robotic arm. It is composed of multiple pneumatic cells interconnected in such a way that a few amount of differential pressure sensors allow us to discriminate among diferent cells and impact energies.

The neural model we chose is a nonlinear feedforward multilayer network with back propagation as the learning algorithm. We have developed a software environment for the design and trainning of these kind of networks. The system includes an interface for connecting the network to the sensors and a file system to store and retrieve conveniently the examples needed during the learning stage.

Finally, we have assembled the coating, data acquisition electronics and neural nets algorithms and tested intensively the system. The results are very satisfactory. The network is able to classify the different locations of the pneumatic skin and different intensities of the impact. With these first level processing concepts we can define elemental actions for survival purposes.

INTRODUCTION

A great effort has been made in the last years on the theory of neural networks. As a result of it, several techniques that allow a new approach to solving traditional problems are now available [1,2]. This powerful tools are specially atractive for applying to some areas of sensor information processing. One of these areas deals with obtaining semantic meaning from row data sensors

Autonomous robots that work in un structured environments need sensorial information. The adquisition of information from the environment is the first step that these systems have to accomplish in order to interact correctly with the real world. With this data, the processing systems of the robot must decide what to do in non expected situations. This task must be carried up by a set of transductors (sensors). The sensorial signals are converted to digital data time series to be processed by a digital computer.

The next step must transform row data into elementary simbolic concepts. These concepts are the base to obtain more complicated simbols through a multilevel hierarchical processing structure. Goal oriented decision makers can interact with these world features representation to generate actions capable of been executed by the system actuators. These actions can be selected towards a specific task such as search, vigillance, mapping, repairing, etc.

In this work, the system must classify the data from the sensors in order to determine the impact location. This task can be accomplished by implementing several techniques[3]. Normally, statistical methods like discriminant or cluster analysis, binary tree clasification, etc. need a set of parameters extracted from the signal to achieve the classification criterium. This characteristic presents the problem of selecting the parameters to use and the weight that must be assigned to each one in order to obtain a high degree of accuracy. In addition, the choice of the correct distance imposes a great influence over the performance of the system.

Finally, all those parameters must be recalculated each time a signal is read. With a properly trainned multilayer feedforward neural network, we obviate all these problems since data are fed directly from the sensor (except scaling). As is widely explained in [1] the network develops an internal model of the structure of the world it is perceiving, and generalizes to the classes impossed by the teacher. When new unfamiliar examples are presented, this model shows like a very high performance classifier.

Along with the algorithms and structures that we use, we present an interactive software system for the design and validation of multilayered neural networks.

THE PNEUMATIC SKIN

Some materials as elastomer foams have been used for extended contact detection purposes [6,7,8,9], but they present severe limitations in temperature, aging, and elastic protection capabilities.

Mechanical protection by inflatable chambers is an old very used technique. The development of small, low cost, integrated pressure sensors allows simple contact sensing devices for manipulators by using air jets [5] or elastic blisters [4]. Our aim was a sensitive covering of a wider extension than a robot griper fingertip with considerable impact energy absortion and extended temperature range, to be used as global sensitive protection for a mobile robot.

The developed skin is built by a flexible and non elastic membrane. This coat is divided in multiple cells whose interior pressure is greater than the atmosferic one. Protection (impact penetration) and sensitibity features are function of the initial inflating pressure. The connection among the cells is such that very few presure diferential sensors can generate enough information to discriminate important features over the skin. The function of the skin is to provide the manipulator controller with simbolic information about location of impacts, energy of impacts, impact surfaces, etc.

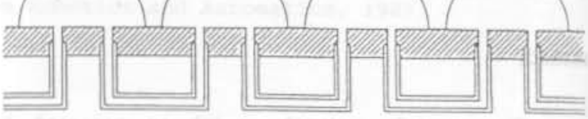

Figure 1 Four cells pneumatic array.

Figure 1 shows the allocation of four cells in a pneumatic array. The complete system is shown in Figure 2. It presents a block diagram of all the modules that form it and its interconnections.

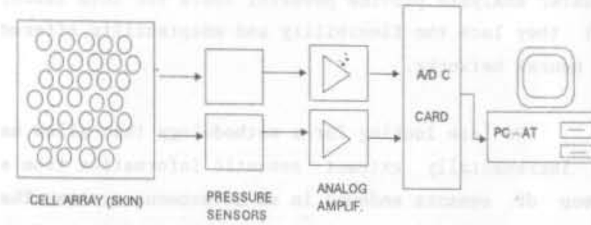

Figure 2. Block diagram of the complete system.

The real world is perceived by the pneumatic skin. As we have showed before an impact on a cell produces a pressure range that is measurable by the differential pressure sensor. This sensor generates an electric signal that is properly acconditioned in order to enter the A/D converter. Finally the time series are adquired and stored by the microcomputer. The categorization task is accomplished by the network. For this purpose we have developed an interactive software environment. This environment has a modular design. This will allow to incorporate new processing subsystems like DSP boards, analog netvoks or data from new sensors.

NEURAL NETWORKS

As stated before, different signals corresponding to the same cell can be quite different depending on the location, the impact energy or the contact surface area. Therefore, we need a learning system capable of extracting the main features of a specific location in the skin under a wide variety of impacts.

The neural network models presented to us as specially well suited for this task. A first approach to these models shows us a clear taxonomy: networks that learn with and without teacher. In these specific case we obviously know, a priori, the cell that corresponds to each signal obtained by the sensor. Aditionally, we have had some experiences with multilayered networks and the Backpropagation training algorithm [1] working on the traditional examples proposed by the literature and also on some different ones focused on the treatment of time series. Starting out from this, our goal was to implement one of these networks (teacher guided) and adjust its weights to discriminate the location of an impact among the different cells of the skin and its energy. In the next section we explain ,more in detail, some of the features of the whole system along with the experimental results obtained actuating directly over the skin.

EXPERIMENTAL DESIGN AND RESULTS

We developed a three layer network in which the number of cells of the first and last layer is determined by the dimensions of the input and output spaces. The input space is formed by 30-dimensional vectors. The components of these vectors are the 30 first values obtained from the AD converter at a 2KHz sample rate and conveniently rescaled. We set 30 because of memory restrictions but it is true also that most of the information contained in the signal is located at the beginning of it.

The output space is a three dimensional vector that codifies in binary seven skin cells. These seven representations of the cells constitute a primary categorization level. With the result of this clasification it is possible to construct more sophisticated concepts and generate specific control commands.

The next step was to retrieve a representative set of examples. This was done by dropping different sized lead balls from different heights over the cells. The signals obtained were saved in files and preserved for the trainning of the network.

By this time we had developed a complete interactive environment in which we could try different configurations of networks, different algorithms and what is more important, keep a detailed tracking on the convergence process of the network. Lately, we could also modify certain parameters of the system on line, that is, pause the process, modify it and reactivate it.

Figure 3 shows a diagram of the modules that compose this software environment.

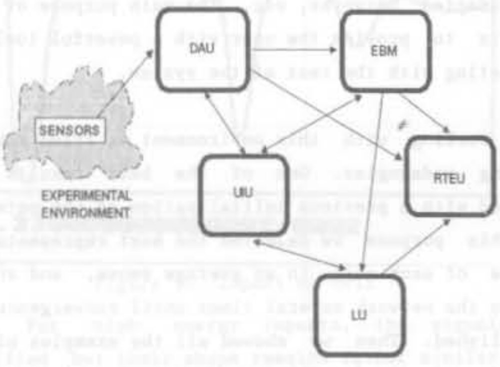

Figure 3. Module Diagram of the Software Environment.

Data Adquisition Unit (DAU)

The DAU controls all the sensorial information flow. It captures the time series from the AD converter and passes them to the Example Base Manager or to the Real Time Execution Unit. When needed, the DAU selects and rescales the time series values. For example, selecting the first 30 significant values from the digitalized signal and rescaling them form its original range (0..4095) to a range suitable of being used by the network (-2..2).

Example-Base Manager (EBM)

The EBM stores and retrieves a set of examples following a particular pedagogy as requested by the user. These selected examples will feed the Learnig Unit and eventually the RTEU for validation purposes.

Learning Unit (LU)

The Learning Unit incorporates the trainning algorithms and interacts with the User Interface Unit in order to modify on line the convergence process. The structure of the network including the dimension of the input and output space and the number of hidden cells is defined directly by the user and maintained in this unit. The user can store different networks with its adapted weights and retrieve them as needed.

The Real Time Execution Unit (RTEU)

The RTEU achieves direct categorization of the row sensors data. for this purpose it is assigned an adapted network from the LU. It is connected to the DAU which provides it with real world examples. The RTEU activates the network and obtains an element of the output space. These elements are presented graphically to the user through the UIU.

The User Interface Unit (UIU)

The UIU is a presentation facility used by the other units. It allows the user to design networks,retrieve already existing networks, select a trainning algorithm, select the group of examples to be learned, validate networks over a new set of examples, save adapted networks, etc. The main purpose of this unit is to provide the user with a powerful tool for interacting with the rest of the system.

Working with this environment we tried several learning pedagogies. One of the best results was achieved with a previous initialization of the network. For this purpose we selected the most representative example of each cell, in an average sense, and showed them to the network several times until convergence was accomplished. Then we showed all the examples of all classes and waited until convergence. Sometimes we had to add a new hidden cell or decrement the learning parameters of the algorithm but in general, convergence was achieved in less than 300 iterations.

We tried also several arrangements of the set of examples, for instance we showed one example of each class iteratively until all the set was shown. Alternatively, we showed all the examples of each class together and one class after the other. The first strategy provides better convergence results and in some complicated cases the second one does not find a solution. In both cases the results are not affected by the specific arrangement of the classes in the set.

Along with all these experiments we were obtaining a precise idea about how the different componentes of a network of this kind interact. We realized that the gradient of the sigmoidal function, when kept the same in all the neurons, defines its "sensibility". When the gradient is made steeper the network converges faster but falls easily in a local minimun. In the other hand, as we made it less steep the network was able to find a slower but more secure, way to convergence. In addition to this, we experimented with the parámeters of the algorithm:

W(t+1) = W(t) - Alfa * Deriv(Error,W(t)) - Beta * Deriv(Error,W(t-1))

Alfa acts as an amplifier of the correcting term and therefore can produce convergence decrease effects and sometimes can produce oscillations or place the network in a local minimum. This occurs when the error from an example is minimized so quickly that the error from another one cannot be decreased.

The parameter Beta, controls the amplitude of the momentum term which normally increases significantly the convergence rate. If we set beta with a high value, this term produces great oscillations in the convergence process that can result also on a local minimum. There is still another parameter that has a big influence in the learning process. It is the number of cells in the hidden layer.

If we can achieve desired learning with the minimun number of cells, we are getting a higher degree of generalization. In the other hand, if we set a high number of hidden cells, the network will do just rote learning [12]. Experimentally, a network with very few cells presents a faster initial rate of convergence but the final precision remains low. If we augment the number of cells, the rate is slower but the final error gets closer to zero.

With all this intuitive knowledge we determined an initial network. This had 30 neurons in the first layer and 12 in the second one. This network was trainned with the real examples obtained from the sensor. Each example belongs to one of 21 classes that represent seven cells (location) and 3 energy levels. Therefore, our classes could be labeled "cell low energy", "cell 5 high energy", and so on.

Figures 4 to 10 show some of the signals that were used in the trainning. All them were obtained with low energy impacts.

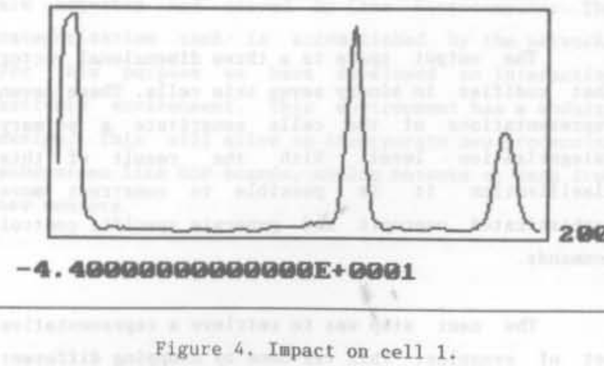

Figure 4. Impact on cell 1.

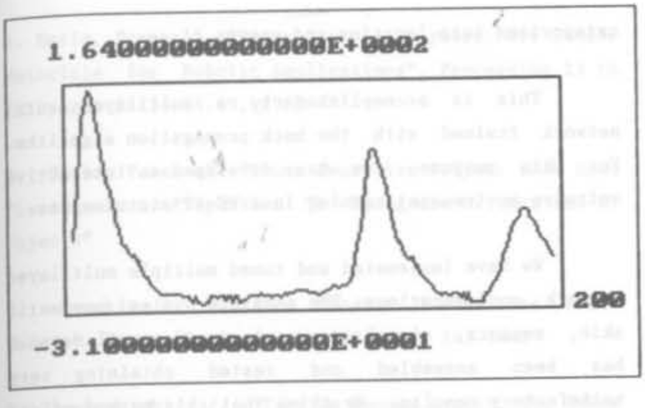

Figure 5. Impact on cell 2.

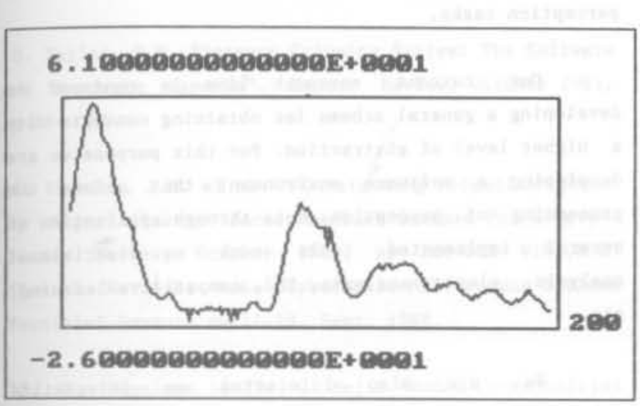

Figure 6. Impact on cell 3.

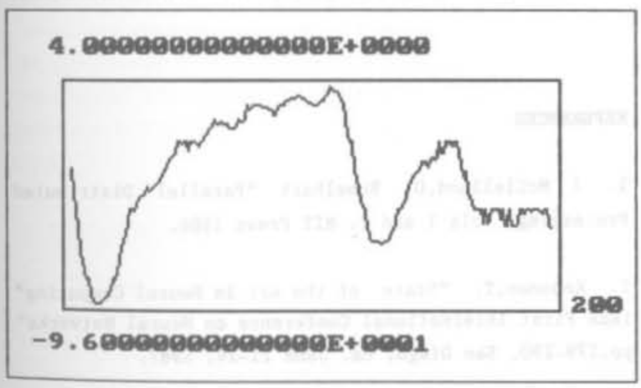

Figure 7. Impact on cell 4.

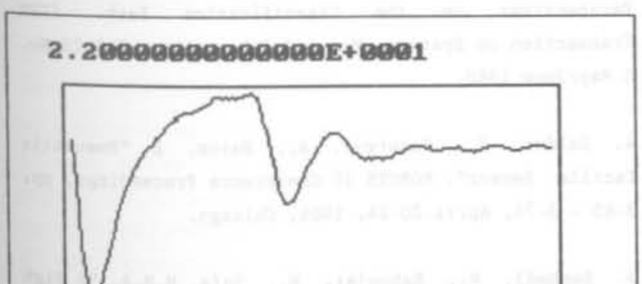

Figure 8. Impact on cell 5.

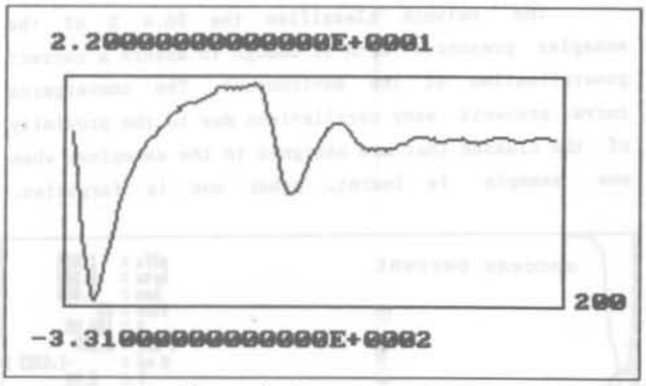

Figure 9. Impact on cell 6.

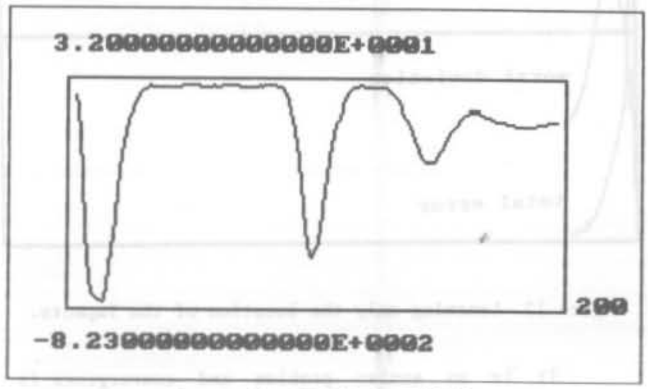

Figure 10. Impact on cell 7.

For high energy impacts, the signals are amplified but their shape remains rather similar. This proximity makes a harder problem to generalize over the 21 classes.

Figure 11 show a convergence result. In the upper right corner of the figure the values of some of the parameters of the process are represented: "alfa" and "beta" are the coeficients of the algorithm, "box" is the quotient in the exponential term of the sigmoidal function, "iter" is the actual number of iterations, "des" is the actual worst deviation and is preceded by the number of the example which holds it, "% vd" is the increment of that deviation in percent,"T" is the sum of the overall error and "vt" is its increment in percent.

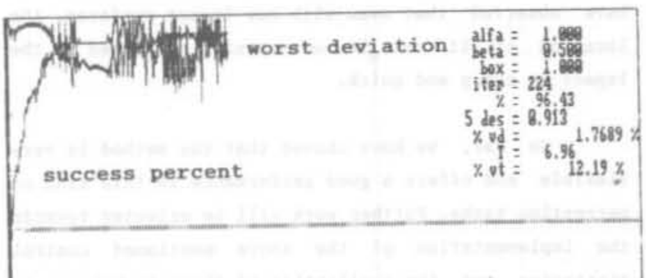

Figure 11. Learning complete. All examples were presented iteratively. The whole process took 224 iterations.

The network classifies the 96.4 % of the examples presented wich is enough to assure a correct generalization of the environment. The convergerce curve presents many oscillations due to the proximity of the classes that are assigned to the examples: when one example is learnt, other one is forgotten.

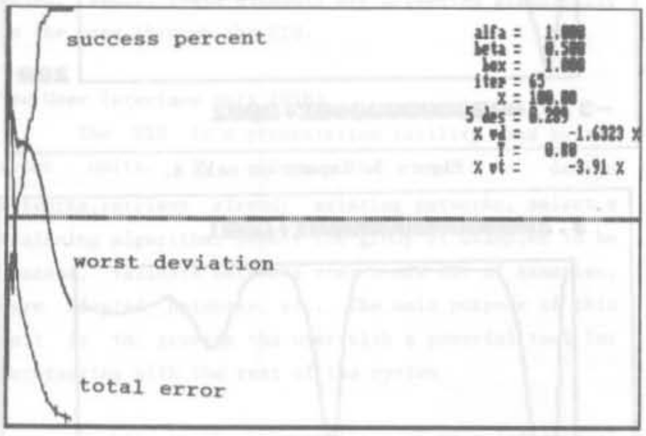

Figure 12. Learning only the location of the impacts.

It is an easier problem and convergence is obtained, with 6 neurons in the second layout in less than 100 iterations.

Once the network has learnt, the system can be set to normal working mode. In this mode, any impact on the skin is recognized and processed. The pressure signal is digitalized and rescaled, then is presented to the network wich, in real time, selects one of the seven cells and a level of energy.

The network will classify correctly almost all the impacts caused by the same kind of balls that were used in the trainning (arbitrary height). Different impact surfaces that the ones used for learning produce rather different pressure signals and so they are less suitable of being correctly classified. However, we have observed that even with new impact surfaces, the location of it can be accurately estimated if the impact is sharp and quick.

So far, we have showed that the method is very flexible and offers a good performance in this kind of perception tasks. Further work will be oriented towards the implementation of the above mentioned control strategies and the application of these techniques to other sensorial information.

CONCLUSIONS AND PERSPECTIVES

In this paper we present a real system in which pressure signals obtained from a pneumatic skin are categorized into location and energy classes.

This is accomplished by a multilayer neural network trained with the back propagation algorithm. For this purpose we have developed an interactive software environment running in a PC-AT microcomputer.

We have implemeted and tuned multiple multilayer network configurations. The complete system: pneumatic skin, sensors, signal processing and neural network has been assembled and tested obtaining very satisfactory results. We think that this method offers flexibility and good performance when applied to perception tasks.

Our current research line is centered in developing a general schema for obtaining concepts with a higher level of abstraction. For this purpose we are developing a software environment that allows the processing of perception data through application of several implemented tools such us discriminant analysis, cluster analysis, ID3, competitive learning, etc.

We are also interested on integrating information from heterogeneous sensors with these techniques. The concepts obtained this way will allow us a more powerful actuation over unknown environments.

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