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Modeling of Technical Objects' Refusal with the Help of Neural Networks

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Abstract: In this research, the refusal of technical objects in mass production uses Neural Network as a model. A neural network is a collection of interconnected elements or units. However, the phrase neural network means an amazing variety of things to a remarkable diversity of researchers. For biologists it refers to a mass of gray matter or, perhaps, a biologically faithful model of some part of the brain. For psychologists and other cognitive scientists, 'neural' (or 'connectionist') network denotes a virtual machine architecture that has come to be seriously considered as a model of the mind. To a theoretical computer scientist, 'neural network' is likely to mean a network of threshold logic gates. But to some computer scientists, a neural network is a Markov process, evolving through time in a stochastic search for globally optimal states. And to still others, a neural network is a collection of analog devices, continuously evolving in time under the direction of certain differential equations. To a physicist, a neural network may be a dynamical system evolving in time toward attractors of various types, or it might be a low-level substrate over which large-scale average behavior can be studied in the manner of statistical mechanics. To a functional analyst, a neural network is likely to be a particular kind of function approximator. To statisticians of various sorts, neural network learning is a realization of a scheme for estimating parameters and selecting among different models using Bayesian or information-theoretic or maximum-likelihood methods.

Key words: Neural Networks (NN), refusal of Technical Objects (TO), modeling of technical objects, dynamical system

INTRODUCTION

In short, of what was mentioned above, neural networks are dynamical systems that compute functions that best capture the statistical regularities in training data: Their study inevitably brings together concepts from dynamical systems theory, computation theory and statistics. Correlated with, but logically independent of, the tripartite division of computational, dynamical and statistical perspectives, there is the following tripartite decomposition of a neural network: Processing-given the architecture and weights, computes output activation from input activation. Learning-given an architecture, computes the weights from training data. Representation-given a task domain, computes the domain interpretation of input/output activation patterns.

The processing component of a neural net is an algorithm (or set of dif- ferential equations) by means of which activation patterns input to the network are converted into activation patterns that comprise the net's output. The computational and dynamical perspectives tend to address this component most, since the input/output function computed is of primary concern to the computational perspective and the dynamics by which it is computed is of central interest to the dynamical perspective.

However, the computational and dynamical perspectives also address the learning component, since the computational difficulty of the learning problem and the weight dynamics of learning algorithms are both of great interest. It is the statistical perspective, though, that has the most to say about the central problem in most neural network learning: what are justifiable procedures for drawing inferences from given training examples to unseen data-the problem of induction.

The third component, representation, is the least-studied aspect of neural networks: it concerns the link between the input/output activation patterns and the items that they encode from whatever domain the network's problem comes. In a vision application, for example, the input activation pattern might be interpreted as an image.

MATERIALS AND METHODS

The method of modeling of refusals in which similarity of technical objects and modeling neural networks reflects not only the structure of object and model, but also a level of their damage is considered.

The major question of Technical Object (TO) durability estimations is a substantiation of criteria of its refusal. The estimation of a resource is closely connected to the decision of this question that is determined by its operating time before a limiting condition after which achievement operation TO should be stopped.

Refusal-the event consisting of infringement of an efficient condition of what is determined by the list of the given parameters and allowable limits of their change-admissions. Infringement of an efficient condition consists of output of value, even one parameter for the established admission. The attributes, allowing establishing the fact of infringement of an efficient condition, are criteria of refusal. For many objects, until now, these criteria are not yet determined which results in inconsistency in estimation of their condition at operation and tests. A basic choice of criteria for a limiting condition is the treatment of resource and probability of non-failure operation as stock of serviceability TO. While the stock is significant, there is no basis to consider a condition limiting. In view of this, there must be an action to distinguish criteria of refusals TO from criteria of its limiting condition (Kogel, 1981).

Attributes of refusals and limiting conditions TO are: The discontinuance of performance of the given functions by it. A deviation of the given parameters of quality from the established norms. Refusals and a limiting condition of components of object that result in the discontinuance of functioning of object or an output of its parameters for the established norms. Occurrence of the processes interfering functioning of object. And exhaustion by object of the appointed resource or the appointed service life. The important factor when accepting the decision on refusal is also economic. Sometimes it is impossible to get a new one so it is necessary to maintain a limiting condition TO. On the other hand, it is impossible to dismiss the social factors: prestige, style and others. There are times when even an automobile is still considerably efficient, it is being replaced only because it has been socially obsolete.

The simplest for many TO criterion of refusal is breakage (Pankratov and Barkovsky, 1998). However, this criterion does not always happen satisfactorily. Process of fatigue failure TO is difficult and completely not investigated, therefore the precise criteria determining the moment of fatigue failure until now are not yet produced. In this connection, criteria of refusal are various: the beginning of macro-crack formation, length of a crack, sharp fall of loading or frequency cycles, significant growth of deformation, etc.

Even the identification of refusal that has occurred in the past represents serious difficulties that are not only technical, but also economic and social in character. The difficulties repeatedly grow when the question is refusal forecasting. It is possible however, to apply identification and forecasting of TO refusal with modern intellectual technology. This is with the help of modeling Neural Networks (NN). TO and NN have established a conformity in their structures, The list of elements and communications between them and their functions (Abovski, 1998). This is for maintenance in similarity.

It is obvious, if such conformity is proved, NN inputs values of parameters of external and internal influences then act on TO in operation on the data NN outputs. It is then possible to interpret its current condition (for example, size of a pressure, deformation, temperature) on which it is possible to judge its serviceability indirectly. Such way is possible to relate such approach to the first level NN-modeling. At the second level of modeling, NN inputs values of parameters of external and internal influences, this also acts on TO, but output only forms one binary signal: “refusal present-refusal is not present”, that is NN takes up the responsibility for refusal identification (Kallan, 2001).

The approach to identification of refusal which can be related to the third level of modeling and on which construction of model TO, is based on where NN is offered. It is accepted what not NN “makes”, but how it “makes”. At this level of modeling TO, NN does not only have structural and functional similarity, but also rules of interpretation of a condition TO, known NN “behaviors” are formulated. The matter is that, an offered method on NN that inputs any information on TO does not move. Hence, NN outputs a condition TO and are not compared to each other. Within the framework of this method and object, NN model performs work that is traditional for them,-for example, NN distinguishes images and TO moves a cargo. An object obtains fatigue damages of natural elements. For example, communications, such “damages” bring artificial, excluding from it separate neural or stopping communications between them. Thus strict conformity between a condition of similar elements and communications-both in NN and in TO- are important.

For identification of refusal, how NN distinguishes images must be maintained. If “damaged” NN continues to make it without mistakes or with below given threshold quantity of mistakes appropriate to its damage, TO is still considered efficient. If “damaged” NN after the next iteration of “damage” looses distinguished image ability, then appropriate TO is considered given up.

RESULTS AND DISCUSSION

The simplified TO as the cascade of mass-changing devices are considered in an example-mixers 1, joint among themselves by pipelines 2 with valves 3. NN model shows them as neurons 4 and links between them 5 (Fig. 1 a, b accordingly).

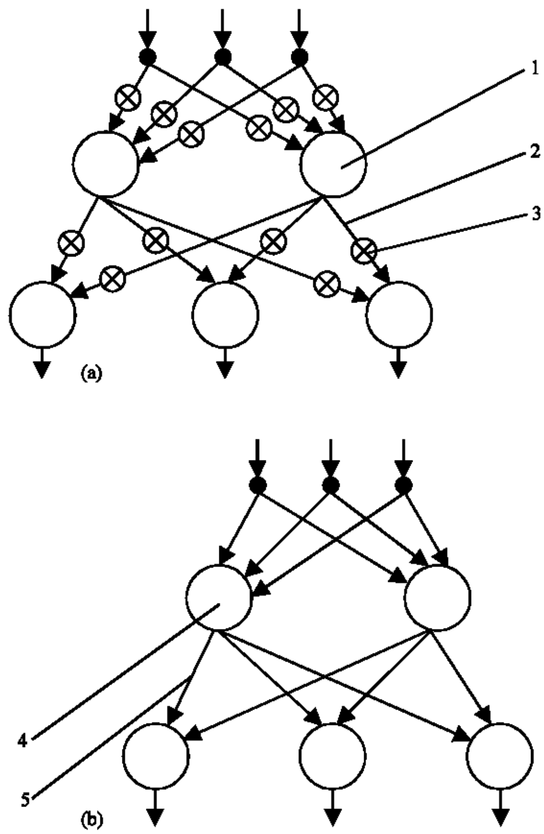

Fig. 1: The cascade of masschanging devices (a) and it NN model (b): 1-The mixer; 2-The pipeline; 3-A valve; 4-A neuron; 5-Llink between neurons

On three TO inputs on pipelines, initial pool components as solutes of different mass density act and from its three outputs products of mass-changing as solutes of other densities are seeded. Results of operation of the cascade depend on amount and density of acting solutes, its structure (an amount of elements 1 and about links between them 2) and customization of the valves 3, located on all pipelines before their input in the appropriate mixer.

To the cascade, damages maybe treat outage of mixers 1 (for example, because of the cage destruction) or termination of operation of pipelines (for example, because of abruption or hard deposit closing). Enough ramified circuit of the cascade outage of some of mixers and pipelines at correct customization of valves does not result in an exit for a field of tolerances of make-ups of solutes in exit from the cascade. As soon as damages reach some quantitative and qualitative degree while connected to their arrangement places, makes up solutes on exit wherein it ceases to match TO tolerances and thus the condition of TO may be qualified as refusal.

Reduce NN structure, which is no problem to model TO refusal and TO may have a structural similarity on elements (the mixer 1-a neuron 4) and links between them (pipelines 2-links between neurons 5).

The functional elements similarity implies from the following reasons. Let the element TO represents the chemical device-the mixer having three bulk fitting pipes-inputs and one drain-an output.

Inputs of the mixer solutes of the same substance in the same solvent, but with different mass densities and fractions from a total amount of the solute, has arrived in the mixer through three inputs act. It is supposed also, that the volume of the mixer is great enough, that during normal maintenance its overflowing did not occur and receipt and exception of initial substances and products of mass-changing occurs discretely at the end of each iteration of simulation.

Let densities of soluble substance on inputs 1, 2 and 3 are accordingly equal c1, c2 and c3 and mass fractions of solutes-$\alpha 1$, $\alpha 2$ and $\alpha 3$ and $\alpha 1+\alpha 2+\alpha 3 = 1$. Then density of soluble substance in mixture is equal:

$$c_\Sigma = \sum_{i=1}^{3} c_i a_i \tag{1}$$

The scheme of the formal neuron structurally similar to the modeled mixer also has three inputs and one output. Believing displacement equal to zero and activation function-linear, the expression linking a signal on an exit of such neuron y with signals on its inputs xi is possible to write down:

$$y = \sum_{i=1}^{3} x_i a_i \tag{2}$$

Where, ai-a flowing condition- is a valve throughput that actually plays a role of a weighting coefficient at the appropriate pipeline.

From formulas (1) and (2) it is visible, that NN image c_Σ is y, images ci -xi and αi represent images of weights ai, appropriate solutes bounding receipt in the mixer. Practically regulation of weights ai on inputs of the mixer is carried out with the help of the appropriate valves.

For the formulation of a condition, TO interpretation rules on known NN “behaviors” is necessary to consider reduced. In an example of TO and modeling, NN is represented as problem spaces A and B. The space A is a set of all combinations of possible damages TO plus an initial unimpaired condition and space B, accordingly, set of all possible combinations NN “damages” plus initial “non-damages” its condition. At exception of those or other elements or the links connected to damages in TO, also elements of spaces A and B the same way vary. The mutual uniqueness between spaces of TO A and model B is isomorphic conformity (Korosh, 1971). At such conformity, functional links between elements of spaces A and B are linear, hence follows that, at any isomorphic changes of condition TO and NN refusal in execution of trial functions occurs at them simultaneously.

CONCLUSION

The method is convenient, if for any reasons immediately to estimate a condition TO inconveniently. In these situations decision making about refusal on a condition similar NN may appear unique. As to the forecast, the NN model is extremely useful. In this case the future "damages" are deposited to model by casual image or with preferences, founded on field experience similar TO (Balan *et al*., 2001).

The offered method is used during projection and maintenance of mass-changing devices. The equipment bolstering given conditions of maintenance at significant damages and providing prediction of its refusals is created.

APPENDIX A-NEURAL-NETWORK COMPUTERS

Computer systems with self-learning and self-adaptive capabilities are increasingly finding their way onto the market. Neural networks, modeled after the human brain, may soon lead to an inexpensive voice typewriter, intelligent household robots and a host of other "smart" technologies.

A simple neural network consists of layers of processors interconnected somewhat like the neurons of biological nervous systems. Users "train" a network by giving it a set of data and the desired outputs. The network "learns" by finding ways to approximate the desired outputs.

Neural networks are already being used in telecommunications, handwriting recognition, risk analysis, machine vision and robotics. Neural-network products are also being tested commercially in systems to diagnose diseases, determine credit ratings and even compose music.

Joseph Weintraub, president of Thinking Software, Inc., of Woodside, New York, predicts that neural networks will lead to an inexpensive voice typewriter, which can be trained to recognize the voices of several users, in three to five years. He also believes neural networks will soon help intelligent robots to do more household chores, including cleaning windows. You will train your personal robot by putting it through its paces once or twice with a handheld remote control device.

Neural networks may also prove a boon in understanding the human brain. Neural modeling permits fascinating interplays between engineers and biologists, says Tyler Folsom, a software engineer at Flow Industries in Seattle. A biological structure may inspire a computer simulation of a simplified neural network. The model in turn may predict behavior that the neurologist has not observed and that may be verified or disproved by further experimentation.

Despite their great promise as a self-learning computer technology, neural networks face many years of development before they can achieve the intelligence of primitive animals, says Folsom. It may be that [the] genetic code includes built-in assumptions about the world that have not yet been incorporated into artificial neural systems, he notes.

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