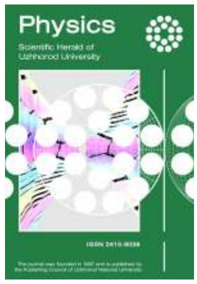
Scientific Herald of Uzhhorod University
Series "Physics"
Journal homepage: https://physics.uz.ua/en
Issue 49, 35-42
Received: 14.01.2021. Revised: 20.03.2021. Accepted: 16.06.2021



УДК 534.1
PACS 84.35.i.67.25.d
DOI: 10.24144/2415-8038.2021.49.35-42

Use of Neural Networks in the Formation of a High-Quality Smoothed Audio Signal

Brittany Flores[1*], Teresa Tran[2]

[1]Washington University in St. Louis
MO 63130, 1 Brookings Drive, St. Louis, United States

[2]Western Washington University
WA 98225, 516 High Str., Bellingham, United States

Abstract

Relevance. High-quality smoothing of sound during its passage in local networks and in stereo systems allows for the transmission of sound over wireless networks with virtually no delays. The basis for this sound remains controversial. Its decoding is possible both on the receiving device and on the transmitter. At the same time, the processors can provide decoding in real time with automatic adjustment by algorithms. Neural algorithms can be used both on the basis of signal sequence and on the parallel use of receivers.

Purpose. The purpose of this study the learning a diagnostic method that combines the analysis of several indicators, which will significantly increase the probability of detecting a malfunction in sound transmission or individual nodes.

Methods. In the process of the study the used of exact algorithms and non-exact algorithms. Exact algorithms are divided into linear programming techniques and dynamic programming techniques. Linear programming methods include: Brute Force method, Branch and Bound method, Gomori method and other.

Results. The authors show that in this regard, the problem of high-quality sound transmission using neural algorithms is reduced to the problem of an optimal transportation project and is solved by optimising the local sound route. The equilibrium distribution of transport routes should be built into the equipment itself and the audio decoding protocol.

Conclusions. The use of a sound receiver with neural algorithms makes it possible to identify the most difficult areas that cause sound delay or distortion. Practical application of the study is possible in conditions of dynamic provision of sound filling of the room to create the effect of presence and volumetric absorption of sound, if necessary

Keywords: algorithm, function, optimised route, fuzzification, sound transport

Introduction

Transporting to site nodes or between sites is a travelling salesman problem. But, given the specifics of functioning, it is necessary not only to convey sound from one node to another, but also to take into account the limitation on the use of an intermedia available at the source, therefore, the purpose of the problem is to minimise the cost, distance and time of transporting. For large dimensions of the transmission problem, a method built on the basis of a recurrent neural network (including when implemented on parallel computing systems) is more attractive if the solution accuracy achieved by the network is satisfactory. This requirement, called the rational rigour principle, presupposes the rejection of an absolutely exact solution to the problem and is typical for situations where the solution to the problem must be obtained as soon as possible. Unlike traditional combinatorial optimisation methods, Hopfield recurrent neural networks do not enumerate options. The Hopfield network converges to a locally optimal solution to the problem, but the intermediate states of processing elements form not a feasible solution, but an approximation to it, which is given by a matrix of real numbers from the interval (0.1). The disadvantage of Hopfield networks is a complex mathematical description, a large number of unnecessary links and, accordingly, unnecessary costs for their support. A complex network can create an extremely confusing region of separation in the state space, for which it is difficult to interpret the effectiveness and adequacy of its operation in the intermediate stages.

Suggested Citation:
Flores B, Tran T. Use of neural networks in the formation of a high-quality smoothed audio signal. *Scientific Herald of Uzhhorod University. Series "Physics"*. 2021;(49):35-42.

*Corresponding author

In wireless networks, one of the important tasks of auxiliary processes is the task of transporting sound both within the site and within the entire room. When scheduling sound transmission, delivery time is important, which is discussed with sources at sites in advance when planning transmission, and delivery delays. In this case, when building routes, the primary role is assigned to the observance of the established time frames and the choice of path for the specified route, the sound delay in which will be minimal. This problem is formulated as follows: given a connected weighted undirected graph $G=(V, E)$; the set of its nodes is a set of points $V=\{0.1, ..., m+1\}$, one of which is a source (node 0), and the rest are destinations (nodes 1, ..., $m+1$); the set of edges represents paths between points $E=\{[i, j]: i, j V\}$. Each destination is assigned a certain period of time during the transmission of the signal when the sound must be delivered to it. The duration of the transmission along the edges cij is introduced; also set the time of receiving sound in each of the points.

The paper proposes a diagnostic method that combines the analysis of several indicators, which will significantly increase the probability of detecting a malfunction in sound transmission or individual nodes. The method under consideration is based on a neural network approach, which has become widespread for solving problems in any industry.

Materials and Methods

Today, there are two global approaches to the problem of finding the optimal route: the use of exact algorithms and non-exact algorithms [1]. The first group, by exhaustive enumeration of all possible options, gives an optimal solution, but the number of cycles reaches n!; the second group of algorithms is used in cases where the complexity of the implementation and search is unjustified, and the resulting quasi-optimal solution is satisfactory [2]. Exact algorithms are divided into linear programming techniques and dynamic programming techniques [3]. Linear programming methods include: Brute Force method; Branch and Bound method; Gomori method (The Cutting Plane).

One of the first algorithms for solving this problem was the Brute Force algorithm [4]. The number of route options in the form of a sequence of nodes when solving a problem by the exhaustive search method is a factorial of the number of nodes in the search graph [5]. Next, it is necessary to iterate over all the obtained options and choose the optimal one among them [6]. Computational complexity gives a quantitative description of the algorithm and shows that in real practical problems, the route construction time will be too long. Therefore, this algorithm is not applied [7].

As an alternative, sometimes, for cases of low dimensionality, the Branch and Bound method proposed by Little is used [8]. This method is analytical, has the ability to search for the optimum, and has computational complexity, which is generally equal to en, where n – the number of nodes in the graph [9]. In this case, the computational complexity is, of course, much less than in the case of a full enumeration of options, but nevertheless it is quite significant [10]. Therefore, the Branch and Bound method is rarely used in its pure form. Very often we can find algorithms that are based on the basic mechanisms of the Branch and Bound method (branching and returning procedures on the search graph). Such variants of the interpretation of the Branch and Bound method usually include procedures for choosing a solution either in the process of branching, or backtracking [11]. An example of such modification is an algorithm where, at each iteration of branching, a node is selected that gives the best value of the objective function, that is, a well-known technique was used, in which nodes are joined for search using the Dijkstra shortest path method. To some extent, this reduces the computational complexity, but the very paradigm of "greed" introduced into such algorithms does not allow finding an optimal solution in the future, given that such algorithms no longer have convergence [12].

The Gomori method (The Cutting Plane) is a "superstructure" for simplex methods. The idea of the method is that at the first stage the problem is solved by one of the methods of the group of simplex methods without taking into account the requirement of integer value [13]. If the obtained optimal solution is an integer one, then the problem is considered solved. At the second stage, an additional constraint (cutoff) is introduced into the system of linear constraints, and the problem is solved again under the original constraints and an additional constraint [14]. If an integer solution is obtained, the problem is solved. Otherwise, it is necessary to repeat the second step.

Dynamic programming – the method used to improve the efficiency of computational iterations by storing intermediate results and reusing them when necessary. Unlike linear programming methods, it can reduce the seek time for the optimal route to $O(n^2*2^n)$ [15]. Inaccurate algorithms offer a potentially suboptimal solution that can be found rather quickly. Such algorithms can be divided into the following categories: C-Approximation algorithms, constructive and iteratively improving heuristic algorithms, meta heuristic algorithms, Kohonen and Hopfield artificial neural networks. Inaccurate algorithms include: Christofides' algorithm; Nearest Neighbou algorithm; Kernighan-Lin algorithm; Tabu Search algorithm; Ant Colony Optimisation; Simulated Annealing method; clonal selection algorithm; genetic algorithm; evolutionary strategies; artificial neural networks.

Christofides' algorithm is a double minimum spanning tree method modified so that the time to solve the problem does not exceed the optimal time by more than 3/2. The main difference is the additional calculation of the pair with the minimum weight. This part is also the most time consuming, so the execution time of the algorithm increases to $O(n^3)$. Tests have shown that Christofides' algorithm is 10% higher than the lower bound of the Held-Karp [16]. The nearest neighbour algorithm is one of the simplest heuristic methods for solving TSP. The main rule of the algorithm is to always choose a nearby node. In the general case, the complexity of solving the problem is $O(n^2)$. The lower bound for the cost of the optimal route is 10% higher than the lower bound for the Held-Karp [17]. The Lin-Kernighan algorithm is considered one of the most efficient methods for finding optimal or near-optimal solutions to the TSP. However, the development and implementation of the algorithm is not straightforward, since the algorithm consists of many steps, most of which greatly affect the operation of the algorithm. The complexity is equal to $O(n^{2.2})$.

The TabuSearch algorithm. The main problem of the nearest neighbour algorithm is that it often hits the local optimum. This can be avoided by using the Tabu Search algorithm [18]. This method allows to pass from one local optimum to another in the search for a global optimum; after the transition, the edge is included in the forbidden list and is not reused, except for cases when it can improve the constructed optimal path. On a practical level, the forbidden set is stored as a combination of previously visited steps, which allows building a further path relative to the current solution and neighbouring nodes. The search process involves aspiration (inclusion in the forbidden list of states around the current state) and diversification, which adds a factor of randomness to the search process [19]. The critical parameters of the algorithm are the depth of the prohibition list, determination of the current state, and the size of the area around the current state. The main disadvantage of this method is its execution time – the complexity of the algorithm is estimated as $O(n^3)$.

Ant Colony Optimisation is an efficient polynomial algorithm based on the behaviour of ants. To solve the transportation problem, ants are placed in random nodes and sent to other locations [20]. They are not allowed to visit the same node twice, unless they complete the route. The ant that has chosen the shortest tour will leave a trail of pheromones, inversely proportional to the length of the route. This trail of pheromones will be read by the next ant when choosing a node, and with a high probability it will follow the same path, strengthening it further. This process will be repeated many times until a route is found that is short enough to be optimal. Among the disadvantages of the algorithm, it is necessary to highlight that the first solution obtained may turn out to be one of the worst in terms of optimisation, however, upon repeated solution, the method provides a fairly accurate result. The Held-Karp Lower Bound. The most common way to measure the performance of a heuristic algorithm for TSP solution is to compare the results with the Held-Karp lower bound. This lower bound is the TSP solution found in polynomial time using the simplex method. The lower bound of the Held-Karp is approximately 0.8% below the optimal route duration. At the same time, it is guaranteed not to exceed the optimal time by more than 2/3.

Local search with k neighbours to replace edges (k-opt) is the most widely used approximate method for solving the transportation problem; k-opt is an algorithm for improving the transportation problem, where at each step k edges of the current route are replaced with other edges so that a shorter route is obtained. In the original version of the Lin-Kernighan heuristic, k-substitutions are admissible, which can be represented as 2- or 3-substitutions followed by 2-substitutions. In Helsgaun's papers, an LKH version of the Lin-Kernighan algorithm is presented, which admits any substitutions represented as k-substitutions for any $k \in 2, \ldots, N$.

To solve the problems of finding the optimal route, evolutionary techniques are widely used that imitate the mechanism of biological selection and allow direct consideration of effective options due to the redistribution of priority for improving solutions of moves and rejection of unwanted routes by optimising the fitness function. The most effective techniques are genetic algorithm and evolutionary strategy.

Genetic algorithm is a method that reflects the natural evolution of problem-solving methods, and primarily optimisation problems. Genetic algorithms are search procedures based on natural selection and inheritance mechanisms. They use the evolutionary principle of survival of the fittest. The main advantages of the genetic algorithm are the simplicity of their implementation; relatively high speed of work (compared to accurate methods); in relation to tasks with both numerical and subject variables, that is, they allow to search in nonmetric parameter spaces; they adapt and "learn" during their execution; should ensure the parallelism of internal processes: parallel search for a solution by several individuals at once, which allows to avoid falling into the trap of local optima (finding the first, but not the most successful, optimum) However, the effectiveness of the genetic algorithm, assessed primarily by the degree of approximation of the solution results to the optimal values, is not always satisfactory.

The main disadvantages of using the genetic algorithm are that genetic algorithms simulate the evolutionary process of the development of biological systems in a random way, while generating a large number of obviously not viable individuals; in the process of evolution, factors (genes) that stimulate an increase in the degree of fitness (quality) of the system or affect a decrease in these qualities are not analysed; there is no process control based on the intellectual analysis of the course of evolution, changes in external conditions; the complexity of choosing a coding scheme, the possibility of population degeneration, the complexity of describing planning constraints. To improve the efficiency of the genetic algorithm, a set of algorithms for the execution of genetic operators has been developed, however, it is not possible to single out the best ones for any tasks. The same should be noted for Heuristics Combination Method (HCM), in which the a priori setting of the probabilities of choosing heuristics is not always successful. A resource, the use of which can significantly increase the efficiency of a genetic algorithm, is the automatic selection of types of genetic operators and other parameters of algorithms during a genetic search.

Another method belonging to the class of evolutionary algorithms is an evolutionary strategy, characterised by the fact that at the first step, an initial population of individuals is formed, which is subsequently modified by using functions such as selection and genetic operators, which allows searching in the solution space. As genetic operators, as a rule, the operators of crossover and mutation are used. This method has much in common with the considered genetic algorithm. Several types of strategies are distinguished: the strategy of elite individuals, the strategy of adding new solutions, changing the population size, parallel evolutions. This or that type of strategy is chosen depending on the formulation of the transportation problem.

Another neural network method is the use of a one-dimensional Kohonen map with self-organisation. With the help of a special competitive mechanism, the structure of an artificial neural network tries to repeat the shape of the pattern created by the samples under study on a two-dimensional data space. For the movement of processing elements, the principle of "winner takes everything" is used, which forms elite selectivity when choosing the processing element closest to the data point at the current time. The described mechanism allows movement to the nearest sample only in one of the grid nodes, which forces processing elements to be purposefully placed over the entire surface without accumulating in a separate area. The disadvantage of this method is that almost 70% of the entire time for finding the optimal route is devoted to training the network. Also, when the number of transportation points changes, it is necessary to change the structure of the network due to the dependence of the number of processing elements on the number of points. With a large number of transportation points, the network becomes too complex.

Results and Discussion

The problem of diagnosing the state of sound transmission is difficult due to the impossibility of clearly stating the correspondence of changes in the input and output parameters of the state in which the diagnostic object is located or to which it seeks. In particular, it is impossible to unambiguously determine all emergency situations or the pre-emergency state (delay) of an object. However, it is possible to single out a set of states of the diagnosed object and try to assess the degree of influence of each information parameter on the probability of the object transition in any of the possible states. Therefore, for diagnostics, it is necessary to use the method of selecting weight numbers based on training fuzzy neural networks, the functioning of which is based on the principles of fuzzy logic, which are used to adapt the parameters of training methods, both with a "teacher" and based on self-organisation.

The proposed method, based on the use of a fuzzy neural network, consists in the fact that it is necessary to assign the input vector containing the values of test values of indicators and output reactions of the object to these vectors, one or several possible technical states of sound transmission from the source, that is, according to the relative values of the determining parameters and given mixed membership functions, using the apparatus of fuzzy logic, the current state of sound transmission using an artificial neural network is estimated using the aggregating functions of minimum and maximum, the state of sound transmission as a whole is determined. The solution to the diagnostic problem consists of the following stages: the formation of fuzzy rules on the basis of which the model is constructed; creating a model structure; development of the analysis procedure for the model; choice of quality criterion for training the model; adaptation of model parameters. Let's consider in detail each of the stages.

1. Formation of fuzzy rules. The rules used in constructing a model of a fuzzy neural network are as follows: RULE k: IF condition is k THEN conclusion is $k(F^k)$ where k – rule number, F^k – certainty coefficient, or the weight number of the fuzzy rule (takes values from the interval [0,1]), $k \in \overline{1,r}$; condition k – a set of subconditions of the kind (Eq. 1):

$$x_1 \in \alpha_1^k \quad TA \ldots TA \quad x_n \in \alpha_n^k \tag{1}$$

conclusion k – conclusion of the form ~y is y, β^k, x_i – the nameof the input linguistic variable, which corresponds to the assessment of the state of sound transmission, $i \in 1, n$, y – the name of the output linguistic variable, corresponds to the complex assessment of the state of sound transmission, α_i^k – the qualitative value of the variable $x_i, i \in \overline{1,n}$, β^k – the qualitative value of the variable $y, k \in \overline{1,r}$.

2. Creation of the model structure. The model of a four-layer fuzzy neural network based on fuzzy rules is formed as follows:

– input (zero) layer contains processing elements that correspond to diagnostic features, the number of processing elements $N^{(0)}=n$;

– the first layer implements fuzzification, and its processing elements correspond to the qualitative values of diagnostic features, the number of processing elements N (Eq. 2):

$$N^{(1)} = \sum_{i=1}^{n} n_i \tag{2}$$

where n_i – the number of qualitative values for the i-th input linguistic variable;

– the second layer implements the aggregation of subconditions, and its processing elements correspond to the conditions, the number of processing elements (Eq. 3):

$$N^{(2)} = \sum_{i=1}^{n} n_i = r \tag{3}$$

where r – number of fuzzy rules;

– the third layer implements the activation of the rules, and its processing elements respond to the conclusions, the number of processing elements (Eq. 4):

$$N^{(3)} = \sum_{i=1}^{n} n_i = r \tag{4}$$

the fourth (output) layer implements the aggregation of conclusions, and its processing elements correspond to the qualitative value of the complex state assessment, the number of processing elements $N^{(4)}=q$, where Q – the number of qualitative values of the output linguistic variable.

3. Development of an analysis procedure for the model. The model analysis procedure includes 4 stages: fuzzification; aggregation of subconditions; intensification of conclusions; aggregation of findings.

Fuzzification (introduction of fuzziness) is a procedure for determining the degree of truth of the subconditions of fuzzy rules. One and the same subcondition can be included in several fuzzy rules. The operating mode of each sound source can be classified as “normal”, “pre-emergency”, “emergency”. Accordingly, each linguistic variable that corresponds to a diagnostic feature can take 3 qualitative values – “standard”, “pre-emergency”, “emergency”. Each qualitative value of a linguistic variable is assigned a certain membership function. Each membership function is described as follows: on the interval that corresponds to a certain qualitative value, the function should have approximately the same value, and outside this interval it should fall to approximately zero. Fuzzification is performed as follows:

– the membership function, which corresponds to the qualitative value “standard”, has the form (Eq. 5):

$$y_S^{(1)} = \begin{cases} 1 & x_i \le a_{1i} \\ \dfrac{b_{1i}-x_i}{b_{1i}-a_i} & a_{1i} < x_i < b_{1i}, s=(i-1)^* N^{(4)}+1, i \in \overline{1,N^{(0)}} \\ 0 & x_i \ge b_{1i} \end{cases} \quad (5)$$

– the membership function corresponding to the qualitative value “pre-emergency” has the form (Eq. 6):

$$y_S^{(1)} = \begin{cases} 0 & x_i \le a_{2i} \\ \dfrac{x_i-a_{2i}}{b_{2i}-a_{2i}} & a_{2i} \le x_i \le b_{2i} \\ 1 & b_{2i} \le x_i \le c_{2i}, s=(i-1)^* N^{(4)}+2, i \in \overline{1,N^{(0)}} \\ \dfrac{d_{2i}-x_i}{d_{2i}-c_{2i}} & c_{2i} \le x_i \le d_{2i} \\ 0 & x_i \ge d_{2x} \end{cases} \quad (6)$$

– the membership function, which corresponds to the qualitative value “emergency”, has the form (Eq. 7):

$$y_S^{(1)} = \begin{cases} 0 & x_i \le c_{3i} \\ \dfrac{x_i-c_{3i}}{d_{3i}-c_{3i}} & c_{3i} < x_i < d_{3i}, s=(i-1)^* N^{(4)}+3, i \in \overline{1,N^{(0)}} \\ 1 & x_i \ge d_{3i} \end{cases} \quad (7)$$

where a_{ij}, b_{ij}, c_{ij}, d_{ij} – parameters of the membership function associated with the j-th qualitative value of the input linguistic variable x_i , and obtained empirically, x_i–i-th clear input variable, $y_S^{(1)}$ – the degree of truth of the s-th subcondition (the degree of truth that the quantitative value of the clear input variable x_i corresponds to the j-th the qualitative value of the input linguistic variable x_i).

Aggregation of subconditions of a fuzzy rule is a procedure for determining the degree of truth of a condition by combining the degrees of truth of the subconditions that make it up. The following method was chosen to aggregate subconditions (Eq. 8):

$$y_k^{(2)} = min\left\{ w_{1k}^{(2)} y_1^{(1)}, \ldots, w_{N^{(1)}k}^{(2)} y_{N^{(1)}}^{(1)} \right\}, k \in \overline{1,N^{(2)}} \quad (8)$$

where $w_{1k}^{(2)}$– binary connection strength determined by the structure of the fuzzy neural network model, $i \in \overline{1,N^{(1)}}$.

The table of weights $w_{1k}^{(2)}$ for each specific value of the input parameter is called the diagnostic weighting matrix. It is also necessary to decide on the optimal number of measured parameters. On the one hand, the greater the number of measured parameters, the more reliably the technical condition of the diagnostic object is determined, but also the greater the complexity and cost of the diagnostic system as a whole. Thus, we should choose the parameters that most fully represent the technical condition of the transmitter during its operation.

Activation of the conclusions of a fuzzy rule is a procedure for determining the degree of truth of the conclusion of this rule by the degree of truth of its condition and its weight number. To activate the conclusions, the following method was chosen (Eq. 9):

$$y_k^{(3)} = w_{kk}^{(3)} y_k^{(2)}, k \in \overline{1,N^{(2)}} \quad (9)$$

where $w_{kk}^{(3)}$ – coupling weight number, $w_{kk}^{(3)}=F^k$.

Aggregation of conclusions of fuzzy rules is a procedure for determining the degree of truth of the final conclusion by combining the same degrees of truth of conclusions. To aggregate conclusions, the following method was chosen (Eq. 10):

$$y_i = max\left\{ w_{1j}^{(4)} y_1^{(3)}, \ldots, w_{N^{(3)}j}^{(4)} y_{N^{(3)}}^{(3)} \right\}, j \in \overline{1,N^{(4)}} \quad (10)$$

where $w_{ij}^{(4)}$– binary connection strength determined by the structure of the fuzzy neural network model, $i \in \overline{1,N^{(3)}}$.

4. Choosing a quality criterion for training the model. To train the model, the criterion of the adequacy of the model was chosen, which means the choice of such parameter values a_{ij}, b_{ij}, c_{ij}, d_{ij} that provide a minimum of the mean square error (the difference between the model output and the test output) (Eq. 11):

$$F = \frac{1}{P}\frac{1}{q}\sum_{p=1}^{P}\sum_{j=1}^{q}\left(y_{pj}-z_{pj}\right)^2 \to \min_{a_{ij},b_{ij},c_{ij},d_{ij}} \quad (11)$$

where P – number of test implementations, $y_p=(y_{p1},\ldots,y_{pq})$ – condition score derived from the model, $z_p=(z_{p1},\ldots,z_{pq})$ – condition test.

5. Adaptation of model parameters. Applying gradient learning methods to fuzzy neural networks is difficult. This raises the problem of developing new metaheuristic methods of adaptation. Most often, a genetic algorithm is chosen as a metaheuristic method. A vector containing

parameters a_{ij}, b_{ij}, c_{ij}, d_{ij}, is used as an individual, and the criterion is used as a fitness function (11).

To study the learning procedure based on the genetic algorithm, three types of it were used. The first type explores the entire search space and is not directional. It is possible for this type to lose the best solutions. It requires a significant search time. The second type is directional. For this type, it is possible to hit the local optimum. The third type is combined, that is, it combines the direction of the search with the study of the entire search space. A second diagnostic method is proposed, which also combines the analysis of several indicators, which will significantly increase the likelihood of detecting a malfunction in sound transmission or individual nodes. The method under consideration is also based on a neural network approach, which consists in the fact that according to the relative values of the determining parameters and the given mixed activation functions, the current state of the equipment is estimated using an artificial neural network of high-order regressions, the state of the object as a whole is determined. The solution to the diagnostic problem consists of the following stages: creation of the model structure; development of the analysis procedure for the model; choice of quality criterion for training the model; adaptation of model parameters. When creating a model structure, it is proposed to use a neural network model, consisting of three layers:

– input (zero) layer contains processing elements corresponding to diagnostic features, the number of processing elements $N^{(0)}=n$;

– the first layer is hidden. It contains processing elements corresponding to the ranges of values of a certain attribute, which is associated with the possible state of the equipment, number of processing elements (2), where n_i is the number of ranges of values of all features;

– the second layer is hidden. It contains processing elements, the number of which corresponds to the number of possible combinations of ranges of feature values, the number of processing elements (Eq. 12):

$$N^{(2)} = \prod_{i=1}^{n} n_i \tag{12}$$

– the output (third) layer contains processing elements, the number of which corresponds to the possible states of the equipment, the number of processing elements $N^{(3)}$.

The proposed model does not require empirical determination of the number of hidden layers and processing elements in hidden layers, since the structure of the neural network model is determined by the number of ranges of values of diagnostic features. The neural network model is presented as (Eq. 13-17):

$$y_j^{(1)} = \begin{cases} \dfrac{1}{1+exp\left(b_{1j}-a_{1ij}x_i\right)} & j=\left(i-1\right)N^{(3)}+1 \\ \dfrac{1}{1+exp\left(b_{2ij}-a_{2ij}x_i\right)}+\dfrac{1}{1+exp\left(d_{2i}-c_{2ij}x_i\right)} & j=\left(i-1\right)N^{(3)}+2, j\in 1,N^{(1)} \\ \dfrac{1}{1+exp\left(b_{3j}-a_{3ij}x_i\right)} & j=\left(i-1\right)N^{(3)+3} \end{cases} \tag{13}$$

$$y_i^{(2)} = f^{(2)}\left(s_j^{(2)}\right) = s_j^{(2)}, j\in 1, N^{(2)} \tag{14}$$

$$s_j^{(2)} = b_j^{(2)} + \sum_{i_1=1}^{N^{(1)}} \dots \sum_{N^{(0)}=1}^{N^{(1)}} w^{(2)}_{i_1\dots i_{N^{(0)}j}} \, y_{i_1}^{(1)*} \; {}^{*} y^{(1)}_{i_{N^{(0)}}} \tag{15}$$

$$y_j^{(3)} = f^{(3)}\left(s_j^{(3)}\right) = s_j^{(3)}, j\in 1, N^{(3)} \tag{16}$$

$$\begin{gathered} S_j^{(3)} = b_j^{(3)} + \sum_{i_1=1}^{N^{(2)}} w^{(3)}_{i_1 j} y^{(2)}_{i_1} + \sum_{i_1=1}^{N^{(2)}} \dots \sum_{i_k=1}^{N^{(2)}} w^{(3)}_{i_1\dots i_{kj}} y^{(2)*}_{i_1} \dots {}^{*} y^{(2)}_{i_k} + \dots + \\ + \sum_{i_1=1}^{N^{(2)}} \dots \sum_{i_{N^{(2)}=1}}^{N^{(2)}} w^{(3)}_{i_1\dots i_{N^{(2)}j}} y^{(2)*}_{i_1} \dots {}^{*} y^{(2)}_{i_{N^{(2)}}} \end{gathered} \tag{17}$$

To train the model, the criterion of the adequacy of the model based on the mean square error was chosen. It semantically shows the choice of such parameter values $w_{ij}^{(1)}$ at which the difference between the model output and the desired output reaches a minimum (Eq. 18):

$$F = \frac{1}{P}\frac{1}{q}\sum_{p=1}^{p}\sum_{j=1}^{q}\left(y_{pj}-z_{pj}\right)^2 \to \min_{w_{ij}^{(1)}} \tag{18}$$

where P – number of test implementations, $y_p=(y_{p1},\dots,y_{pq})$ – diagnosed condition derived from simulation, $z_p=(z_{p1},\dots,z_{pq})$ – realistic estimate of the condition.

The purpose of model adaptation is to adjust its parameters: $w_{ij}^{(1)}$. For this, the Back Propagation procedure is used in the neural network model. The essence of the method lies in the fact that pre-known data are fed to the input of the network, after which the network calculates the output value. Further, this value is compared with the existing ones, and in accordance with the difference between these values, the weight coefficients of the neural net-work are adjusted. And this operation is repeated many times in a circle. As a result, we get a trained network with new values of the weight numbers. Let us consider it in more detail:

Training iteration number $n=1$. The weight numbers of the first layer are set $w_{ij}^{(1)}\left(n\right), i\in \overline{1,N^0}, j\in \overline{1,N^1}$, and if the processing element of the i-th input layer is connected with the j-th processing element of the first layer, then $w_{ij}^{(1)}\left(n\right)$ is initialised by a uniform distribution on the interval (0.1), otherwise $w_{ij}^{(1)}\left(n\right)=0$. The boundary $b_j^{(2)}\left(n\right), j\in 1,N^{(2)}$ initialised by uniform distribution over the interval (0.1). The weight numbers of the second layer are set $w^{(2)}_{i_1\dots i_{N(0)j}} \in \{0,1\}, i_1,\dots,i_{N^{(0)}}$ $\in 1,N^{(1)}, j\in 1,N^{(2)}$, and if the processing element of the i-th first layer is connected with the j-th processing element of the second layer, then $w^{(2)}_{i_1\dots i_{N^{(0)}j}}=1$, otherwise $w^{(2)}_{i_1\dots i_{N^{(0)}j}}=0$. The boundary $b_j^{(2)}\left(n\right)$, $j\in 1,N^{(2)}$. The weight numbers of the third layer are set $w^{(3)}_{i_1 j}\left(n\right),\dots,w^{(3)}_{i_1\dots i_{k_j j}} \in\{-1,0,1\}, i_1,\dots,i_{k_j} \in \overline{1,N^{(2)}}, j\in \overline{1,N^{(3)}}$, and if the processing element of the i-th second layer is connected with the j-th processing element of the third layer, then $w^{(3)}_{i_1\dots i_{k_j j}}=1$ (if k_j is uneven) or $w^{(3)}_{i_1\dots i_{k_j j}}=-1$ (if k_j is even), otherwise $w^{(3)}_{i_1\dots i_{k_j j}}=0$ The boundary $b_j^{(3)}\left(n\right)=0, j\in \overline{1,N^{(3)}}$. The initial set is given $\left\{\left(x_\mu,z_\mu\right) \mid x_\mu\in R^2, z_\mu \in R^{(3)}\right\}, \mu\in\overline{1,P}$ where x_μ – μ-th initial input vector, z_μ – μ-th initial output vector, P – the final result of the multiplication. Limit values are calculated as μ=1.

Calculation of the output signal (forward trace) (Eq. 19-22):

$$y_j^{(1)}(n) = f_j^{(1)}\left(s_j^{(1)}(n)\right), j \in \overline{1, N^{(1)}} \quad (19)$$

$$s_j^{(1)}(n) = b_j^{(1)}(n) + \sum_{i=1}^{N^{(0)}} w_{ij}^{(1)}(n) x_{\mu i} \quad (20)$$

$$y_j^{(2)}(n) = f^2\left(s_j^{(2)}(n)\right) = s_j^{(2)}(n), j \in \overline{1, N^{(2)}}$$
$$s_j^{(2)}(n) = \sum_{i_1=1}^{N^{(1)}} \dots \sum_{i_{N^{(0)}}=1}^{N^{(1)}} w_{i_1 \dots i_{N^{(0)}} j}^{(2)} y_{i_1}^{(1)}(n) \dots y_{i_{N^{(0)}}}^{(1)} \quad (21)$$

$$y_j^{(3)}(n) = f^3\left(s_j^{(3)}(n)\right) = s_j^{(3)}(n), j \in \overline{1, N^{(3)}}$$
$$s_j^{(3)}(n) = \sum_{i_1=1}^{N^{(2)}} w_{i_1 j}^{(3)} y_{i_1}^{(2)}(n) + \dots +$$
$$+ \sum_{i_1=1}^{N^{(2)}} \dots \sum_{i_{N^{(2)}}=1}^{N^{(2)}} w_{i_1 \dots i_{N^{(2)}} j}^{(3)} y_{i_1}^{(2)}(n) \dots y_{i_{N^{(2)}}}^{(2)}(n) \quad (22)$$

Calculating the error energy of a neural network (Eq. 23-24):

$$E(n) = \frac{1}{2}\sum_{j=1}^{N^{(3)}} e_j^2(n) \quad (23)$$

$$e_j(n) = y_j^{(3)}(n) - z_{\mu j} \quad (24)$$

Synaptic weight numbers based on the generalised delta rule (forward trace) (Eq. 25-26):

$$b_j^{(1)}(n) = b_j^{(1)}(n) - \eta \frac{\partial E(n)}{\partial b_j^{(1)}(n)} \quad (25)$$

$$w_{ij}^{(1)}(n) = w_{ij}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w_{ij}^{(1)}(n)} \quad (26)$$

Checking the termination condition. If $n \ modP > 0$, $\mu = \mu + 1$, $n = n + 1$ then go to step 3. $n\, modP = 0 \frac{1}{P}\sum_{s=1}^{P} E(n - P + s) > \varepsilon$ $n = n + 1$, then go to step 2. If $n\, modP = 0$ $\frac{1}{P}\sum_{s=1}^{P} E(n = P + s) < \varepsilon$, then it will end.

Conclusions

As part of a unified approach to the development of sound transmission methods that ensure integrated safety, methods have been developed for diagnosing sound transmission parameters and analysing the state of sound sources. For a comprehensive analysis of the technical state of sound transmission, two models of static artificial neural networks have been developed: based on fuzzy logic; based on high order regression models. The advantages of the proposed models are: the possibility of using different membership and activation functions in one layer, taking into account the peculiarities of the input parameters; no need to determine the number of hidden layers and the number of hidden processing elements; universality and extensibility for any required number of input parameters characterising the technical state of sound transmission and the state of sound sources; the ability to analyse a set of diagnostic signs of various physical nature; the use of fuzzy logic simplifies communication between a person and a computer system through the use of qualitative values of controlled features. The adaptation of the parameters of the complex diagnostics models was carried out using an error backpropagation algorithm, which is an example of local search, and a combination of a genetic algorithm with backstage imitation, which combines local and random search. The criteria for the quality of adaptation were the speed of learning and the adequacy of the models. In addition to improving the safety of mine operations, it is necessary to accelerate the transmission of sound between sound sources.

References

[1] IEEE Computer Society. Proceedings of the 1996 1st International Workshop on Neural Networks for Identification, Control, Robotics, and Signal/Image Processing, NICROSP'96 [Internet]. Washington: IEEE Computer Society; 1996 [updated 2021 February 15; cited 2021 Apr. 5]. Available from: https://dl.acm.org/doi/proceedings/10.5555/524736.

[2] Hageman J, Smith M, Stachowiak S. Integration of online parameter identification and neural network for in-flight adaptive control [Internet]. Austin: American Institute of Aeronautics and Astronautics; 2003 [updated 2012 Jun 22; cited 2021 Apr. 7]. Available from: https://arc.aiaa.org/doi/10.2514/6.2003-5700.

[3] Yang T-G, Gui W-H. Stator resistance identification for induction motor based on particle swarm optimization neural network observer. *Dianji yu Kongzhi Xuebao/Electr. Mach. Control*. 2015;19(2):89-95.

[4] Abdallah MA, Samu TI, Grissom WA. Automatic target identification using neural networks. *Proc. SPIE*. 1995;(2588):556-65.

[5] Tutunji TA. Parametric system identification using neural networks. *Appl. Soft Comput.* 2016;(47):251-61. https://doi.org/10.1016/j.asoc.2016.05.012.

[6] Zhao J, Wang F. Parameter identification by neural network for intelligent deep drawing of axisymmetric workpieces. *J. Mater. Process. Technol.* 2005;166(3):387-91. https://doi.org/10.1016/j.jmatprotec.2004.08.020.

[7] Doherty SK, Gomm JB, Williams D. Experiment design considerations for non-linear system identification using neural networks. *Comput. Chem. Eng.* 1997;21(3):327-46. https://doi.org/10.1016/S0098-1354(96)00003-8.

[8] Sugimoto S, Matsumoto M, Kabe M. System identification using neural networks. Proceedings of the IEEE International Conference on Systems Engineering; 1992; Kobe. Kobe: IEEE; 1992. pp. 79-82.

[9] Oishi A, Yamada K, Yoshimura S, Yagawa G. Defect identification using neural network and computational mechanics (its application to ut-based nondestructive evaluation). *Trans. Jpn. Soc. Mech. Eng. A.* 1994;60(569):264-71. https://doi.org/10.1299/kikaia.60.264.

[10] Lu S, Başar T. Robust nonlinear system identification using neural-network models. *IEEE T. Neur. Net. Lear.* 1998;9(3):407-29. https://doi.org/10.1109/72.668883.
[11] Zaman MHM, Mustafa MM, Hussain A. Critical equivalent series resistance estimation for voltage regulator stability using hybrid system identification and neural network. *Int. J. Adv. Sci. Eng. Inf. Technol*. 2017;7(4):1381-88. https://doi.org/10.18517/ijaseit.7.4.1746.
[12] Bondarets A, Kreerenko O. Using of artificial neural networks (ANN) for aircraft motion parameters identification. *Commun. Comput. Inf. Sci.* 2009;(43):246-56. https://doi.org/10.1007/978-3-642-03969-0_23.
[13] Dackermann U, Li J, Samali B. Dynamic-based damage identification using neural network ensembles and damage index method. *Adv. Struct. Eng.* 2010;13(6):1001-16. https://doi.org/10.1260/1369-4332.13.6.1001.
[14] Chang H-H, Yang H-T, Lin C-L. Load identification in neural networks for a non-intrusive monitoring of industrial electrical loads. *LNCS.* 2008;(5236):664-74. https://doi.org/10.1007/978-3-540-92719-8_60.
[15] Guerra FA, Ayala HVH, Lazzaretti AE, Sans MR, Coelho LS, Tacla CA. Multivariable nonlinear boiler power plant identification through neural networks and particle swarm optimisation approaches. Proceedings of the 9th IEEE/IAS International Conference on Industry Applications, INDUSCON 2010. Sao Paulo. Sao Paulo: IEEE; 2010. pp. 1-6. https://doi.org/10.1109/INDUSCON.2010.5739862.
[16] Sio KC, Lee CK. Identification of a nonlinear motor system with neural networks. *AMC.* 1996;1:287-292.
[17] Rubio JDJ, Yu W. Stability analysis of nonlinear system identification via delayed neural networks. *IEEE Trans. Circuits Syst. II Express Briefs IEEE T CIRCUITS-II.* 2007;54(2):161-65. https://doi.org/10.1109/TCSII.2006.886464.
[18] Lamanna R, Uria M, Jaramillo L, Ricardo F. Neural network identification of a saponification reactor. *Rev. de la Fac. de Ing.* 2000;15(2):XXIX-XXX.
[19] Sun J, Kalenchuk DK, Xue D, Gu P. Design candidate identification using neural network-based fuzzy reasoning. *Robot. Comput. Integr. Manuf.* 2000;16(5):383-96. https://doi.org/10.1016/S0736-5845(00)00017-X.
[20] Riley C, Work P, Miller R. Visual entity identification: A neural network approach. *IJCNN.* 1991;(2):article number 909.

Використання нейронних мереж під час формування якісного згладженого звукового сигналу

Бріттані Флорес[1], Тереза Тран[2]

[1]Університет Вашингтона в Сент-Луїсі
MO 63130, Бруклінг Драйв, 1, м. Сент-Луїс, Сполучені Штати Америки

[2]Університет Західного Вашингтона
WA 98225, вул. Хай, 516, м. Беллінгем, Сполучені Штати Америки

Анотація

Актуальність. Якісне згладжування звуку за його проходження в локальних мережах і у домашніх стереосистемах дозволяє забезпечити передачу звуку бездротовими мережами практично без затримок. Суперечливим залишається основа проведення подібного звуку. Його декодування можливе як на пристрої прийому, так і на передавачі. Водночас процесори можуть забезпечувати декодування у режимі реального часу з автоматичним підстроюванням за алгоритмом. Нейронні алгоритми можуть використовуватися як на основі послідовності сигналів, так і на паралельному використанні приймачів.

Мета. Мета цього дослідження – вивчення діагностичного методу, що поєднує у собі аналіз кількох показників, що значно збільшують ймовірність виявлення несправності у передачі звуку або окремих вузлах.

Методи. У процесі дослідження використовуються точні алгоритми та неточні алгоритми. Точні алгоритми поділяються на методи лінійного програмування та методи динамічного програмування. До методів лінійного програмування належать: метод Бруте Форс, метод розгалуження та прив'язки, метод Гоморі та інші.

Результати. Автори показують, що у цьому аспекті завдання якісної передачі звуку з використанням нейронних алгоритмів зводиться до задачі оптимального транспортувального проекту і вирішується шляхом оптимізації локального звукового маршруту. Рівноважний розподіл транспортувальних маршрутів має бути закладено у самому обладнанні та протоколі декодування звуку.

Висновки. Використання звукоприймача з нейронними алгоритмами дає можливість виявити найскладніші ділянки, що спричиняють затримку чи спотворення звуку. Практичне застосування дослідження можливо в умовах динамічного забезпечення звуковим наповненням приміщення для створення ефекту присутності та об'ємного поглинання звуку, якщо це необхідно

Ключові слова: алгоритм, функція, оптимальний маршрут, фазифікація, транспортування звуку