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Avtomatizirani ultrazvočni pregled materialov z nevronsko mrežo

Automatic Ultrasonic Testing of Materials with Neural Network

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Članek obravnava raziskavo uporabe modela nevronske mreže pri ultrazvočnem testiranju materialov. Opisan je eksperimentalni merilni sistem, ki sestoji iz ultrazvočnega defektoskopa, digitalnega osciloskopa in nevronske mreže, simulirane na osebnem računalniku. V ta namen sta predstavljeni tudi struktura in delovanje nevronske mreže s povratnim učenjem. Preizkuševalni sistem z običajno ultrazvočno sondo je bil testiran na več umetno narejenih napakah, kakor tudi na napakah, ugotovljenih v praksi.

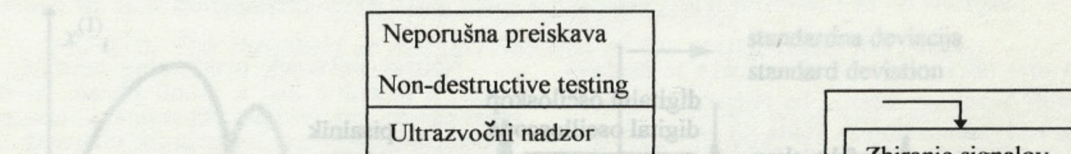
The applicability of the neural network model to ultrasonic testing of materials is investigated. An experimental measuring system consisting of ultrasonic defectoscope, digital oscilloscope and a computer is described. The structure and the operation of the back-propagation neural network is represented. The system with a single ultrasonic normal probe was tested on several artificial, and real defects occurring in industrial products.

0 UVOD

Preizkušanje materialov z ultrazvokom sodi med najbolj uporabljane metode neporušnega nadzora kakovosti materialov. Zasnovano je na zaznavanju odbitega visokofrekvenčnega elastičnega valovanja na napakah v materialu. Na podlagi merjenja amplitude odbitega ultrazvočnega signala lahko operater z uporabo posebnih diagramov in preglednic ter glede na poprejšnje izkušnje oceni velikost in nevarnost napake v materialu. Cilj avtomatiziranega testiranja je nadomestiti ročno merjenje in intuitivno ocenjevanje kakovosti z računalniškim sistemom (sl. 1). Glavna naloga avtomatiziranega ultrazvočnega nadzora je avtomatizirati določanje običajnih napak,

0 INTRODUCTION

One of the most applicable methods in the field of non-destructive testing is ultrasonic flaw inspection of materials. The foundation for ultrasonic testing of material is based on the reception of the high frequency sound wave which is reflected from the obstacles in the material. The magnitude of the defect and the degree of the critical state can be determined by an experienced operator according to the signal image observations, special diagrams and tables. So the aim of automatic testing is to replace manual examination and intuitive decision – making with a computer decision system (Fig. 1). The main task is the automatic characterisation of expected defects,



Sl. 1. *Shematičen prikaz običajnega in avtomatiziranega nadzora kakovosti materiala*
Fig. 1. *Schematic diagram of the common and automatic material quality control*

medtem ko bo materiale s posebnimi napakami še vedno moral pregledati izkušen operater. Doslej so se kot nadomestilo operaterjevega odločanja o pomenu detektiranega ultrazvočnega signala najpogosteje pojavljali modeli, zasnovani na uporabi metod umetne inteligence in ekspertnih sistemov [1]. Vendar ta način običajno terja časovno zamudno programiranje in veliko ekspertnega znanja. Temu se lahko izognemo, če uporabimo avtomatizirano učenje in razpoznavanje z modeli nevronske mreže, ki omogoča hitro delovanje in zato ocenjevanje kakovosti materiala v realnem času [2] do [4].

V nadaljevanju je opisan poskus rešitve tega problema z uporabo modela nevronske mreže, ki se uči s povratnim popravljanjem ocenjevalne napake. Opisano je tudi ustrezno predprocesiranje ultrazvočnih signalov, ki je potrebno za računalniško obdelavo in izboljšanje ocenjevanja napak. Naš cilj je bil prilagoditi nevronsko mrežo za razpoznavanje ultrazvočnih signalov, odbitih na preprostih vzorcih z umetno oblikovanimi napakami in tako preveriti uporabnost metode in natančnost razpoznavanja.

1 ULTRAZVOČNI DEFEKTOSKOP Z NEVRONSKO MREŽO

1.1 Predprocesiranje ultrazvočnih signalov

Ultrazvočni defektoskop z nevronsko mrežo je sestavljen iz merilnega in razpoznavnega sistema. Laboratorijska oprema za ocenjevanje signalov je sklop analognega ultrazvočnega defektoskopa z normalno ultrazvočno sondo, digitalnega osciloskopa z analogno-digitalnim pretvornikom in osebnega računalnika z računskim in pomnilniškim delom (sl. 2). Nadgradnja merilnega sistema je razpoznavni sistem s predprocesirnim delom in delom za nevronsko procesiranje signalov.

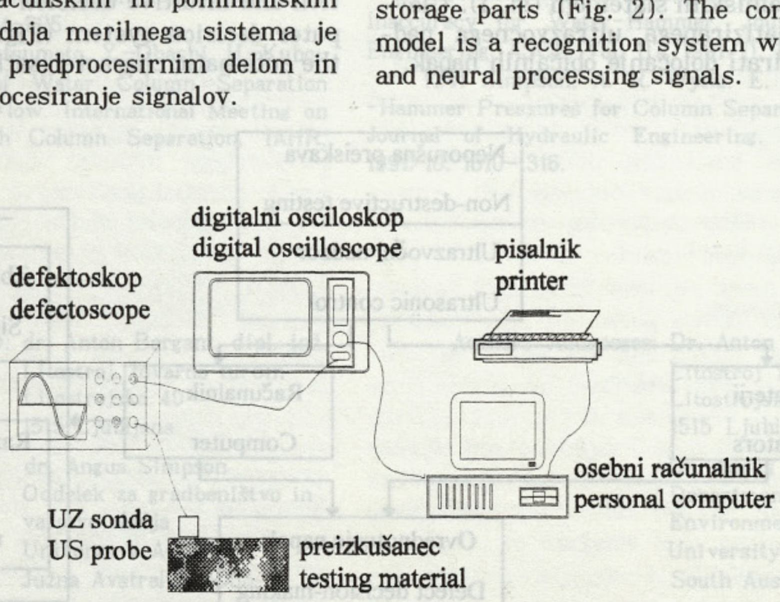
while the materials with special defects will additionally be inspected by experienced operators. In recent years, artificial intelligence and expert systems have been applied to replace manual evaluation on the importance of the detected ultrasonic signal by use of a computer decision system [1]. This approach generally leads to problems with time--consuming computer programming, and requires a large amount of expert knowledge data. These problems could successfully be resolved by automated learning and recognition by neural networks [2] to [4].

In the following sections the solution of this problem by means of a back-propagation neural network is described. The preprocessing of ultrasonic signals, which is necessary for computer designing and the improvement of defects assessment, is also represented. Our task was to adjust the neural network to identify ultrasonic signals reflected from the simple patterns and thereby improve the signal analysis reliability and precision of recognition.

1 ULTRASONIC DEFECTOSCOPE WITH NEURAL NETWORK

1.1 Preprocessing of ultrasonic signals

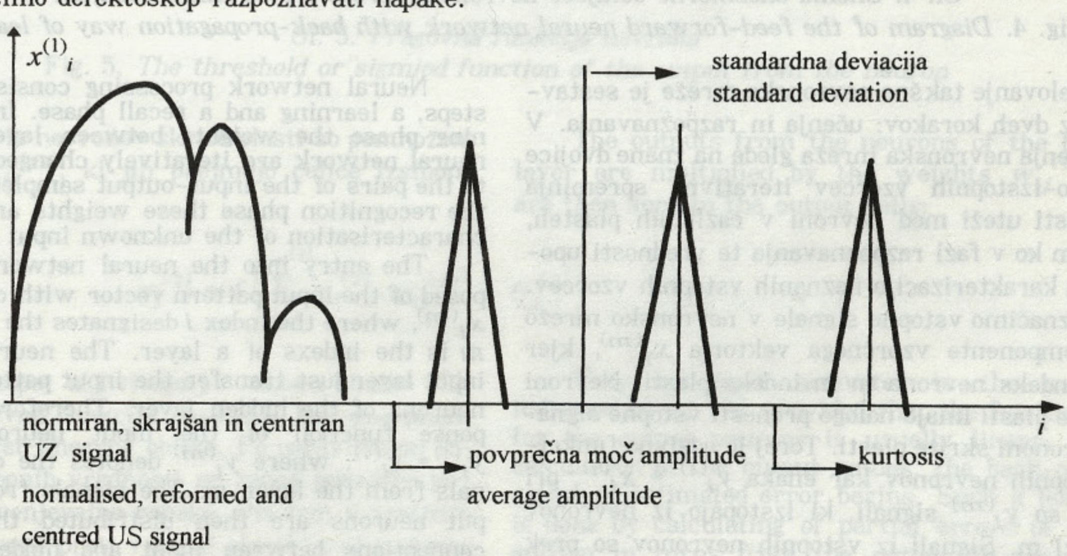
The ultrasonic defectoscope with neural network consists of a measuring and recognition system. The laboratory equipment for signal evaluation connects the analogue ultrasonic defectoscope with a normal probe, digital oscilloscope and personal computer with processing and memory storage parts (Fig. 2). The continuation of the model is a recognition system with preprocessing and neural processing signals.



Sl. 2. *Shema pretoka ultrazvočnih signalov za razpoznavanje z nevronsko mrežo*
Fig. 2. *Schematic design of ultrasonic signals flow for neural network recognition*

Najprej kratko opišimo sprejemanje ultrazvočnih signalov. Z defektoskopom in merilno sondo oddamo in nato sprejmemo izbruh ultrazvočnega valovanja. Digitalni osciloskop spremeni sprejeti analogni signal v ustrezen digitalni zapis, ki ga nato prek vmesnika pošljemo v računalnik. Tam se začne faza predprocesiranja. Najprej je signal normiran. V ta namen je uporabljena evklidska norma. Ob tem je najnižja vrednost postavljena na 0 in najvišja na 1. Hkrati je prikazana tudi največja amplituda signala relativno glede na velikost odboja od zadnje stene, kar je standardna mera za velikost ovire, ki je povzročila odboj ultrazvočnega valovanja. Iz signala nato odrežemo del, ki pomeni odboj od zadnje stene. Pojav iznihavanja ultrazvoka v vzorcu ni upoštevan. Tako je razpoznavanje omejeno le na tisti del signala, ki pomeni odboj od ovire v materialu. Če je odbojev več, so ustrezni odseki signala obravnavani vsak zase. Ob tem je ocenjena in ohranjena globina, pri kateri se odboji pojavijo. Naslednji korak v predprocesiranju je ovrednotenje odboja s statističnimi merami, npr.: povprečna amplituda, standardna deviacija in tretji moment (kurtozis). Zaradi majhne zmogljivosti osebnih računalnikov je nato signal odboja komprimiran le na 50 točk, pri čemer je njegova sredina glede na največji amplitudni del postavljena na isto mesto. S tem dosežemo globinsko razpoznavanje signalov ne glede na njihovo lego. Zbrani podatki o odbitem ultrazvočnem signalu so komponente prvega dela vstopnega vzorčnega vektorja, ki ga pošljemo v nevronsko mrežo. Drugi del vzorčnega vektorja sestavljajo statistični deskriptorji. Deskriptor je enoten impulz, postavljen na določeno mesto v polju komponent (sl. 3). Deskriptorje napak pridobimo z drugimi defektoskopskimi postopki ali na podlagi vgradnje napak v preizkusni material, na katerem učimo defektoskop razpoznavati napake.

First, we would like to describe the reception of ultrasonic signals. By means of the defectoscope and determined measuring probe the ultrasonic wave is sent, and the reflection from the obstacles is received. The digital oscilloscope digitalizes the received analogue signal, and the digitalized signal is then transmitted through interface into the computer. This is the beginning of the preprocessing phase. First the signal is normed in the sense of the Euclidean norm. The minimum and maximum signal values are placed on the new values 0 and 1, respectively. At the same time the computer reprints the extreme peak of the signal and its height according to the back-wall, by which the principal measure for real height of the defect is now obtained. If the signal has a back-wall reflection we reprint and then remove it. The occurrence of the decay of the oscillation is not taken into consideration. Thus the recognition of the signal is limited to that part of the signal which represents the reflection from the defect in the material. If these defects are numerous we determine each by itself. Then the received depth of the signal reflection is estimated and registered. The next step in preprocessing is to treat the signal with statistical measures, such as average amplitude, standard deviation and kurtosis. Regarding the computer performances, the digitalized signal is reformed to 50 points and its average is placed to the same point in each signal. Herewith we acquire the depth invariation, that is recognition of defects regardless of their position. In this way reformed and centred signals form the components of the pattern vectors, which are the inputs into the neural network. The input pattern vectors are completed with the defect descriptors. They are represented as an unit impulse in the space of the components (Fig. 3). They can be received with supplementary non-destructive testing, or they can represent a characteristic feature of artificial defects built into the testing sample.



Sl. 3. *Vhodni vzorčni vektor, rezultat predprocesiranja ultrazvočnih signalov*
Fig. 3. *The input pattern vector as a result of the preprocessing of ultrasonic signals*

1.2 Model enosmerno delujoče nevronske mreže s povratnim učenjem

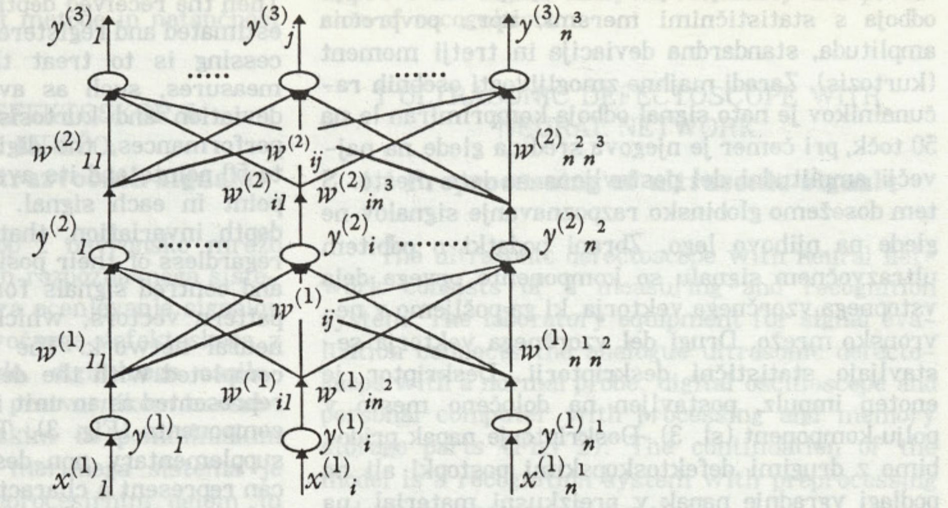
Model enosmerno delujoče nevronske mreže s povratnim učenjem je v literaturi največkrat uporabljeni primer. Zato bomo tukaj le kratko opisali način učenja. Primeren je zlasti za preslikavanje ene vrste signalov v drugo, kakor je to pogosto potrebno pri empiričnem modeliranju naravnih zakonov [5].

Enosmerno delujočo nevronsko mrežo običajno sestavljajo tri plasti simuliranih nevronov (sl. 4). Število nevronov v prvi ali vstopni plasti je enako dimenziji vstopnega vzorca, ki ga nevronska mreža razpoznava, število nevronov v tretji ali izstopni plasti je enako številu parametrov ali klasifikatorjev, s katerimi želimo opisati vstopne vzorce, medtem ko je število nevronov v drugi ali skriti plasti poljubno in ga izbiramo glede na zapletenost problema, ki naj bi ga nevronska mreža reševala [5], [6].

1.2 Feed-forward neural network with back-propagation way of learning

In the field of applications of neural networks, the most frequently applied model in real practice is the feed-forward neural network with back-propagation way of learning. Therefore in the following section a short description of the model is offered. The principal advantage of the proposed model is in mapping one sort of signals into another, which is often necessary in the empirical modelling of the natural laws [5].

The feed-forward neural network is generally composed of simulated neurons located in three layers (Fig. 4). The number of neurons in the first or input layer is the same as the dimension of the input pattern which have to be recognised by the neural network, the number of the neurons in the third of output layer being equal to the number of input pattern parameters or the classificators with which we wish to describe the input patterns, while the number of neurons in the second or hidden layer is not previously fixed, but is selected with regard to the complexity of the problem to be solved by the neural network [5], [6].



Sl. 4. *Shema enosmerno delujoče nevronske mreže s povratnim učenjem*

Fig. 4. *Diagram of the feed-forward neural network with back-propagation way of learning*

Delovanje takšne nevronske mreže je sestavljeno iz dveh korakov: učenja in razpoznavanja. V fazi učenja nevronska mreža glede na znane dvojice vstopno-izstopnih vzorcev iterativno spreminja vrednosti uteži med nevroni v različnih plasteh, medtem ko v fazi razpoznavanja te vrednosti uporabi za karakterizacijo neznanih vstopnih vzorcev.

Označimo vstopne signale v nevronsko mrežo kot komponente vzorčnega vektorja $x_i^{(m)}$, kjer sta i indeks nevrona in m indeks plasti. Nevroni vstopne plasti imajo nalogo prenesti vstopne signale nevronom skrite plasti. Torej je odzivna funkcija vstopnih nevronov kar enaka $y_i^{(1)} = x_i^{(1)}$, pri čemer so $y_i^{(m)}$ signali, ki izstopajo iz nevronov v plasti m. Signali iz vstopnih nevronov so prek povezav med vstopnimi in skritimi nevroni pomnoženi z utežmi $w_{ij}^{(12)}$, kar pomeni, da je vsak

Neural network processing consists of two steps, a learning and a recall phase. In the learning phase the weights between layers in the neural network are iteratively changed regarding to the pairs of the input-output samples, while in the recognition phase these weights are used for characterisation of the unknown input samples.

The entry into the neural network is composed of the input pattern vector with components $x_i^{(m)}$, where the index i designates the neuron and m is the indexs of a layer. The neurons in the input layer just transfer the input patterns to the neurons of the hidden layer. Therefore the response function of the input neurons equals $y_i^{(1)} = x_i^{(1)}$, where $y_i^{(m)}$ denotes the output signals from the layer m. The signals from the input neurons are then distributed through the connections between input and hidden neurons $w_{ij}^{(12)}$ to all neurons in the hidden layer. The input signal in the particular neuron of the hidden nevron vstopne plasti povezan z vsakim nevronom skrite plasti. Vstopni signal v posamezen nevron skrite plasti je torej enak vsoti vseh komponent vstopnega vzorčnega vektorja, pomnoženih z ustreznimi utežmi:

layer is then a sum of multiplication of the input sample components with the corresponding weights belonging to the connections between neurons in the input layer and a particular neuron in the hidden layer:

$$x_j^{(2)} = \sum_{i=1}^{p^{(1)}} x_i^{(1)} \, w_{ij}^{(12)} \qquad j = 1, \ldots, p^{(2)} \qquad (1).$$

kjer sta $p^{(1)}$ — število nevronov vstopne plasti in $p^{(2)}$ — število nevronov v skriti plasti.

where $p^{(1)}$ and $p^{(2)}$ denote the number of neurons in the input and hidden layer, respectively.

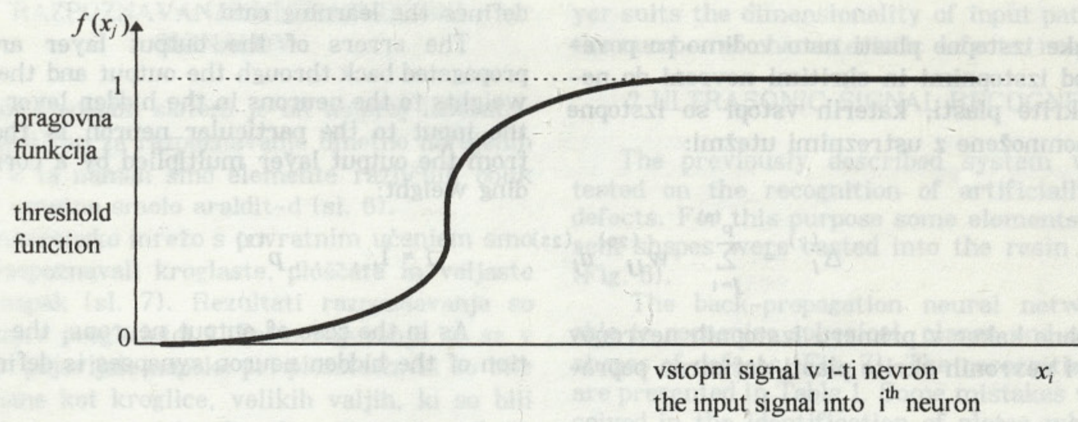
Nevroni skrite plasti se odzivajo na vstopne vzorce s pragovno odzivno funkcijo (sl. 5), ki jo navadno izpeljemo s funkcijo $f(x) = (1 + e^{-x})^{-1}$. Tako je izstop iz nevrona j, opredeljen z enačbo:

The significant output function for the neurons in the hidden layer is a threshold response function (Fig. 5), which is usually realised by function $f(x) = (1 + e^{-x})^{-1}$. Therefore the output from the j-th neuron is described by the term:

$$y_j^{(2)} = f\left(\sum_{i=1}^{p^{(1)}} x_i^{(1)} \, w_{ij}^{(12)} + \Theta_j^{(1)}\right) \qquad j = 1, \ldots, p^{(2)} \qquad (2),$$

kjer je $\Theta_j^{(1)}$ pragovna vrednost, ki jo mora vsota vstopnih signalov preseči, da se nevron na vstopne signale odzove.

where $\Theta_j^{(1)}$ is the threshold value which because of response of the neuron in the hidden layer have to be exceeded.



Sl. 5. *Pragovna funkcija nevrona*

Fig. 5. *The threshold or sigmiod function of the output from the neuron*

Signali iz nevronov skrite plasti so pomnoženi z utežmi $w_{ij}^{(23)}$, ki jih prejmejo celice izstopne enote:

The outputs from the neurons of the hidden layer are multiplied by the weights $w_{ij}^{(23)}$ and are then sent to the output cells:

$$y_j^{(3)} = f\left(\sum_{i=1}^{p^{(2)}} y_i^{(2)} \, w_{ij}^{(23)} + \Theta_j^{(2)}\right) \qquad j = 1, \ldots, p^{(3)} \qquad (3).$$

Te se zopet aktivirajo po zakonu enačbe (2), le da je odzivna funkcija nevronov izstopne plasti $f()$ največkrat linearne oblike. Po opravljenem izračunu izstopnih vrednosti se začne povratno popravljanje ocenjevalne napake. Pri tem v vrstnem redu od izstopne proti vstopni plasti izračunavamo delne napake razpoznavanja in hkrati računamo popravek vrednosti ustreznih uteži.

They are again activated in the manner indicated by eq. (2), provided that the function $f()$ for the output neurons is usually linear. After calculation of the output values, the back-propagation of estimated error begins. Such a learning is done by calculating of partial errors of recognition in turns from the output to the input layer, with simultaneously corrections of corresponding weights.

Cilj učenja je dobiti na izstopu iz mreže želene izstopne vzorce kot odziv na pripadajoče vstopne vzorce. Vendar iteracijsko učenje omogoča le omejeno natančnost ujemanja želenih in dejansko dobljenih vrednosti komponent izstopnih vzorčnih vektorjev. Zato izračunamo razliko med ocenjeno $\tilde{y}_j^{(3)}$ in želeno vrednostjo $y_j^{(3)}$ po enačbi:

The main learning task is to approach output patterns to the desired ones as a response to the input patterns. But this scope is usually reachable only with a limited similarity between desired and real components of output sample vectors. For this purpose the difference between estimated value $\hat{y}_j^{(3)}$ and $y_j^{(3)}$ desired value is calculated:

$$\Delta_j^{(3)} = \tilde{y}_j^{(3)} - y_j^{(3)} \qquad j = 1, \ldots, p^{(3)} \tag{4}$$

S to razliko, pomnoženo z vrednostjo $y_j^{(3)}(1 - y_j^{(3)})$ [5], nato definiramo napako uteži $w_{ij}^{(23)}$:

With this difference, multiplied by the term $y_j^{(3)}(1 - y_j^{(3)})$ [5], the error of the weights $w_{ij}^{(23)}$ is defined:

$$d_j^{(23)} = y_j^{(3)}\left(1 - y_j^{(3)}\right)\Delta_j^{(3)} \tag{5}$$

in popravek zadnjih vezi izračunamo z enačbo:

and the correction of the last links is calculated:

$$\Delta w_{ij}^{(23)} = \alpha^{(2)}\, y_i^{(2)}\, d_j^{(23)} \qquad i = 1, \ldots, p^{(2)} \quad j = 1, \ldots, p^{(3)} \tag{6}$$

kjer je $\alpha^{(2)}$ pozitivna konstanta, ki definira hitrost učenja.

Napake izstopne plasti nato vodimo po povezavah med izstopnimi in skritimi nevroni do nevronov skrite plasti, katerih vstopi so izstopne napake, pomnožene z ustreznimi utežmi:

where $\alpha^{(2)}$ is a positive constant value, which defines the learning rate.

The errors of the output layer are then propagated back through the output and the hidden weights to the neurons in the hidden layer, where the input to the particular neuron is the error from the output layer multiplied by a corresponding weight:

$$\Delta_i^{(2)} = \sum_{j=1}^{p^{(3)}} w_{ij}^{(23)}\, d_j^{(23)} \qquad i = 1, \ldots, p^{(2)} \tag{7}$$

Podobno kakor v primeru izstopnih nevronov je tudi pri nevronih skrite plasti definiran popravek:

As in the case of output neurons, the correction of the hidden neuron synapses is defined as:

$$d_i^{(12)} = y_i^{(2)}\left(1 - y_i^{2}\right)\Delta_i^{(2)} \qquad i = 1, \ldots, p^{(2)} \tag{8}$$

Glede na izračunane napake nato popravljamo uteži povezav med nevroni vhodne in skrite plasti:

Regarding the calculated corrections, the weights between neurons in the input and hidden layers are modified:

$$\Delta w_{ij}^{(12)} = \alpha^{(1)}\, x_i^{(1)}\, d_j^{(12)} \qquad i = 1, \ldots, p^{(1)} \quad j = 1, \ldots, p^{(2)} \tag{9}$$

Poleg spremembe uteži se spremenijo tudi pragovne vrednosti nevronov:

Beside weight modification there is also a threshold value change:

$$\Delta\Theta_j^{(k)} = \alpha^{(k)}\, d_j^{(k\,k+1)} \qquad k = 1, 2 \tag{10}$$

Proces učenja se iteracijsko ponavlja, tako da v eni iteraciji na vstop pripeljemo zaporedoma vse učilne vzorce, katerih komponente se nato vzporedno procesirajo skozi mrežo. Učenje končamo, ko so napake $\Delta_j^{(3)}$, $j = 1, \ldots, p^{(3)}$ dovolj majhne.

The learning phase is iteratively repeated, so that one iteration contains successively propagation of all learning samples, the components of which are then processed in parallel through the network. The learning phase is finished when the errors, $\Delta_j^{(3)}$ $j = 1, \ldots, p^{(3)}$ are sufficiently small.

Priklicna ali razpoznavna faza ustreza enosmerno delujoči nevronski mreži, ki razpoznava neznane in/ali nepopolne vzorčne vektorje. Ti so v našem primeru opisani z ultrazvočnim signalom z dodanimi statističnimi deskriptorji. Tako oblikovani vstopni vzorci se skozi mrežo preslikajo v deskriptorje napake v materialu. Preslikava vstopnih v izstopne vzorce poteka prek uteži $w_{ij}^{(12)}$ in $w_{ij}^{(23)}$, ki imajo v procesu priklica konstantne vrednosti. Priklicna faza torej sledi enačbama (2) in (3). Pomen vstopnega vzorčnega vektorja oziroma zaznane napake je nato dobljen glede na razmerja vrednosti posameznih izstopnih signalov.

Opisana nevronska mreža je dober klasifikator za nepopolne vzorce in vzorce s šumom, vendar je za njeno optimalno konstrukcijo potrebno dolgotrajno učenje z različnim številom nevronov v skriti plasti. Za naš poskus razpoznavanja ultrazvočnih signalov in karakterizacijo ustreznih napak smo uporabili 30 nevronov v skriti plasti, medtem ko smo v izstopni plasti s tremi oziroma štirimi izstopnimi nevroni opisovali pomen vstopnih vzorcev.

2 RAZPOZNAVANJE ULTRAZVOČNIH SIGNALOV

Zgoraj opisani sistem je bil najprej laboratorijsko testiran za razpoznavanje umetno narejenih napak. V ta namen smo elemente različnih oblik zalili v umetno smolo araldit-d (sl. 6).

Z nevronsko mrežo s povratnim učenjem smo lahko razpoznavali kroglaste, ploščate in valjaste oblike napak (sl. 7). Rezultati razpoznavanja so prikazani v preglednici 1. Pri ocenjevanju so se v glavnem pojavljale napake pri ploščicah, ki so bile razpoznane kot kroglice, velikih valjih, ki so bili prav tako razpoznani kot kroglice, ter pri majhnih valjih, ki so bili razpoznani kot ploščice. Pravilnost rezultatov je bila tako pri 28 preizkušanih vzorcih za kroglico 100%, za ploščico 73% in za valj 72% [7].

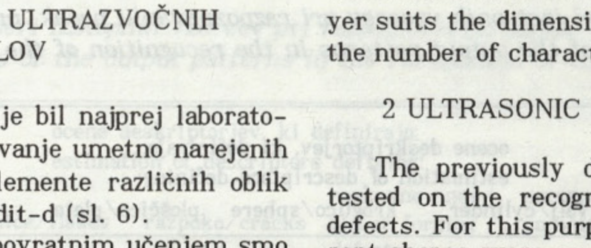
The recall phase or phase of reconstruction corresponds to the feed-forward network, the entries of which are unknown and/or imperfect pattern vectors. In our case the input pattern vectors are determined by ultrasonic signals with additional statistical descriptors. Input patterns are mapped through the network into the corresponding descriptors of defects in the tested material. The mapping of input pattern into the output ones goes over the weights $w_{ij}^{(12)}$ and $w_{ij}^{(23)}$, which have in the phase of recognition constant values. The recall phase thus follows the processes destinated by the eq. (2) and (3). The estimation of the input pattern vector significance or corresponding defect is determined according to the ratio among the output signals.

The described neural network satisfactorily performs the classification of imperfect patterns and patterns with noise, however for its optimum construction the learning phase has to be reiterated with various numbers of hidden neurons. In the case of the recognition of ultrasonic signals we select 30 neurons in the hidden layer, while the number of neurons in the input and output layer suits the dimensionality of input patterns and the number of characteristic defects, respectively.

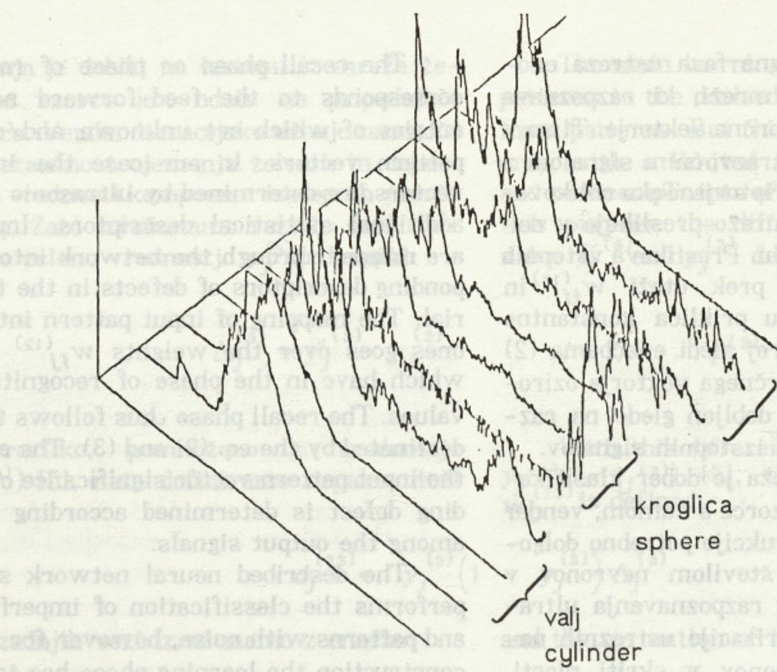
2 ULTRASONIC SIGNAL RECOGNITION

The previously described system was first tested on the recognition of artificially formed defects. For this purpose some elements of different shapes were casted into the resin Araldit-d (Fig. 6).

The back-propagation neural network was able to recognise spherical, planar and cylindrical shapes of defects (Fig. 7). The recognition results are presented in Table 1. Some mistakes were perceived in the identification of plates which were recognised as balls and in the exchanges of small cylinders with plates. The correctness of the results for 28 testing patterns was 100% for ball, 73% for plate and 72% for cylinder [7].



Sl. 6. *Prikaz izdelka iz umetne smole in v njem zalitih elementov različnih oblik*
Fig. 6. *The look of the resin product with cast elements of different shapes*



Sl. 7. *Signali ultrazvočnih odbojev od različnih oblik za razpoznavanje z nevronsko mrežo*
Fig. 7. *Ultrasonic signal reflections from elements of different shapes for neural network recognition*

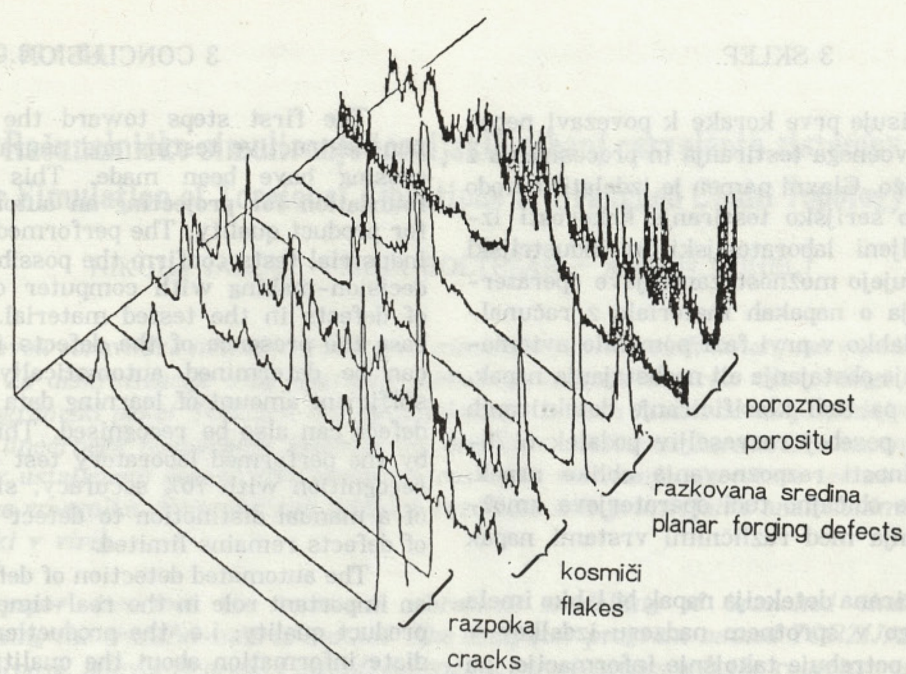
Preglednica 1: *Primeri izstopnih vzorcev pri razpoznavanju napak, prikazanih na sliki 7*
Table 1: *Examples of the output patterns in the recognition of the defects in Fig. 7*

zaporedna številka vzorca / sequence number of pattern	ocene deskriptorjev, ki definirajo: / estimation of descriptors defining: valj/cylinder	kroglico/sphere	ploščico/plate	
1	**0.9428**	0.0302	0.000	
2	**0.9935**	0.1425	0.000	
3	**0.0365**	0.8839	0.0481	
4	0.0270	**0.9141**	0.0746	(največja mogoča vrednost = 1)
5	0.0446	**0.8651**	0.392	(maximal possible size = 1)
6	0.0414	**0.8981**	0.0421	
7	0.0418	0.8506	**0.0409**	
8	0.0013	0.0728	**0.9677**	
9	0.0022	0.0970	**0.9368**	

Pri pravem pomenu ultrazvočnega signala je rezultat odebeljen
The bolt results should represent the correct recognition output signals

Naslednji poskus je bil razpoznavanje napak, ki se pojavljajo pri proizvodnji jekla v Železarni Ravne. Nevronska mreža se je učila ločevanja med razpokami, kosmiči, poroznostjo in razkovano sredino (sl. 8). Velikosti izstopnih signalov, s katerimi se odločamo o pomenu vstopnega vzorca, so prikazane v preglednici 2. Napake razpoznavanja so se pojavile pri klasificiranju razpoke, ki je bila razpoznana kot razkovana sredina, kosmičev, ki so bili kodirani kot poroznost. Razlogi za te napake so v veliki podobnosti signalov in se pojavijo tudi pri delu operaterjev.

The next test was the recognition of real defects occurring in the iron-works products of the Železarna Ravne. The neural network was trained to distinguish between cracks, flakes, porosity and planar forging defects (Fig. 8). The sizes of the output signals with which the input signals are identificated are presented in Table 2. The system functioned well except for some mistakes regarding the recognition of cracks, which were recognised as a planar forging defects, and the recognition of flakes which were coded as a porosity. The reasons for these faults lie in the strong likeness of the signals, and they are also noticed in the estimation of operators.



Sl. 8. *Ultrazvočni signali napak v materialu za razpoznavanje z nevronsko mrežo*
Fig. 8. *Ultrasonic signal reflections from the defects in the material for neural network recognition*

Preglednica 2: *Primeri izstopnih vzorcev pri razpoznavanju napak, prikazanih na sliki 8*
Table 2: *Examples of the output patterns in the recognition of the defects in Fig. 8*

zaporedna številka vzorca / sequence number of pattern	ocene deskriptorjev, ki definirajo: / estimation of descriptors defining: kosmiče/flakes	razpoko/cracks	razkovno snov/ planar forging defects	poroznost porosity	
1	0.0170	**0.9805**	0.0279	0.000	
2	0.1093	**0.8647**	0.0023	0.0001	
3	**0.1753**	0.0038	0.0122	0.0012	(najv. mogoča vredn. = 1)
4	**0.8717**	0.0686	0.000	0.9822	(max. possible size = 1)
5	0.0095	0.0409	**0.9487**	0.000	
6	0.0271	0.1155	**0.4830**	0.000	
7	0.0585	0.0089	0.000	**0.9826**	
8	0.7877	0.0089	0.000	**0.6409**	

Pri pravem pomenu ultrazvočnega signala je rezultat odebeljen
The bolt results should represent the correct recognition output signals

V našem primeru nismo upoštevali, da pri izbrani kakovosti preizkušanega izdelka ter njegovi poprejšnji tehnološki in toplotni obdelavi ni mogoče pričakovati vseh naštetih napak. Zato lahko sklepamo, da je ultrazvočni defektoskop z nevronsko mrežo dovolj preprost, hiter, učinkovit in zato primeren za serijsko ultrazvočno testiranje pričakovanih napak. Seveda naj bi posebne napake oziroma tiste, ki bi bile z eno samo ultrazvočno sondo nerazpoznavne, še vedno klasificirali izkušeni operaterji. V ta namen lahko ultrazvočni defektoskop po znanih primerih naučimo, da sporoči nerazpoznano napako.

In our case we did not consider the possibility of limited types of enumerating defects in relation to previous technological and thermal forming of the tested material. As a conclusion we find the ultrasonic defectoscope with neural network simple to use, fast to operate and therefore also useful for the serial automating testing of expected defects. The special defects or defects which would be unrecognised with just one ultrasonic probe would still be identified by experienced operators. On the basis of the well-known samples, we can for this purpose teach the ultrasonic defectoscope to inform us about unrecognised defects.

3 SKLEP

Članek opisuje prve korake k povezavi neporušnega ultrazvočnega testiranja in procesiranja z nevronsko mrežo. Glavni namen je izdelati metodo za avtomatično serijsko testiranje kakovosti izdelkov. Opravljeni laboratorijski in industrijski preizkusi potrjujejo možnost zamenjave operaterjevega odločanja o napakah materiala z računalniškim. To bi lahko v prvi fazi pomenilo avtomatično določevanje obstajanja ali neobstajanja napak, v nadaljevanju pa tudi klasificiranje detektiranih napak. Zato je posebej razveseljiv podatek o 76-odstotni pravilnosti razpoznavanja oblike napak, saj vemo, da je običajno tudi operaterjeva zmožnost razločevanja med različnimi vrstami napak majhna.

Avtomatizirana detekcija napak bi lahko imela pomembno vlogo v sprotnem nadzoru izdelkov v proizvodnji, ki potrebuje takojšnje informacije, na podlagi katerih lahko sklepamo o pravilnosti izbrane tehnologije za določen material. Seveda pa bi bilo za serijski nadzor avtomatiziran razpoznavni sistem treba prilagoditi na točno določen in definiran problem ter ob nastanku nove napake omogočiti nadgrajevanje znanja.

Za popoln nadzor kakovosti bi morali povezati več metod neporušnega testiranja materialov.

3 CONCLUSION

The first steps toward the connection of non-destructive testing and neural network processing have been made. This could be the foundation for projecting an automatic test line for product quality. The performed laboratory and industrial tests confirm the possibility of manual decision-making with computer characterisation of defects in the tested material. In the worst case the presence of the defects in the material can be determined automatically. But with a sufficient amount of learning data the type of the defect can also be recognised. This is confirmed by the performed laboratory test of defect shape recognition with 76% accuracy, since the ability of a manual distinction to detect different kinds of defects remains limited.

The automated detection of defects could have an important role in the real-time control of the product quality: i.e. the production needs immediate information about the quality of a particular material for the decisions about the correctness of the selected technology. However, for serial control the automated recognition system must be adapted to the exact problem defined, and in the case of the appearance of a new defect the complement of knowledge must also be assured.

For entire control quality, various methods of non-destructive testing of materials need to be interconnected.

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