neurological disease classification,
Parkinson disease, hemiparesis, ischemic stroke,
automatic conclusion, neural networks

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THE DISEASES CLASSIFICATION METHOD ON GAIT ABNORMALITIES CHARACTERISTIC CONTRIBUTIONS

Present medicine uses computers in various applications, especially in a field of a diseases level classification and diagnosis. In many cases an automatic conclusion making units are the main goal of the computer systems usage. The software units are developed for the diseases classification or for monitoring of the disease medical treatment. An example application was described in this paper. It concerns a gait abnormalities level analysis that is described by a data records gathered by insoles of Parotec System for Windows (PSW) [17,18]. The PSW software package is used for visualisation of the gait characteristic static and dynamic characteristic features. In the authors' works many additional data components were distinguished. The field of the applications is located within the neurological gait characteristics also the source applications concern orthopaedics [16,18]. Careful analysis of the data provided the developers with new areas the PSW applications [4,11,13]. For conclusion making units the artificial networks theory was implemented [2,4,11,13]. For more effective training of the neural networks specific characteristic measures were introduced [4,5]. They allow controlling the training process more precisely, avoiding mistakes in current records classification.

1. INTRODUCTION

The computer systems for data processing are often used in modern medical diagnostics. The example works with neural network applications and final clinical evaluations were described bellow. For the data collection the Parotec System for Windows (PSW) was implemented [16]. It contains electronic recorder of the pressure distribution on insoles. The equipment characteristics and construction were described in details by several works [11,13,18]. For additional applications new software units were made. They are able both to estimate several neurological diseases level [4,6] and to process the recovery program [11,13]. The automatic conclusion process was also provided by artificial neural networks applications [1,11]. The new software units, called the neurological classifiers, are used for an automatic conclusion of the disease classification. They allow analysing the abnormalities of static and dynamic characteristics of a patient gait description.

The paper shows two new methods of a neural network training process and algorithms of starting point in this training process selection. The carried out investigations proved that an automatic classification of the selected diseases can successfully been achieved. They were clinically evaluated for four diseases: the Parkinson disease, left-lateral and right-lateral hemiparesis after ischemic stroke and the control (comparison) group.

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Very critical inconveniences occurred to the selected diagnosis subjects. It is caused by their complexity factors of analysis. Although the most representative measures of the diseases were defined anyhow for the diseases early stages they are comparable with calculations faults margins. What is more, the neurological diseases are often combined with various diseases of different kind (ex. orthopaedic troubles) that make the diagnosis very troublesome.

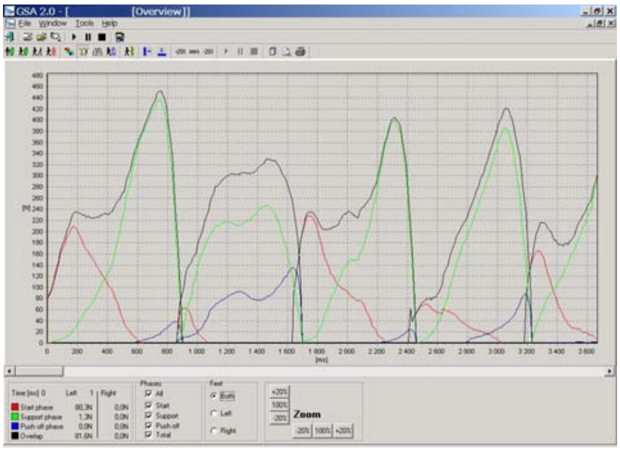

Fig. 1. Time diagram of the pleasure distribution in a patient walking time

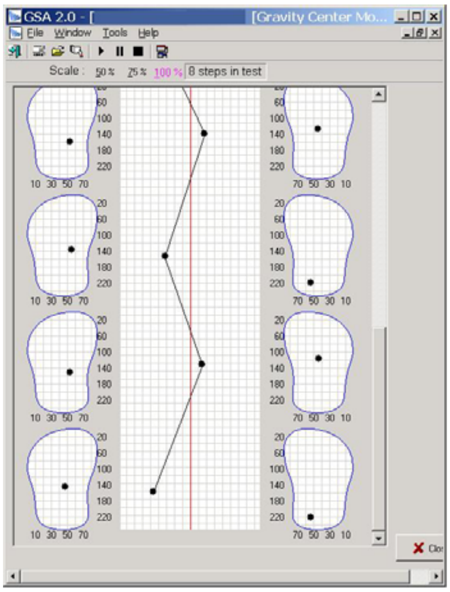

Fig. 2. The patient body balance time diagram

The pressure distribution on the PSW insole was illustrated by Fig.1 and Fig.2.

The neurological disease is described by couple of the disease symptoms as limbs and a face shaking or body balance disturbances. The PSW records allow analysing the way of walking by a one of the neurological diseases description factors [7, 17].

For an automatic conclusion making the artificial neural network classifier was used, where the Counter Propagation (CP) model was implemented, as the most effective one [4]. For the network training process control the characteristic features of the gait description were selected. The measures definition of these features was also found [4]. Theories were empirical evaluated in Clinics of Silesian Medical Academy in Katowice, by 94 selected (early classified) data records. They were used for all measures definition, for the control group and for the defined earlier diseases groups.

2. IMPLEMENTATION

Beside the pressure distribution maps the record provides us with number of additional data units, as: the insole type, measuring frequency, a personal data of the patient and others [15]. Early experiments with automatic conclusion units [1,11,14] by a source data record produced very discouraging results. The huge data size entered into the neural network was the reason of many possible classification faults [1,11,13]. The network training process was this way not effective in spite of a long lasting training.

Due to reduce the input data size several characteristic disturbances were distinguished. This way remarkable better training solutions were achieved. Finally several extractions have been considered due to diagnostic measures finding. Thanks to these measures (roles) the source data record can be analysed (filtered) in a way of pre-processing procedures. The distinguished filtering formulas (extracted characteristic measures) allow controlling the network training process. They constitute the classification formulas of the data record pre-processing.

Our investigations were carried out for three networks:

- multilayer back-propagation (BP) network with the controlled training process,
- hybrid CP network, where supervised and unsupervised training process is parallel used,
- resonance ART1 network, where unsupervised training process was implemented.

The obtained results were satisfying for both BP and CP networks [1]. Anyhow the CP networks conclusions were more effective and more insensitive for external disturbances (information noise). They were faster and more precise.

2.1. THE VIRTUAL DATA RECORD

The global minimum calculation of a network training process goal function requests big number of pattern data records entered into the network. What is more, the proper network architecture selection depends on weights vector finding. They are selected empirically as none of the selection roles exist. Well organised learning process of the network is involving big number of properly classified learning series. Operating on properly recognised frames of the disease abnormalities an artificial data record was produced.

Let us assume that we can distinguish disturbances that describe the disease characteristic features. In the same way the range of the disturbances has to be also defined. The extracted functions of the diseases disturbances allow to produce many additional data records by concatenation of a physiological records (from the control group) an the disturbances functions [4,5]. This operation produces a new data record with a new pressure distribution (F_{ST}) on a foot.

For this purpose a function of a pressure difference were distinguished:

$$H(t) = F_R(t) + E(t) \tag{1}$$

where: F_R is the function of pressure differences extracted from the control group of data record, which is distinguished by the expression:

$$F_R(t) = F_{ST}(l,t) - F_{ST}(r,t) \tag{2}$$

E expresses the function of the current data record disturbances:

$$E(t) = F_{R_1}(t) - F_{R_2}(t) \tag{3}$$

where: F_{R_1}, F_{R_2} express differences of pressures obtained from the formula (2); for two adequate data records R_1 and R_2.

This way one can find any number of records that are of the same class as the extracted disturbances and to fulfil the condition of a proper number of training records.

The process of the differences functions finding has to be predicted by algorithms of a data sampling rates normalisation. The records differences (comparison) have to be related into the same point of the step cycle. The discrete source values of the data records are sampled by a constant clock of the data processing unit when the gait duration depends on an individual patient way of walking, by the transformation:

$$F_j : R_X \rightarrow R^+ \cup \{0\} \quad R_X = \{x : x \in R \wedge x_1 \leq x \leq x_{S_{FRQ}}\};\, x_1, x_{S_{FRQ}} \in X_p$$
$$F_j(x_i) = f_i \qquad x_i \in X_p;\ f_i \in Y_j;\ j = 1,2,\ldots,24 \tag{4}$$

where: R_x is a set of a pressure sampling time intervals,
f_i are the recorded values in i-th sampling time.

This transformation makes possible the comparison of two data records that were sampled in different time intervals and in a different scale of a gait cycle. The discrete values of a data record were used to produce the continuous function F_j (Fig. 3):

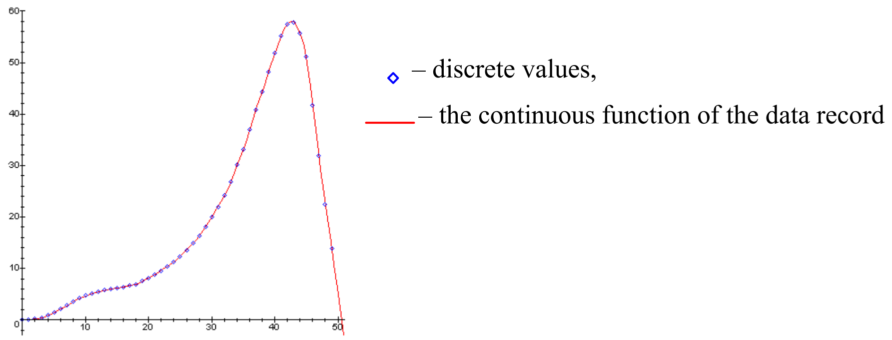

Fig. 3. The estimated continuous function of the data record

The continuous functions of the pressure values are a product of two algorithms usage: by a Lagrange's polynomial [1]:

$$F_j(x) = \sum_{i=0}^{n} f_i p_i(x) \tag{5}$$

where: $p_i(x)$ expresses the Lagrange's classical polynomial, and by a spline interpolation [3]:

$$s(x) = f_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3 \ \ for \ \ x \in [x_i, x_{i+1}] \tag{6}$$

where: constant b_i, c_i, d_i are defined for every sub-range $[x_i, x_{i+1}]$ by classical methods.

The methods analysis proved effectiveness of these methods combination and composition in the continuous functions of data records finding.

MODIFICATION OF CP NETWORK TRAINING ALGORITHM

Counter Propagation network is a combination of Kohonen theory (the input layer) with a Grossberg theory (the output layer). For complex Kohonen networks DeSieno training algorithm was implemented. An original training approach was called *conscience mechanism* (for neurons tiring) [8], overworked on observations of biological neurons behaviour, where the winning neuron is relaxing longer time (is not involved into the competition). Although this method is more effective then in a classic Kohonen algorithm it reduces the cell of the network potential, even in case the neuron exactly classified the input vector. In time of the neural classifier was under development, several modifications were introduced. It mainly concerns the necessary condition of the cells p_i potentials reduction in a k step, as it was assigned bellow:

$$p_i^{(k+1)} = \begin{cases} p_i^{(k)} + \dfrac{1}{N_k}, & dla\, i \neq w \\ p_i^{(k)} - p_{\min}, & dla(i = w) \wedge (y_i < y_{\min}) \end{cases} \tag{7}$$

where: N_k - neurons number in an input layer,
w - the winning neuron current index,
y_i - is the answer if *i*–th neuron,
$y_{\min}$ - is a coefficient of potential decrease.

Properly selected values of the above parameters cause the potential reduction of the winner cell.

Analysing this method principles allow us to define several conclusions, as it is listed bellow. The modified training algorithm improves the DeSieno algorithm, giving:

- the training time reduction, with a satisfying (illegible) faults,
- the time of a remarkable mean-square error extraction (about seven times),
- reduction of the stabilisation time till the training process is stable (about eight times),
- the minimal architecture of the CP vector definition.

2.2. A NEURON WEIGHT STARTING POINT DEFINITION

In time of a self training algorithm running the most important are properly done first steps, as they decide about a success in the whole training process. What is more the wrong selection in Kohonen layer may cause to stop the training process in minimal value of the goal function. That is why for this first steps a modified input data vector was distinguished. This algorithm allows separating and normalising weights vectors that are covering the *n*–dimension unit surface, by means of the following vector component separating function (VCS):

$$f_i(x) = \frac{1}{2}\left(1 - \cos\left(2\Pi\frac{(x-1)}{n} - (m-1)\Pi\frac{(i-1)}{m}\right)\right) \tag{8}$$

where: $i = 1,2,...,m$,
m – express number of the input vector *X* components.

This approach simplifies the calculations complexity and necessity of input vectors modifications; as it is in convex combination method (CCM). All these speculations remarkable reduce the network training time with an acceptable faults level of the classification process.

2.3. CLASSIFIER KEY PARAMETERS

For the optimisation parameters finding many sample check-up procedures were made. Finally, the CP classifier was implemented with 137 neurons in input layer and 4 neurons in output layer with additional parameters, as:

- the input vector size $|X| = 67$,
- in the Kohonen layer the modified algorithm of training was implemented, with neurons tiring (ready for competition p_{min}=0,64 and the potential decrease of the cell potential y_{min}=0,62),

- the starting values of the vectors in Kohonen layer were defined according to VCS functions,
- variable training coefficients with starting values: on the input layer $\eta = 0{,}4$ and on the output layer $\alpha = 0{,}18$,
- the training sequence was defined by the virtual (discussed earlier) records set,
- the training series size was: N=51750.

All additional parameters (not distinguished in the above discussion) were defined as for the classical CP network.

3. THE CLINICAL VERIFICATION OF INVESTIGASIONS

The neural classifier was evaluated by four disease classes:

- the control group (for comparison),
- left-lateral hemiparesis,
- right-lateral hemiparesis,
- Parkinson disease.

For this evaluation 94 well classified (by traditional methods) cases were used, with:

- 30 records of the control group,
- 28 records recognised as a left-lateral hemiparesis,
- 26 records right-lateral hemiparesis,
- 10 records for the Parkinson disease.

These records allow us constructing 94 examining units that defined the classification error of the conclusion making unit:

- 28 samples were not properly recognised and classified, what gives the total classification fault on an 29,8% level,
- for the control group 5 records were not recognised properly that means 16,7% faults in recognition,
- for left-lateral hemiparesis 10 records were classified in a not satisfactory level that gives 35,7% fault ratio,
- for right-lateral hemiparesis 9 records were not recognised as a proper class that is 34,6% fault ratio,
- for Parkinson disease 4 records were not classified properly; 40% of fault.

Although in the automatic conclusion many mistakes were observed the medical specialists were not astonished. In their everyday works classification faults occur very often; mainly in case of Parkinson disease recognition. What is more they were also not sure if the records with faulty recognition, the traditional classification was done in a satisfying level. Moreover, majority of neurological diseases are usually combined with many additional pathologies of the patients' old age.

3.1. THE CROSS VALIDATION METHODS COMPARISON

The results of the automatic classification were also compared with results obtained for other networks, as 10-*fold cross validation* (10-FCV), recommended for small sets of data [10]. They were worse then the results of our network CP. What is more, for these four diseases classes, trained by virtual records, the classification results were remarkable better then for the 10-FCV network trained by the real records set.

Fig. 3 illustrates classification faults for training; CP network with the virtual records, contra 10-FCV by real records set.

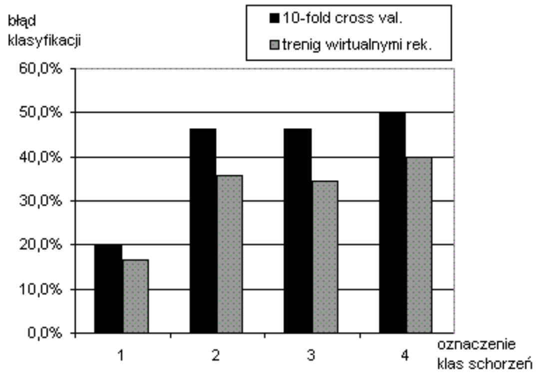

Fig. 4 Faults classification comparison for networks trained by method 10-FCV and by virtual records of CP (1 – the control group, 2 – left-lateral hemiparesis, 3 – right-lateral hemiparesis, 4 – Parkinson disease

4. CONCLUSIONS

In the result of carried out investigations and analysis the effectiveness of a conclusion making (the disease classification) occurred possible. The carried out clinical analysis and classification proved that the given neural network classifier brings the medical stuff with 70% effective automatic diagnosis.

The only doubtful results concern Parkinson disease classification, but we can expect more satisfying conclusions in case we will have more (well classified) cases for better training. From the other side, this case is usually very complex for recognition and for the disease level definition. In fact it is one of the diseases with not properly recognised aetiology.

Besides the disease recognition (usually in not advanced level of the disease) very important factor of the diagnosis is the recovery process monitoring, where the computer methods give the doctor unusually big help. Very satisfactory looks the control group recognition, with its above 83% properly classified cases. What is more we can expect better results after this system exploitation, when his knowledge will grow steadily.

BIBLIOGRAPHY

[1] CHANDZLIK S., KOPICERA K.: Experiments with neural network parameters – selection for Foot abnormalities Recognition, Journal of Medical Informatics & Technologies. Vol. 5, pp: CS-71 – CS-78. ISBN 83-909517-2-7, 2000.

[2] CHANDZLIK S., PIECHA J.: Modelling the data record of a patient walk by Lagrange-polynomial method. Journal of Medical Informatics & Technologies. Vol. 3, pp: MI-143 – MI-152, 2002.

[3] CHANDZLIK S., PIECHA J.: A patient walk-data-record modelling using a spline interpolation method. Journal of Medical Informatics & Technologies. Vol. 3, pp: MIT-153 – MIT-160. ISSN 1642-6037, 2002.

[4] CHANDZLIK S., PIECHA J.: The body balance measures for neurological disease estimation and classification. Journal of Medical Informatics & Technologies, Vol. 6, pp: IT-87 – IT-94, 2003.

[5] CHANDZLIK S., PIECHA J.: The interference spectrum extraction of a gait characteristics data record. Journal of Medical Informatics & Technologies. Vol. 7, pp: KB-23 – KB-31, 2004.

[6] CHANDZLIK S., PIECHA J.: The Gait Characteristic Data Spectrum Extraction. Proc. 4th Inter. Conf. on Computer Recognition System CORES'05, Vol. 18, pp. 493-501, 2005.

[7] CLANE D.B.: Treatment of Parkinson Disease. New England J. Med., pp: 1021-1027, 1993.

[8] DESIENO D.: Adding a conscience to competitive learning. IEEE International Conference on Neural Networks, IEEE Press, New York, Vol. 1, pp: 117-124, 1988.
[9] FLOATER M.S.: Parameterization and smooth approximation of surface triangulations. Comp. Aided Geom. Des., Vol. 14, pp: 231-250, 1997.
[10] HURVICH C.M., TSAI C.L.: Regression and time series model selection in small samples, Biometrika, Vol. 76, pp: 297-307, 1989.
[11] KOPICERA K., PIECHA J., ZYGUŁA J.: The neural networks in diagnostics support for PSW system. Proc. of Int. Conference ASIS'99, pp. 113-118, Krnov, 1999.
[12] LEVIN D., NADLER E.: Convexity Preserving Interpolation by Algebraic Curves and Surfaces. Numerical Algorithms, Vol. 9, pp: 113-139, 1995.
[13] PIECHA J.: The neural network conclusion-making system for foot abnormality recognition. Proceedings of IMACS World Congress, Lausanne, Switzerland, August 2000.
[14] PIECHA J.: The neutral network selection for a medical diagnostic system using an artificial data set. Journal of Computing and Information Technology CIT, Vol.9, pp: 123–132, 2001.
[15] PIECHA J., KOPICERA K.: The conclusion making method using pathology classifiers, Proc. on KOSYR'01, pp: 29-33, 2001.
[16] PIECHA J., ZYGUŁA J., ŁYCZAK J., GAŹDZIK T., PROKSA J.: The advanced measuring system for orthopaedic pathologies diagnostics using a static and dynamic footprints, Chirurgia narządów ruchu i ortopedia polska vol. LXI 1996, suplement 3B, pp.119-124. (in polish)
[17] ZBROJKIEWICZ J.S., PIECHA J.: Parkinson disease examination using walk disturbances characteristics. Journal of Medical Informatics & Technologies. Vol. 3, pp: MI-134 – MI-142, 2002.
[18] ZYGUŁA J.: Przetwarzanie danych pomiarowych dla systemu wnioskowania o patologiach w obszarze stopy. PhD monograph available in main library of Silesian University of Technology in Gliwice (1997).

Works supported by Polish Committee for Scientific Research funds. The PhD, KBN Grant No. 3 T11E 055 26 in 2004/2005.