

# SELF-ORGANIZING MAPS AS DATA CLASSIFIERS IN MEDICAL APPLICATIONS

Jana Tuckova, Marek Bartu, Petr Zetocha and Pavel Grill

*Czech Technical University, Faculty of Electrical Engineering, Department of Circuit Theory, Prague, Czech Republic*

**Keywords:** Self-organizing maps, Classifier, Medical applications.

**Abstract:** Many researchers use mathematical-engineering methods in different domains of life, and medical research is no exception. One area for application of such methods is to assist people with different forms of disabilities. The methods described in the following text are oriented towards the analysis of disordered children's speech with the diagnosis of Specific Language Impairment (SLI), also named as Developmental Dysphasia (DD), and the analysis of the expressive speech. Both methods make use of Kohonen Self-Organizing Maps (KSOM) or Supervised Self-Organizing Maps (SSOM) for the analysis and the classification of features from utterances of healthy and ill children, or adult speakers for emotions analysis. The possibility of cluster visualisation is used for monitoring of disorder trends and therapy success. These experiments also demonstrate the ability of the KSOM or SSOM to classify emotions.

## 1 INTRODUCTION

Many problems in technology, medicine, and the natural and social sciences still remain unsolved, on the grounds of the complexity of their solutions and the considerable quantity of data that requires processing. Seeking help through new information technology is highly desirable; one such method is through the development of artificial neural networks (ANN). Success in the application of ANN depends on the thorough knowledge of their function, which cuts across a wide range of academic disciplines – mathematics, numerous technical fields, physiology, medicine, phonetics, phonology, linguistics and social sciences. The robustness of the solutions for real methods by means of ANN is a great advantage.

One area where researchers are applying tested mathematical engineering methods is that of helping people with different forms of disabilities. The nervous system and the brain are ranked among the most crucial components of a living organism, with particularly great influence on the quality of human life. For this reason, biological neural networks have become the inspiration for computer modelling of their features and modelling of their function. Our research in this area is focused on searching for the relation between the clinical and the electrophysio-

logical symptoms of children with SLI. Our experiments take as their starting point our long research into speech signals. Bearing in mind that speech is one of the most complex human activities, we work towards an interaction of methods grounded in the results from both engineers and neurologists, in the hope that our method helps in the therapy of SLI patients. Language impairment can be caused by a number of brain disorders. Our long-term effort, of which the present submission is one part, will be to confirm the hypothesis that KSOM can classify these different disorders.

Specific language impairment is one of the most frequently occurring neurodevelopmental disorders, affecting five percent of the paediatric population (Dlouha et al., 2007). The condition is frequently defined as an inability to acquire and learn normal communication skills in proportion to age, even though with the presence of adequate peripheral hearing and intelligence, and the absence of a broad sensorimotor deficit or congenital malformation of the speech or vocal systems.

Developmental dysphasia, as a central disorder of speech signal processing, affects not only all speech modalities (phonetic-phonologic, morphological-syntactic, lexical-semantic as well as memory) but also other developmental aspects of the child's personality.

We can establish a relation between developmental dysphasia (Hrncir and Komarek, 2004); (Pospisilova, 2005) and the assessment of the degree of perception and impairment of the speech. The partial problems are mentioned from the point of view of logopaedics in (Love and Webb, 2001), which represents an engineering-based approach to the solution on the part of complex research.

Our method involves clustering the pattern characteristics visible through the allocation of the vowels, or respectively through the changes in allocation of the vowels pronounced by the patients. This characteristic is the formant frequency of the vowels shift. These formants are computed by a modified Burg algorithm from the vaw signal of monosyllabic and multi-syllabic words. Analysis of layout and movement of the features in the map can be one of the symptoms in identification of neurological disease. Also, it is important to monitor the ability to perceive and reproduce emotional speech in neurological patients.

Much research around the world focuses on the processing of emotional speech, a task of particular difficulty. The language of emotion includes thousands of words with myriad shades of feeling, degrees of redundancy, and shared meaning. Bearing in mind its high complexity, it may be impossible to describe these characteristics analytically. Nonetheless, neural network training can offer one satisfactory solution. Briefly to characterise the publications of international researchers concerning emotional speech by ANN application, the specific projects differ in the number and type of classified emotions, acoustic characteristics, the type of classifiers, and the degree of precision. Comparison of the SVM (Support Vector Machine), RBF (Radial Basis Function), kNN (k-Nearest Neighbours), Naive Bayes and MLNN (two hidden layers with 15 neurons) in emotions analysis is described in (Xiao et al., 2010). The success for the five classes was 81%. A description of the five emotional states (pleasure, sadness, fear, anger, and neutral state) is undertaken in (Mahmoud and Hassan, 2009). Here, the algorithm is based on the relationship of a height note versus the 12 half tones of the melodic scale. The last-mentioned publication is closest to our methods described in (Tuckova and Sramka, 2010).

A preference for self-organizing maps (SOM) has been assumed from the nature of our problem. For many real problems, the target values for all the patterns of the database are unknown (as is true in our case too). Nor do we know all the characteristics of the patterns.

## 2 HYPOTHESIS

Kohonen's Self-Organizing Features Map (KSOM) is a form of ANN that is trained by unsupervised learning rules. It is an iterative process which transforms multidimensional input data into decreasing-dimensional space. This process is based on the clustering method; cluster analysis methods search for interdependences and joint properties in a set of submitted patterns. T. Kohonen was inspired by the self-organising procedure in a human brain, by its adaptation and learning ability (more in Kohonen, 2001). At the basis of this method lies the fact that a human brain creates a map with specific areas, the areas that concentrate and treat different impulses.

The clusters are allocated on the map and indicate the number of dominant properties in one training epoch; clusters can point to movement in the input data and "re-grade" any characterization into different groups in the course of repetition.

### 2.1 Speech Analysis of the Patients with SLI

Specific Language Impairment has a direct impact on children's speech ability. Utterances of SLI children are different from the utterances of a healthy child of the same age. Usually, these differences are examined and classified by a speech therapist. Our long-time aim is to develop software capable of classifying temporal and frequency differences in children's speech. We have started from the hypothesis that SLI involves a disorder of movement of the vocal organs in articulation, influencing the formant generation (Tuckova and Komarek, 2009). The vowel mapping of patients is different in comparison to the vowel mapping of healthy children. The utterances are merged into a set of patterns using KSOM (Kohonen, 2001).

The software enables the quick extraction of the measure of distortion between patterns obtained from the particular utterance and the selected set of similar utterances. The software will help to observe trends in the progress of the disorder and assist in selecting an appropriate therapy, as well as improving and making more objective the diagnosis of the disease. The ability to distinguish emotions is also one of the important aims in the therapeutic process.

### 2.2 Emotions Analysis

It is possible to use prosody characteristics, such as timbre, intensity and rhythm, which are part of the

melody. Important indicators for the emotional and voluntary attitude of a speaker (Krcmova, 2008), (Palkova, 1994) are expressive changes of melody (i.e. change of a height of voice in a sentence).

The method presented here is based on the idea of the musical interval (Tuckova and Sramka, 2010). In speech, we can find a parameter which corresponds to the tone relationship, and for speech emotions it may have important perceptual values even in changes of the frequency range appearing in speech intonation. Compound tone is not only the tone of all music instruments: it is also a tone of speech, and its spectrum is a set of integral multiples of the fundamental frequency, known as the harmonic row. The amplitude of the exciting tone is the fifth relationship by the series of the harmonic row, which is coded by the frequency differences of successively proceeding harmonic tones. The relationship of any two tones to their fundament is perceived independently of the tones being sounded at the same time (interfluence over colour of speech, interrelations between fundamental frequency and speech formants or between speech formants respectively) or gradually (influence over intonation behaviour of fundamental frequency). Musical scales are nothing other than banks of tones all bound together by specifically given conditions whose sequence has a common relationship to tone F1. We talk about tonality, which has a strong emotive context: e.g. minor scales are perceived as sad and major scales as happy. Recalling this fact, the mutual relationships of tones can code emotions even in speech. Musical interval is the frequency difference between a specific n-tone and reference tone.

### 3 METHODS

Our team has created specific speech databases. For the first method described, it is a speech database of children with SLI, and a comparative database of healthy children. For this purpose, only utterances of healthy children without even any minor speech disorders are used. The same methodology is used, but with a different database from patients utterances that will be recorded. For the second described method, emotional speech is pronounced by professional actors in the pilot study.

#### 3.1 Speech Analysis of the Patients with SLI

All the utterances in our database (Zetochá, 2007)

were divided into two parts: the first (major) part to train KSOM and the second (minor) part is reserved for comparison to the features extracted from utterances of children suffering from SLI (DD). This separation is to avoid the problem of adaptation to specific speakers. The utterances are divided in the ratio of approximately two to one. Separated maps are trained for different types of utterances (e.g. vowels, monosyllables, etc.). The utterances are stored in the wave files. Standard methods – MFCC, PLP and LPC – are utilized to encode speech before the processing by KSOMs. There are separate networks for each type of coefficient, thus implying three different maps (one for each type of coefficient) for each group of utterances. PLP and MFCC were made for speech recognition tasks and therefore have a tendency to generalize, whereas LPC coefficients could describe particular vocal tracts with regard to specific features of the speaker. LPC coefficients have proven to offer very good results with utterances of very young children and also children with speech disorders. Our original intention was to compare the results obtained by each type of coefficients and choose the best-suited one. After several experiments, we decided to keep all three speech parametrizations being evaluated at one time, but taken separately.

KSOMs are utilized to find identical characteristic features in utterances. Features in the signal spatially or temporally adjacent are represented by patterns. By training the nets, the characteristic set of patterns for a given set of utterances is found. If the maps are trained with healthy children's utterances, the patterns represent the distribution of the feature in their speech. Moreover, this distribution will differ from the distribution obtained from the utterances of SLI children. The differences could be enumerated in proportion to the progress of treatment being described: in cases of effective therapy, the differences tend to decrease.

The maps and the unified distance matrix (U-matrix) form a representation of the KSOM that visualizes clusters and the distance between the neurons and their neighbours. The KSOM neurons are represented by hexagonal cells (in our experiment). The distance between the adjacent neurons is calculated and displayed in different colours. Light colours (from yellow to red) between neurons correspond to a large distance and thus represent a difference between the values in the input space. Dark colours (blue) between the neurons mean that the vectors are close to each other in the input space. Dark areas represent clusters and

light areas represent cluster boundaries. A new SOM variant has been put into use for vowel classification, namely the supervised self-organizing map (SSOM), which combines aspects of the vector quantization method with the topology-preserving ordering of the quantization vectors. The algorithm of the SSOM represents a very effective method of classification.

### 3.2 Emotions Analysis

The sentences in the pilot study were read by professional actors, two female and one male. Speech recording was performed in a recording studio with professional equipment (format “wav“, sampling frequency 44 kHz, 24bit). Utterances were recorded for four types of emotions: anger, boredom, pleasure and sadness.

The changes in the melody of the sentence are defined as its intonation, a quality also related to the meaning of the sentence, and its emotional timbre. Recorded emotional speech was subjectively evaluated by four persons. The final database contained 720 patterns (360 patterns for one-word sentences and 360 patterns for multiword sentences).

One-word sentences are important for analysis of disordered children’s speech. The ability to formulate emotions is unbalanced among children with a massive disorder, leaving them able to perceive and formulate only isolated words. The ability to distinguish emotions is one of the important aims in the therapeutic process.

The success of prosody control is clearly dependent on the labelling of the natural speech signal in the database. Labelling (determination of boundaries between speech units) and phonetic transcription of sentences from the speech corpus is performed in the phase of pre-processing.

As we mention in paragraph 2.2, the musical intervals (for example the quint – the ratio of the fifth tone divided by the first tone, with a numerical value of 1.498) were used for emotion characterization. The reference frequency, i.e. the fundamental frequency in our case, is given by the choices in each utterance feature, for which we use the autocorrelation function. The frequency ratios are compared with the music intervals and the input vector for KSOM training is computed.

### 3.3 Software

One of the goals of our research is to create a software pack with a user-friendly interface for medical doctors or other medical staff. Its base is

formed with SOM Toolbox, developed in the Laboratory of Information and Computer Science (CIS) of the Helsinki University of Technology and is built using the MATLAB script language. The SOM Toolbox contains functions for creation, visualization and analysis of the Self-Organizing Maps, and is available free of charge under the General Public License from (Vesanto at al., 2000). For the project, new special M-files, which should be a part of the supporting program package, were created (Tuckova at al., 2009). The batch algorithm was chosen because it ignores the order of vectors in the training set and the results are therefore more stable.

The software compares between patterns retrieved from healthy children’s utterances and the utterances of children with the disorder. The comparison is per-formed on two sets: the first is the set of patterns obtained from utterances of healthy children menti-oned above. The second is the set of patterns from dysphatic child utterances. The processing is the same for both input sets: after parametrization, they are classified utilizing previously trained maps, which is performed separately for each parametriza-tion and for each group of utterances. The resulting vectors are then compared on the basis of the occu-rrence of specific features in each input set. Additi-onally, the software allows for comparison of the utterance of one dysphatic child to the utterances of a specific group of children (based on age, gender, similar disease, etc.). The same software was inde-pendently used for emotion classification.

## 4 EXPERIMENTS

In the experiments describing disordered speech analysis, we analyzed the vowel mapping. Our method involves clustering the pattern characteristics visible by the allocation of the vowels respectively by changes in allocation of the vowels pronounced by the patients. To avoid such a mal-adaptation, we built up a database consisting of utterances of 72 healthy children (44 female and 28 male) between the ages of 4 and 10. The number is not final, as we are still working on the extension of the database. The database is not limited solely to the purpose of the described method: it is also intended for use by the students in advanced signal processing courses. Figures 1 and 2 display the results of the classification. Each figure shows the trained KSOM for vowels, with each colour representing one vowels ( red colour for “a”, orange

colour for “e”, blue colour for “i”, green colour for “o” and yellow colour for “u”). The training set consists of the utterances of all healthy children in the database. Utterances from a child with SLI are then classified and shown within the map. White units indicate the successful classifications from the map trained by the speech data of healthy children, black units represent classification errors (wrong vowel indications are written in units). Their number and location in the map change after each recording, depending on the change of the state of health of the patients. Likewise, the ability for good pronunciation depends on age. The aim of medical therapy is to achieve a minimum of wrong classifications. Data analysis is, however, aggravated by the following fact: afflicted children are not able to pronounce certain vowels (the monitored children have displayed problems with the pronunciation of “e”, “i”, and at certain times with “u”). The obtained results are confirmed by psychological evaluation of patients and by the results of the EEG.

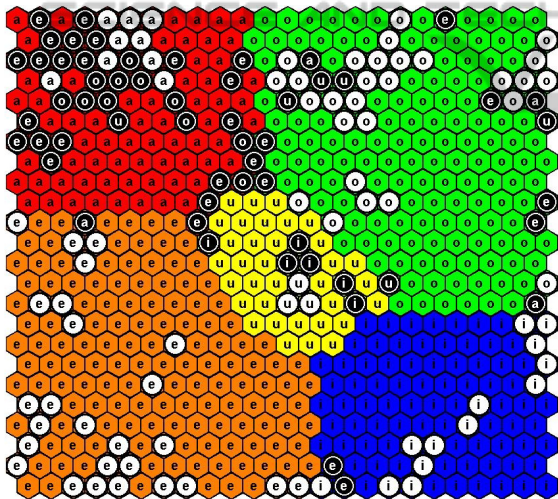


Figure 1: Map for vowel classification of the children with SLI – the first record.

The same children were examined in the course of three or four-month periods, when they underwent logopaedic therapy. After each period, the same utterances are recorded and analyzed. The classification result is given in figure 2. As could be observed, the number of misclassified features is significantly lower, which shows improvement, and this finding is confirmed by the results of medical examinations.

As described above, these results could also be quantified, which allows us to perform statistical evaluations and calculate the accuracy of the results.

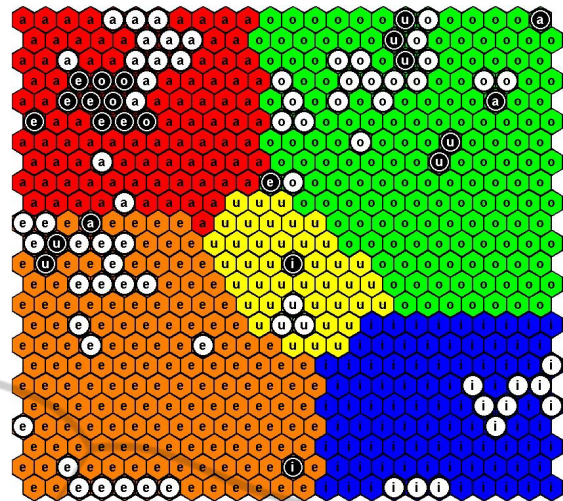


Figure 2: Map for vowel classification of the same children with SLI – 6 months later.

The other problem which we address through KSOM is the specification of the SLI level. We evaluated 22 healthy children (for KSOM training) and 22 patients. Our goal was distribution of the patients into 3 classes according to SLI level (level 1-mild, level 2-medium, level 3-severe SLI) – figure 3. We located the success rate (SR) of the vowel classification in a map with a grid size of 24x24. Input data were created by the vectors with 8 autoregressive coefficients. The speech therapists specified 3 groups of patients, which were marked as group 1 for mild SLI, group 2 for medium SLI and group 3 for severe SLI.

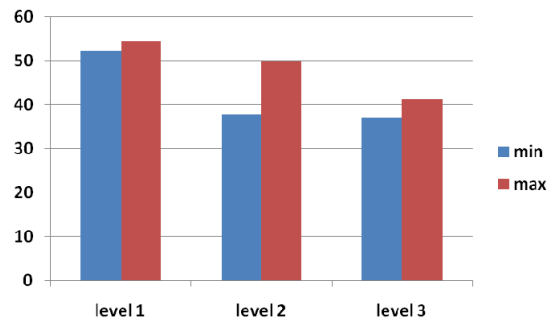


Figure 3: Success rate for SLI levels. The blue colour represents the minimal value, the violet colour represents maximal value of SR.

The blue or violet colours represent the minimal resp. maximal value of SR. Levels of SLI are represented on the x-axis as levels 1, 2, and 3 from the left. Table 1 summarizes minimal, maximal and average values of SR for 3 categories of SLI. The classification success for all 22 patients is shown in Figure 3. We can deduce that through the use of

KSOM on the base of vowels classification, it is possible to distribute the patients into several classes (in our case 3). The average values of SR were 53%, 44% and 39%, for healthy children 87% (rounded). The coefficient of correlation between SR and SLI relevance levels was -0.7755.

Table 1: SLI levels: level 1 for mild, level 2 for medium, level 3 for severe SLI.

| level | min [%] | max[%]  | average[%] |
|-------|---------|---------|------------|
| 1     | 52.2407 | 54.4056 | 53.3237    |
| 2     | 37.6723 | 49.8029 | 44.0436    |
| 3     | 36.9919 | 41.3514 | 38.7180    |

In the experiments describing emotion classification, we prepared the input vector for SSOM training with 29 patterns, which were created from 20 values containing the ratios relating to the musical intervals and 9 values describing the acoustic qualities of the utterance feature (arithmetic average of absolute value, standard deviation, maximum and minimum in the time domain, the fundamental frequency  $F_0$  and formant frequency  $F_1, F_2, F_3, F_4$  in the frequency domain). The size of the map was 15x15, while quantization (QE) and topographic (TE) errors of the map were also computed. The TE figure predicts the conservation of data topology between input and output space, while QE reflects the accuracy of the mapping (related to the number of the input matrix elements and the size of the map). The success of the SOM training depends on the size of the maps and on the number of training samples. Table 2 shows TE and QE for one-word (I) and multi-word (II) sentences.

Table 2: The success of emotion classification by SSOM for input data based on musical intervals and for input data supplemented with acoustic features.

| Error                               | I             | II            |
|-------------------------------------|---------------|---------------|
| TE <sub>20</sub> / TE <sub>29</sub> | 0.014 / 0.011 | 0.017 / 0.006 |
| QE <sub>20</sub> / QE <sub>29</sub> | 0.274 / 0.431 | 0.275 / 0.439 |

The U-matrix in Figures 4-5 represents the emotion classes for one-word and multi-word sentences (for 29 input parameters). The KSOM neurons are represented by hexagonal cells (in our experiment) marked by 'H' for anger, 'N' for tedium, 'R' for pleasure and 'S' for sadness. Each cell is also marked by a character for class, by real classified the font and number registered patterns.

The most separated clusters (largest distance) are also most different in colour coding - dark blue (down) and dark red (up). It relates to emotions as Anger or Pleasure - dark blur and Sadness - dark red. Tediousness is marked by light blue, close in the

scale to yellow used for Sadness.

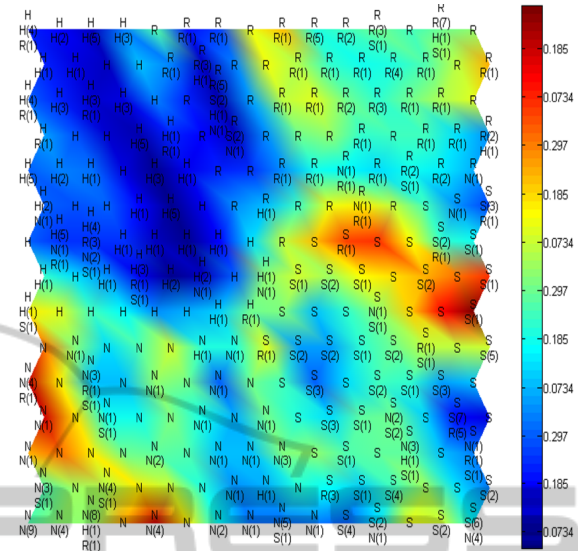


Figure 4: U-matrix for one-word sentences.

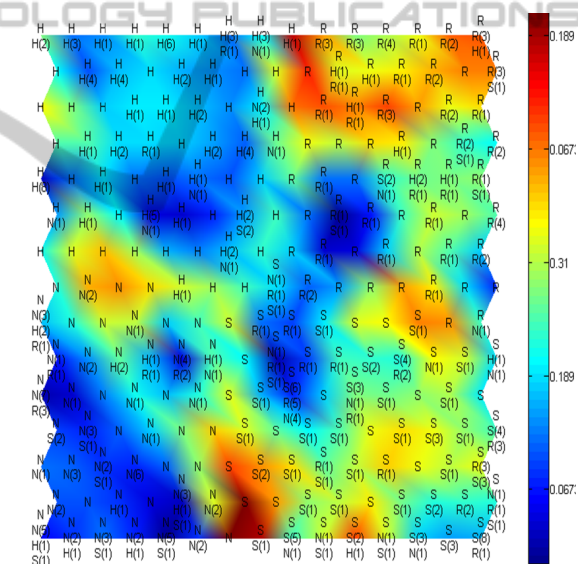


Figure 5: U-matrix for multi-word sentences.

The results depend also on the precise identification of the emotions by listeners at process of the database creation. Both passive emotions are negative, unpleasant for listeners. The pair of active emotions, by contrast, gives a better feeling to the listeners.

## 5 CONCLUSIONS

Our research involves an original method for the

intensity of speech defect monitoring in child patients with developmental dysphasia. We draw upon a body of knowledge consisting of phonetics, acoustics and ANN applications. The KSOMs were chosen for solving part of the project. New variants of the SSOM were tested theoretically and experimentally after the first experiments with the Kohonen SOM.

We will concentrate on deeper analysis of child speech, mainly devoting attention to longer speech units (syllables, multi-syllabic words) and the inability to formulate multi-syllabic words (three and four syllables) or phoneme overlap faults, which are other symptoms of developmental dysphasia. The processing of speech signals is complicated by the effect of the real environment (non-professional speakers, high noise in the environment if the speech was recorded in ordinary rooms). The second problem that we have to address is the fact that we are analyzing children's speech. Often, its own specific development is not complete for a particular age group, or the quality of the utterances is strongly influenced by emotion, the latter factor being one of the reasons why we start with emotional speech research. Also, we have at our disposal only a small amount of speech data, especially for patients, even though a permanent database is kept of child speakers. The size of the database of healthy child speech is also limited by the possibilities of data recording in preschool and primary school institutions, especially with respect to the concern over parent permissions. We assume that it would be necessary to open a sizable screening project during preventive medical checkups of small children. The self-organizing maps are favourable for persons without an engineering background, primarily for the ability to visualize higher-dimensional data samples in a low-dimensional display. In the initial phase of our research project we have been concentrated on the verification of KSOM ability to classify SLI patients into three classes. This classification has been based on their speech analysis. The pilot study confirms our premises (see Figures 1, 2 and 3). In the future, we aim to focus on the search for correlation between disordered speech analysis and the localization of the brain failure, in order to achieve a SLI diagnosis jointly with neurologists.

One of the long-time goals of our research is to create a soft-ware pack with a user-friendly interface for doctors or other medical staff.

## ACKNOWLEDGEMENTS

This research was supported by grant GACR No. 102/09/0989 and by the research program Transdisciplinary Research in Biomedical Engineering No. II. MSM 6840770012 of the Czech University in Prague.

## REFERENCES

- Dlouha, O., Novak, A., Vokral, J., 2007. Central Auditory Processing Disorder (CAPD) in Children with Specific Language Impairment (SLI). In *International Journal of Pediatric Otorhinolaryngology*, Vol. 71, Issue 6, pp.903-907.
- Hrnčir, Z., Komarek, V., 2004. Analyses of EEG recordings. In *Neural Network World, Int. Journal on Non-Standard Computing and Artificial Intelligence*, vol. 14, no. 1, pp. 21–25.
- Kohonen, T., 2001. *Self-Organizing Maps*. Springer-Verlag, 3rd edition.
- Krcmova, M., 2008. *Phonetics and phonology* [online]. Brno : Masarykova univerzita, [cit. 2010-04-04], (in Czech) <http://is.muni.cz/elportal/?id=766384>. ISSN 1802-128X.
- Love, R. J., Webb, W. G., 2001. *Neurology for the Speech-Language Pathologist*. Elsevier Inc., New York, USA. ISBN-13: 973-0-7506-7252-8.
- Mahmoud, A. M., Hassan, W. H., 2009. Determinism in speech pitch relation to emotion. In *Proceedings of the 2nd international Conference on interaction Sciences: information Technology, Culture and Human*, Seoul, Korea, Nov. 24–26, vol. 403, ACM, New York, NY, pp. 32–37.
- Palkova, Z., 1994. *Phonetic and phonologic of the Czech*. Karolinum, Prague (in Czech).
- Pospisilova, L., 2005. Diagnostics questions of developmental dysphasia. In *Vox pediatric, journal of general practitioner for children and young*, vol. 5, no. 1, pp. 25–27, (inCzech).
- Tuckova, J., Komarek, V., 2009. Effectiveness of speech analysis by self-organizing maps in children with developmental language disorders. In *Neuroendocrinology Letters*, vol. 29, no. 6, pp. 939–948.
- Tuckova, J., Bartu, M., Zetocha, P., 2009. *Artificial neural network applications in signal processing* (in Czech). Teaching text, Česká technika-nakladatelství ČVUT, Praha, ISBN 978-80-01-04400-1.
- Tuckova, J., Sramka, M. 2010. Emotional Speech Analysis using Artificial Neural Networks. In *Proc. Int. Multiconf. on Computer Science and Information Technology (IMCSIT2010)*, Wisla, Poland, ISBN

978-83-60810-22-4.

Vesanto, J., Himberg, J., Alhoniemi, E., Parhankangas J., 2000. *SOM Toolbox for Matlab 5*, Helsinki University of Technology, ISBN 951-22-4951-0. Homepage of SOM Toolbox: [www.cis.hut.fi/projects/somtoolbox](http://www.cis.hut.fi/projects/somtoolbox)

Xiao, Z., Dellandrea, E., Dou, W. W., Chen, L., 2010. Multi-stage classification of emotional speech motivated by a dimensional emotion model. In *Multimedia Tools and Applications Journal*, Springer Netherlands, vol. 46, Nu 1/January, pp. 119–145, ISSN 1380-7501.

Zetocha, P., 2008. Design and realization of children speech database. In *Ministry of Education grant FRVS*, No.2453/2008 (in Czech)

