Computer-aided processing of the oculomotor signal

Tomasz Lewandowski[1*], and *Anna* Lewandowska[2]

[1]Institute of Technical Engineering, State School of Technology and Economics, 37-500 Jaroslaw, Czarniecki Street 16, Poland
[2]Institute of Healthcare, State School of Technology and Economics, 37-500 Jaroslaw, Czarniecki Street 16, Poland

Abstract. Specific features of oculomotor signal and availability of high-end measurement equipment, as well as using modern IT techniques and tools creates the possibility of automatic processing of this type of data and extensive use of developed algorithms. Analysis of such data is a tedious and complex process so computer processing of the oculomotor signal makes the process less time-consuming, more precise and effective. The article discusses data filtering and removing noise, detection of saccades and fixations and determination of characteristic oculomotor parameters and then analysis using neural networks (unidirectional, two-layer neural network with backpropagation learning method and Kohonen's self-organising network) and application supporting the analysis process. The proposed test method allows registration of a view path followed by its automatic analysis to obtain objective parameters characterising the movement of the eyeball. The motor apparatus of the eyeball, due to its high sensitivity to changes in the body, can serve as a measure of general health.

1 Introduction

Registration and computer processing of biomedical signals is currently the subject of numerous works in the field of biomedical engineering, with ECG, EEG and EMG being the most frequently examined signals. Other biomedical signals, such as the oculomotor signal, are examined relatively less frequently [1]. However, considering the complex structure and mode of action of the organ of sight, as well as significance of information transferred to the brain, understanding of the substance and determining the characteristic parameters of the oculomotor signal are an extremely important scientific and practical aspect. The most frequently undertaken studies concern the use of the oculomotor signal in usability tests [2-4], tests on reading [5-8] or sleep phase classification [9-11]. The usage of the oculomotor signal in medicine is extremely important, taking into consideration care for human life and health, and specific features of this signal, availability of high-end measurement equipment, as well as using modern IT techniques and tools, creates the possibility of automatic processing of this type of data and extensive use of developed algorithms, e.g. in the diagnosis of neurological diseases.

* Corresponding author: tomasz.lewandowski@pwste.edu.pl

Analysis of such data is, however, a tedious and complex process which necessitates exceptional computational discipline and the use of heuristic computational methods. A medical specialist or an oculography scientist can easily indicate the place of the fixations and saccades in the eye movement chart. However, computer processing of the oculomotor signal makes the process less time-consuming, more precise and effective.

2 Acquisition of the oculomotor signal

Useful signal parameters. On the basis of literature analysis and medical consultations, parameters of eye movement important for the diagnosis of Parkinson's disease were determined, and the method of their acquisition was proposed, e.g. resting amplitude measured during the observation of a static object, spontaneous saccade latency measured during spontaneous transfer of sight between immovable objects.

Visual tasks. In order to obtain relevant measurement data, a set of visual tasks was prepared in terms of duration, resolution, dynamics, readability and the possibility of estimating oculomotor parameters. The oculatory data obtained as a result of the conducted measurements are characterised by high precision, so their processing requires the use of specific calculation tools in order to isolate the characteristic behaviour of the eyeball and the parameters that make it possible to classify the measurement.

Measurement method. The oculomotor signal was obtained by the photoelectric method which is based on the measurement of the beam of light reflected by the surface of the eyeball, generated by an artificial source, most often – infra red radiation. The radiation is emitted by a pair of LED illuminators, placed symmetrically to the eyeball, which, after reflection from the iris, is registered by two IR photodetectors. Due to the scleral and iris reflectivity, the intensity of the reflected radiation is a function of the angle of rotation of the eyeball [12,13]. The main advantages of this method are: non-invasiveness, high measurement accuracy, low interference sensitivity.

Research group. Visual tests were carried out on patients with diagnosed Parkinson's disease, as well as on young and healthy people as a control group. This division was used in order to distinguish between ocular disorders caused by age and those caused by the disease.

3 Stages of processing of the oculomotor signal

Automatic analysis of the oculomotor signal requires the use of appropriate algorithms based on finding a method of distinguishing between real changes in the position of the eyeball from those generated by various types of interference. In the literature several techniques of identifying oculomotor events are described: based on speed, based on variability, based on areas [14].

Every detection algorithm for oculomotor events has three important tasks to perform: removing interference from the signal, detecting fixations and saccades and determining the parameters of eyeball movements (duration of the saccade, speed of the saccade, speed of free movement etc.) that would allow formulation of conclusions concerning the work of the sight organ.

3.1 Filtering and removing noise

The registration of the oculomotor signal is accompanied by the registration of disturbances of various origins (innate eye properties, abnormal measurement conditions, head movements etc.) that have a significant impact on the quality of measurement data. Very often, measuring devices pre-filter the measured signal values, but in most cases it is necessary to perform additional data cleaning.

The most undesirable phenomenon during the measurement, having a huge impact on the quality of the results, was a movement of the head accompanying tracking of the objects moving during the show. The consequence of a sudden head movement is the vestibulo-ocular reflex that negatively affects the value of the collected data.

In order to filter out disturbances of the oculomotor signal, the filtration method was applied to eliminate the samples that go beyond the empirically determined tolerance range [15,16]. The direction and sense of the movement, as well as the reference signal value at every measurement point was known, and this fact was used during the filtration. On this basis, the tolerance range for the signal value can be determined. Above this range, the signal would be considered as a disturbance and removed from further analysis (Fig. 1). This threshold is selected experimentally, depending on the type of visual task.

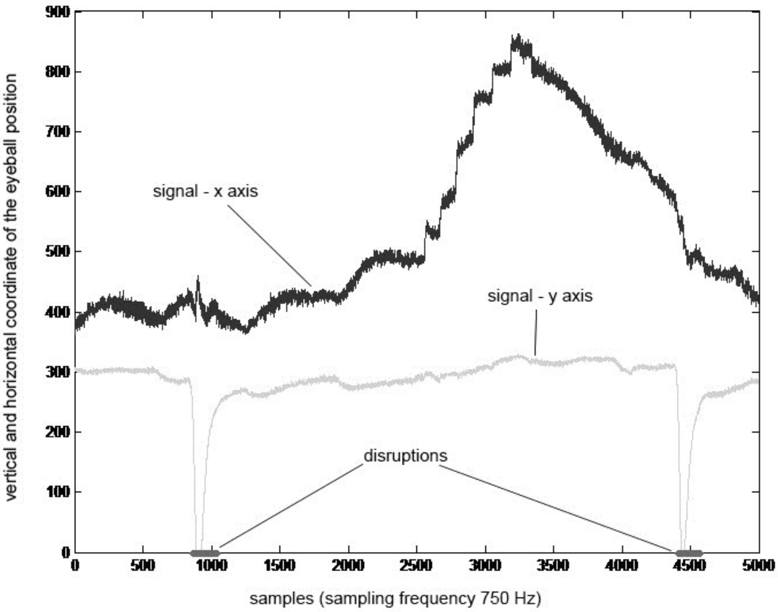

Fig. 1. Results of the filtration of the oculomotor signal by applying a reference signal

The second method of filtration used was identification of the areas containing disturbances by comparing the signal value with the average of signals in the proximity. The selection of the size of the proximity is of great importance in this case – if it is too small, its size causes the omission of disturbances, if too big – it may be the cause of classifying the correct saccade as interfering noise. Signals in each axis were filtered separately and then correlated due to the fact that the disturbance may occur both in the horizontal and vertical axis (Fig. 2).

Both methods of disturbance detection produced good results for the analysed data. In order to confirm the correctness of the selection of areas excluded from the analysis, both methods were applied and the obtained results were compared.

Many researchers in this field state that for the filtration of the oculomotor signal, median filters can be used, as they enable preserving of key signal characteristics while reducing the noise [17,18]. As part of the described test, a one-dimensional median filter was additionally used. By comparison, a low-pass Butterworth filter was used (filter order selected experimentally), obtaining satisfactory results in both cases – the signal was cleared while maintaining its characteristic features (Fig. 3).

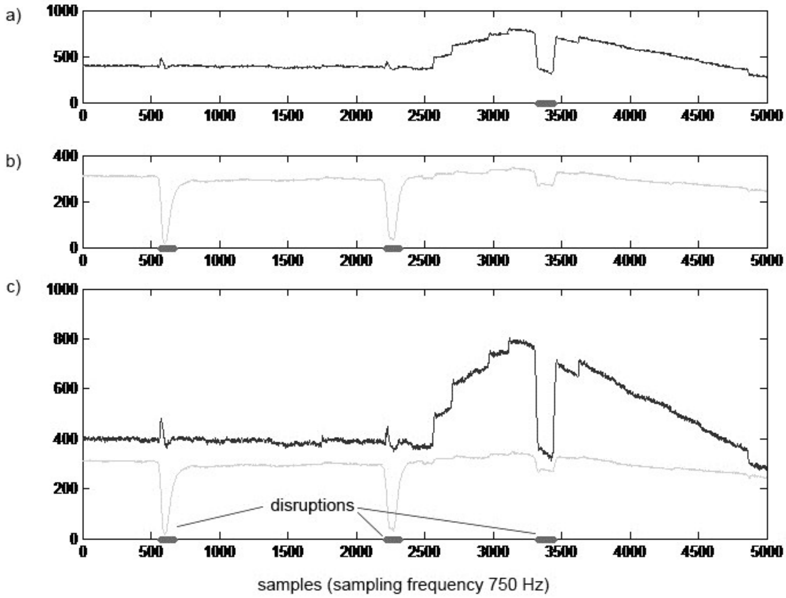

Fig. 2. The results of filtration of the oculomotor signal by examination of the average: a) horizontal component of the oculomotor signal with the detected disturbance, b) vertical component of the oculomotor signal with the detected disturbance, c) both components of the oculomotor signal with marked interference points

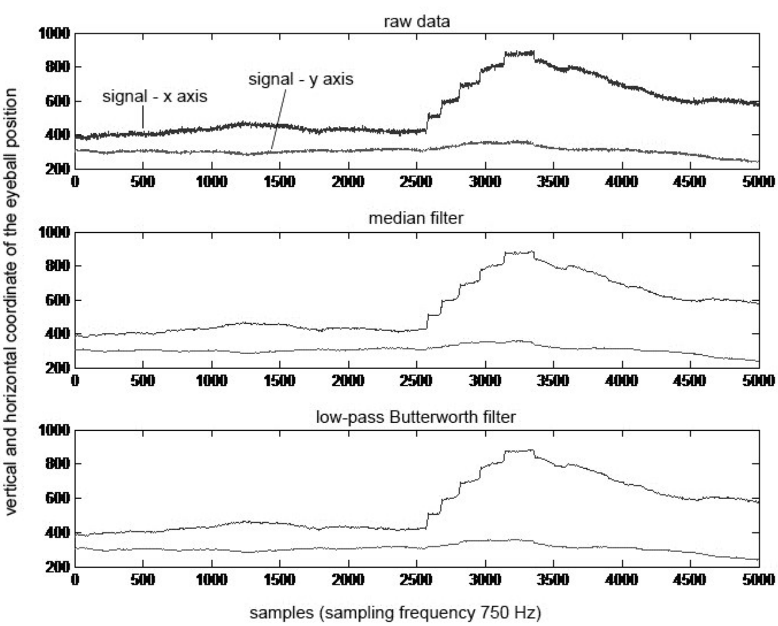

Fig. 3. The oculomotor signal after applying the median filter and the Butterworth filter

3.2 Detection of saccades and fixations

Assuming that the output of the ophthalmograph is a series of pairs (x_i, y_i), i=1..n, corresponding to the ocular position at the i-th moment of measurement, to determine saccades in the oculomotor signal, an algorithm was designed to detect a sudden change in the average value of the signal by comparing the Euclidean distance *d* measured for two adjacent samples up to the set threshold h. If, however, the saccadic movement includes several samples and *d*>*h* for every comparison, then the algorithm would return the information about several saccades. In order to eliminate this limitation, the average value of *d* may be calculated for every sample (1) [16,19]. The right choice of the *r*-factor influences the right marking of all saccades in the signal.

$$d_i = \sqrt{(spx_i - swx_i)^2 + (spy_i - swy_i)^2} \tag{1}$$

where:

$$spx_i = \frac{1}{r}\sum_{k=1}^{r} x_{i+k}\,, swx_i = \frac{1}{r}\sum_{k=1}^{r} x_{i-k}$$

$$spy_i = \frac{1}{r}\sum_{k=1}^{r} y_{i+k}\,, swy_i = \frac{1}{r}\sum_{k=1}^{r} y_{i-k}$$

While determining the value of the *r*-factor, it should be taken into account that the average length of a saccade is 30-120 ms, while the average length of a fixation is 150-600 ms [15]. Therefore, with the measuring frequency of 750 Hz, the analysis was conducted with the *r*-factor=15, taking into account the possibility of faster saccades.

When the averaged value *d* is calculated (Fig. 4), p_i peaks can be easily selected (2).

$$p_i = \begin{cases} d_i, for\ d_i > d_{i-1} \wedge d_i > d_{i+1} \\ 0, for\ d_i \le d_{i-1} \vee d_i \le d_{i+1} \end{cases} \tag{2}$$

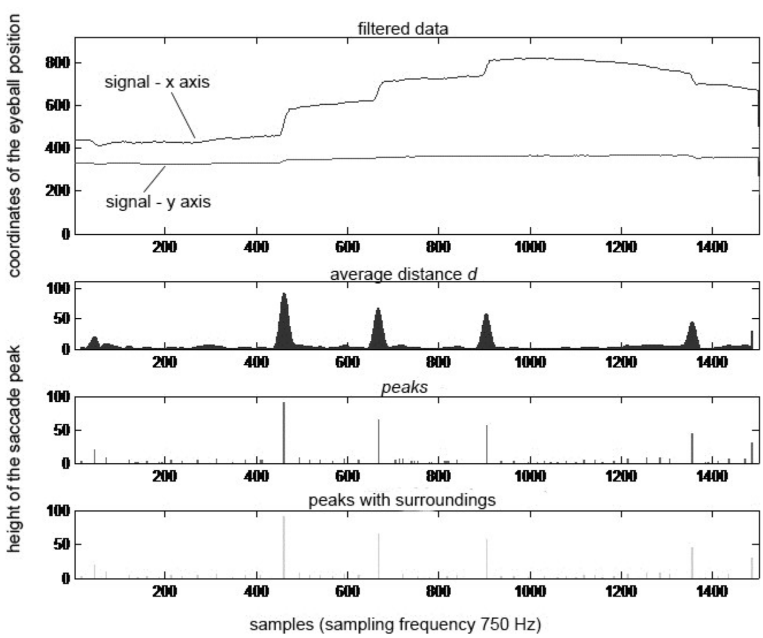

Fig. 4. Stages of peak detection in the oculomotor signal

The saccades are hence marked in the input signal (Fig. 5).

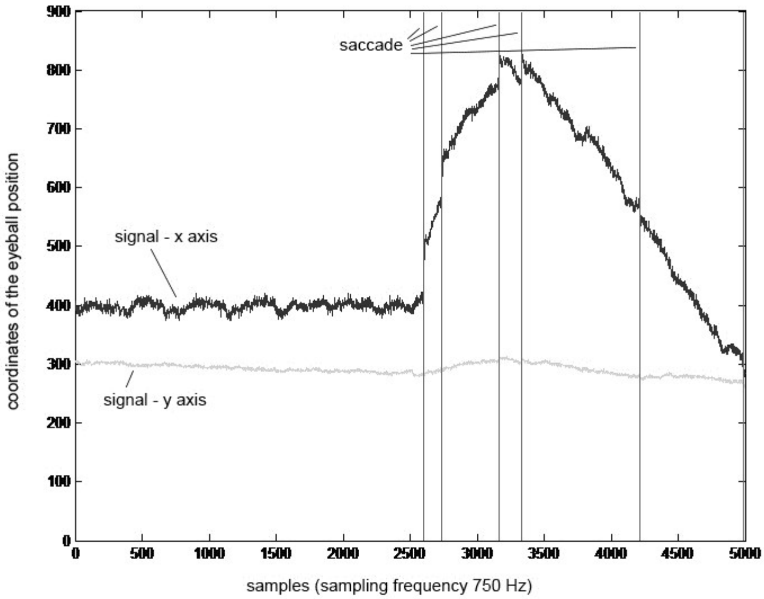

Fig. 5. The oculomotor signal with marked places of saccade occurrence

The next step of the algorithm is the estimation of points of attention focus. This can be achieved by calculating the median of all samples in the ranges determined by the vector *p* indices, for which values are greater than 0 [19]. This results in a sequence of pairs (f_x, f_y) that constitute the coordinates of points of attention focus (fixations). These points provide important information about places where the eye movement of the examined person has been stopped, and in combination with the knowledge of content of the presentation they can be a starting point for considerations regarding the classification and assessment of oculomotor disorders (Fig. 6).

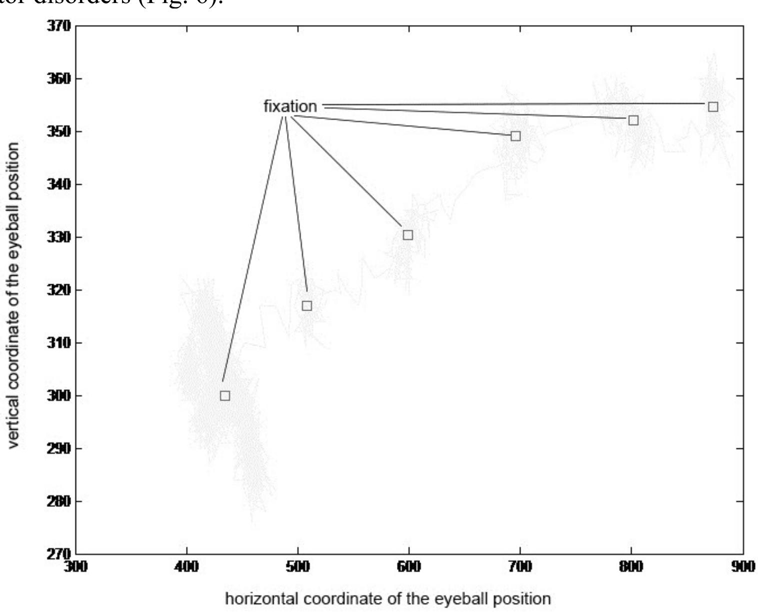

Fig. 6. Trajectory of eye movement during a visual experiment with marked points of attention focus (fixations)

3.3 Determination of characteristic oculomotor parameters

Having designated places for the occurrence of saccades and fixations, it is possible to proceed with the determination of oculomotor parameters. In order to perform further calculations, it is necessary to register coordinates of the eye in degrees of viewing angle [15], taking into account the resolution and physical measurements of the measurement monitor.

To determine the duration of the saccade, it is possible to use a method based on the information about the previous eye condition (fixation or saccade), the average absolute value of the signal for previous samples and appropriately selected threshold values [15,20], whose task is to estimate if the current values of the signal can be assigned to the current state, or whether the state should be changed (Fig. 7). The selection of appropriate threshold values in this case is particularly important, as it directly affects the accuracy and precision of the estimation. Thanks to the knowledge of the frequency of measurement and the number of samples belonging successively to states of fixation and saccades, the time of the duration of each and every saccade can be calculated as the sum of samples belonging to the state of the saccade divided by the measurement frequency.

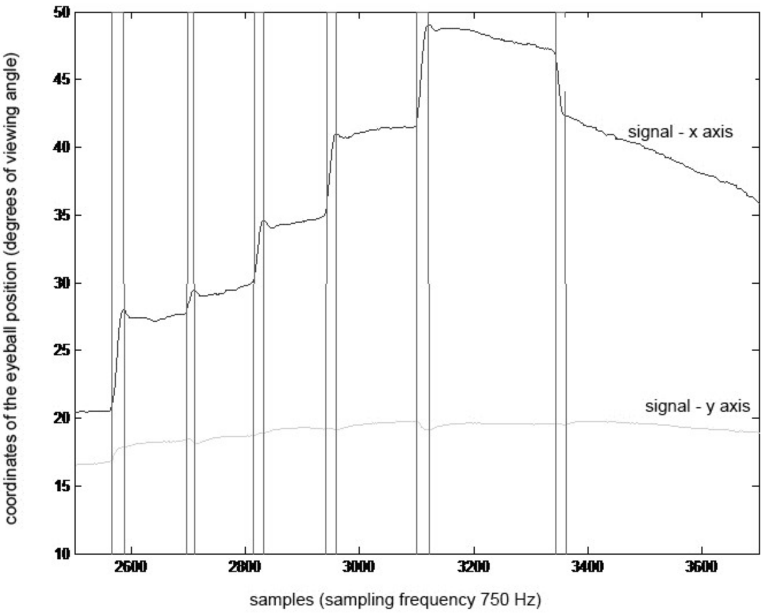

Fig. 7. The oculomotor signal with marked places of beginning and end of every saccade

Knowing the duration and coordinates of individual samples that make up the saccade, it is possible to calculate average (3) and maximum (4) speeds of saccades as the average value of Euclidean distances of individual samples multiplied by the sampling frequency.

$$v_{śr} = \frac{1}{k}\sum_k \frac{\sqrt{\left(x_k^e - x_k^b\right)^2 + \left(y_k^e - y_k^b\right)^2}}{n_k} f_p \tag{3}$$

$$v_{max} = \max_k \frac{\sqrt{\left(x_k^e - x_k^b\right)^2 + \left(y_k^e - y_k^b\right)^2}}{n_k} f_p \tag{4}$$

where:

k – number of the saccade; n – quantity of samples; x^e, y^e – coordinates of the end of the saccade; x^b, y^b – coordinates of the beginning of the saccade; f_p – sampling frequency.

3.4 Analysis using neural networks

Taking into consideration the dynamic development of artificial intelligence methods together with enormous possibilities of their application, automatic classification of the oculomotor signal has been achieved by means of neural networks. Their ability to learn, generalise knowledge and tolerate faults, give an opportunity to estimate the input data in a manner similar to the natural one [21,22]. On the basis of scientific experience [22-26], considering the specificity of the input data for the purpose of classification, two models of neural networks were selected.

The first solution was based on a unidirectional, two-layer neural network, and the network learning process was carried out in the form of supervised learning (backpropagation method) [21,22], using the unipolar sigmoid function as a function of activating neurons. The mean square error was used as the function of the target [25,27,28], setting an error threshold value at 0.001. In order to increase the speed of the neural network learning process, the method of adaptive selection of the learning speed factor was used [25]. Parameters were selected by means of a heuristic method, so that the process dynamics would be as high as possible.

The second solution was based on the Kohonen's self-organising network. Networks of this type, having only the input patterns, during the learning process (competitive learning) create the output patterns themselves, at the same time creating a structure that would be mapping dependencies in the space of input vectors in the best possible way [24,29]. In the presented model, the Manhattan metric was adopted. It determines the distance between two points as a sum of absolute values of their coordinate differences [30].

The task of neural networks was to classify unknown oculomotor signals in terms of belonging to one of three groups: healthy young people, healthy elderly people, sick people.

In each of the solutions the matrix of input vectors consisting of selected fragments of the eye movement path was determined. Both the location of the fragment and its length can be determined arbitrarily. An important aspect of the success of the learning and testing process is appropriate selection of the trajectory fragment on the basis of which classification is to take place. It can be, for example, a moment at which the following movement begins or when the subject observes a stationary object. In order to adjust the value, this matrix was subjected to a min-max standardization process.

The learning was carried out for three variants of data forming a matrix of input vectors: Network 1 – the matrix of input vectors is created by selected parts of the eyeball movement path, Network 2 – the matrix of input vectors is created by differences between the reference and the actual value in selected parts of the eyeball movement path, Network 3 – the matrix of input vectors is created by differences between consecutive measurements in selected parts of the eyeball movement path.

For the neural network architecture adopted in the task, with the input vectors defined above, the learning processes were carried out and the training of the network, with the assumed criteria, was successful.

As a result of testing the first solution for particular networks, the following results were obtained: Network 1: a sick person is correctly diagnosed in 60% of cases, in 30% as an elderly person and in 10% as a young person; a young person is diagnosed correctly in 80% of cases, in 20% as an elderly person, an elderly person is correctly diagnosed in 60% of cases, in 20% as a young person or a sick person. Network 2: a sick person is correctly diagnosed in 60% of cases, a young person in 70%, and an elderly person – in 50%.

Network 3: a sick person is correctly diagnosed in 50% of cases, a young person in 70% and an elderly person – in 30%.

While testing the second solution, for every network highly satisfactory results were obtained in the form of unambiguous classification of signals to specific groups: the closest to the neuron representing patterns are data representing young people, in the immediate vicinity of both neurons there are also data representing healthy elderly people. The results obtained from sick people stimulate the neuron located at a distinct distance from the remaining neurons on the Kohonen map.

3.5 Application supporting the analysis process

In order to improve the process of visual path analysis of people subjected to visual experiments described above, an application was prepared using Graphical User Interface, working in the MATLAB computing environment (Fig. 8).

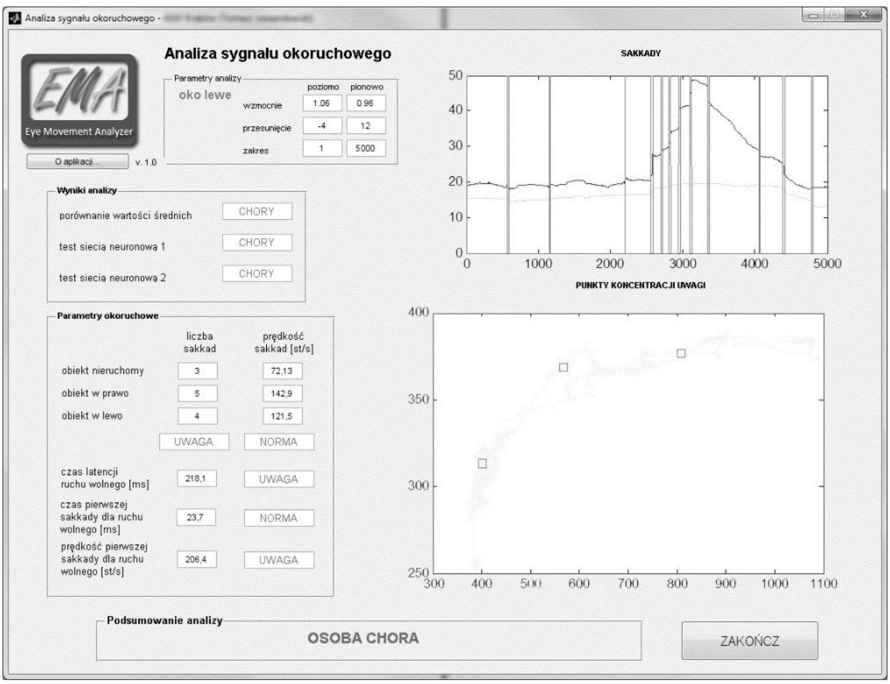

Fig. 8. The window of the application supporting the process of analysis of oculomotor data presenting the result of analysis of the selected visual path (polish translation)

The presented application is of a demonstration nature only. As far as its diagnostic use is concerned, it is necessary to consult with specialists the selection and presentation of parameters and the possibility of regulation of selected threshold values.

4 Conclusions

As a result of the measurements taken, analysis of the data obtained, and design and testing of proper processing algorithms, the following conclusions can be made:

- it is possible to effectively classify a visual path to one of the three groups defined by the study (sick, healthy young and healthy elderly) on the basis of a discrimination analysis by median differences between successive measurement

points and on the basis of discrepancies between the measurement data and the standard,
- the use of neural networks in order to classify oculomotor signals into one of the three groups gives satisfactory results (about 80% of the recognition efficiency),
- correct process of filtering the measurement data has a direct impact on the results of further analyses, while the development of filtration methods that take into account the specificity of the data under consideration and knowledge of their model shape brings good results,
- selection of the right parameters enabling the automatic processing of oculomotor data is carried out experimentally and is a time-consuming process,
- combined use of the classification methods presented in the article allows obtaining reliable results.

To sum up, it should be stated that the proposed test method allows registration of a view path followed by its automatic analysis to obtain objective parameters characterising the movement of the eyeball. The motor apparatus of the eyeball, due to its high sensitivity to changes in the body, can serve as a measure of general health.

References

1. P. Augustyniak, *Determination of diagnostic parameters of time-frequency scanners with characteristics adapted adaptively - PhD dissertation* (AGH Univ.of Sci&Tech, Kraków, 1995)
2. S. Chu, N. Paul, L. Ruel, Inf. Des. J. **17**, 31–43 (2009)
3. Z. Guan, E. Cutrell, SIGCHI Conf. Hum. Fact. in Inform. Syst. 417–420 (2007)
4. Y. Yesilada, C. Jay, R. Stevens, S. Harper, 17th Int. Conf. WWW, 11–20 (2008)
5. H.S.S.L. Joseph, S.P. Liversedge, H.I. Blythe, S.J. White, S.E. Gathercole, K. Rayner, T.Q J.Exp.Psych. **61**, 708–723 (2007)
6. B.J. Juhasz, Lang.&Cogn. Proc. **23**, 1057–1088 (2008)
7. S.J. White, J.Exp.Psych.: HP&P **34**, 205–223 (2008)
8. M.H. Yen, J.L. Tsai, O.J.L. Tzeng, D.L. Hung, Mem.&Cogn., **36**, 1033–1045 (2008)
9. S. Devuyst, T. Dutoit, T. Ravet, P. Stenuit, M. Kerkhofs, E. Stanus, 13th IFMBE **23**, 146–150 (2008)
10. B. Jammes, H. Sharabty, D. Esteve, Somn.S&S **12**, 227–232 (2008)
11. N. Khasawneha, M.A.K. Jaradatb; L. Fraiwanc, M. Al–Fandib, Appl.AI Int.J. **25**, 163–179 (2011)
12. M. Klemensowicz, *System for performing visual psychophysiological experiments using the Jazz multisensor - master thesis* (Poznan Univ.of Tech, Poznan, 2003)
13. J. Winiarska, *Examination of the information stream acquired by the human eye system - master thesis (*AGH Univ. of Sci&Tech*,* Kraków, 2005)
14. D. Salvucci, J. Goldberg, Eye Track. Res.&App.Symp (2000)
15. A. T. Duchowski, *Eye tracking methodology* (Springer, London, 2007)
16. M. Nyström, K. Holmqvist, Beh.Res.Meth. **42**, 188–204 (2010)
17. R. Krupiński, P. Mazurek, 14th IEEE/IFAC Int. Conf.Meth&Mod.Aut&Rob MMAR (2009)
18. P. Larsson, *Automatic visual behavior analysis - master thesis* (Linköping Univ., Sweden, 2002)

19. P. Olsson, *Real–time and offline filters for eye tracking - master thesis* (KTH Royal IofT, Sweden, 2007)
20. P.M.J. Van Diepen, L. Ruelens, G. d'Ydewalle, Act.Psych. **101**, 91–103 (1999)
21. J. Herz, A. Krogh, R.G. Palmer, *Introduction to the theory of neural calculations* (WNT, Warszawa, 1995)
22. D. Witkowska, *Artificial neural networks and statistical method* (C.H. Beck, Warszawa, 2002)
23. W. Kwiatkowski, *Methods of automatic pattern recognition* (Bel Std., Warszawa, 2007)
24. M. Nałęcz, *Biocybernetics and biomedical engineering Vol. 6. Neural networks* (EXIT, Warszawa, 2000)
25. S. Osowski, *Neural networks in the algorithmic perspective* (WNT, Warszawa, 1996)
26. R. Tadeusiewicz, *Neural networks* (RM, Warszawa, 1993)
27. T. Lewandowski, Z. Gomółka, M. Pieszko, AI Met. 115–130 (2010)
28. T. Lewandowski, M. Piróg, Polish J. Env.Stud. **17**, 219–223 (2008)
29. T. Kohonen, *Self–Organizing Maps* (Springer, Heidelberg, 1997)
30. Z. Gomółka, T. Lewandowski, Tech-Comp-Edu. 51–56 (2006)