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Detection of the Tonometrical Measurements Error Adapting the Radial Basis Function Method Versus Multilayer Perceptron

I. Sliesoraityte
*Departament of Signal Processing, Kaunas University of Technology,
Studentų st. 50, LT-51368 Kaunas, Lithuania, phone: +370 686 51103; e-mail: sliesoraityte@yahoo.com*

V. Paukstaitis
*Departament of Applied Electronics, Kaunas University of Technology,
Studentų st. 50, LT-51368 Kaunas, Lithuania, phone: +370 650 34300; e-mail: vpaukstaitis@yahoo.com*

V. Sliesoraitiene
*Department of Mechanics, Vilnius Gediminas Technical University,
J.Basanaviciaus str. 28a, LT-10225, Vilnius, Lithuania*

Introduction

Intraocular pressure (IOP), temporal variation of central corneal thickness (CCT) and various forms of glaucoma interdependence undoubtedly are the problems of the main importance in daily practice of theoretical as well as clinical approach. In this regard, increased tend of pseudohypertension frequency is observed, accrued the numbers of side effects defined treatment, pro rata numerical and experimental modeling is complicated as a concern of eye composite structure individualities.

Intraocular pressure per se is a dominative factor in ocular hypertension diagnosis. The values of IOP are scattered widely across experimental continuum. While true IOP values (8 to 21 mm Hg) estimated by subject norm are sufficiently wide even for healthy people, the mean statistical norm of IOP accepted in clinical practice is 15 mm Hg. Goldmann applanation tonometer (GAT) almost for the half of the century was the "Gold standard" and rated to be the most valid and reliable device, is still the most widely applied technique for IOP measurements. Although, GAT construction is based on assumption that CCT value is constant, consequently, the measured IOP values are increased for the thick corneas, in opposition, IOP readings are decreased for thin corneas.

Via experimental modeling the amplitude of IOP variation was defined, conditioned by the age, the sex, complementary diseases, pharpaceuticals, exposure to allergens, etc [1]. Accordingly, the GAT error requires the creation of new IOP measurement devices, calibration methods and mathematical models. Error sensitivity analysis of experimental data proved CCT to be confounding factor for GAT [2]. Thus additional numerical analysis must be provided for measured IOP values, when fixing the reliability of the IOP magnitudes via GAT.

This research targets to create the system, which models the detection of tonometric measurement error. Modeling the target relations (IOP vs CCT) threshold classifier and radial-basis function (RBF) classifier versus multi-layer perceptron (MLP) classifier was applied. Strictly determined discriminative function of threshold classifier, the variability of MLP training results, the stability of RBF training results guarantee the optimal detection of errors in analyzed function. Tonometric error detection is positive perspective of the disease autonomic diagnostic system when avoiding the invasive procedures, treatment based on side effects and incurable disease stigma, which in some cases is only the result of the device reading error. The discrete model realized optimal synergy between artificial neural networks and biosubject, with the purpose of minimizing the frequency of diagnostical mistakes in daily clinician practice.

Error Detection of Tonometrical Measurments by Classification Differences

Error minimization of GAT is derived from classical error elimination procedure:

$$p(h) = p'(h) - \varepsilon(h); \tag{1}$$

where $\varepsilon(h)$ - experimental pressure error, mmHg; $p'(h)$ - experimental pressure data, mmHg; $p(h)$ - real pressure data, mmHg, h - CCT, μm. Function $\varepsilon(h)$ apriori is indetermined, as the result of the uncontrollable CCT vs IOP relation even in the invasive estimation.

The researchers defined the manometrical and tonometrical association as the linear function [3]. The tonometrical measurements error was minimized through determined association, as it is presented in fig. 1, while the remaining error regarding to anaestetical influence to the eye dynamics and consequently onto ophtalmothonus is converging to zero. Thus, the experimental pressure data can be evaluated according to this equation:

$$p(h) = 40(p'(h) + 5)/55 - \varepsilon_d(h), \tag{2}$$

where - $p'(h)$ – experimental pressure, mmHg; ε_d – persistent CCT error.

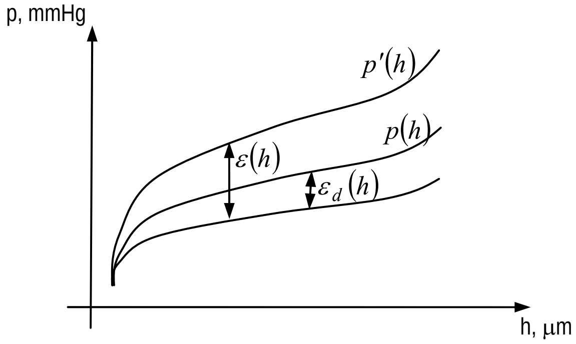

Fig. 1. Error minimization and elimination

As the thresholding factors are known apriori, we define the discriminative function for separation the classes:

$$y = \begin{cases} 0, p(h) < p_T \wedge h < h_T \\ 1, p(h) \geq p_T \wedge h \geq h_T \end{cases}, \tag{3}$$

where p_T - manometrical pressure threshold, h_T - CCT threshold.

ε_d is identified on the edge conditions, i.e. subjects with thick CCT ocular hypertension is diagnosed vice versa individuals with thin corneas glaucoma is not diagnosed. The real error function is identified when the number of edge conditioned subjects (ECS) is approaching the infinity:

$$\varepsilon_d(h) = \eta(h) \cdot \lim_{N \to \infty} f_D(h), \tag{4}$$

where $\eta(h)$ - function fitting the dimension for $\varepsilon_d(h) \equiv f_D(h)$; N - ECS number; $f_D(h)$ - ECS appearance frequency. When CCT values are discrete ones, ECS frequency is defined as follows:

$$f_D(h) = \frac{N(h)}{M}; \tag{5}$$

where $N(h)$ - ECS number for corresponding h; M - total subjects number. $N(h)$ is calculated applying the created error detection system.

Created algorithm numerically models target relations: the detection of applanation tonometry error applying the method of difference between threshold classifier and RBF network (RBFN) versus MLP results (fig. 2). Threshold classifier is not learnable, in opposition classifier based upon artificial neural network (ANN) is trained before simulating with test patterns. ANN training matrix is constructed of averaged vectors (p, h) for which p is equal. ANN test matrix is derived from vectors (p, h) for which p is identical.

The designed error detector identifies difference between classification results: erroneous are vectors (p, h) for which $y_1(i) \neq y_2(i)$, when i is column number of the test matrix. $N(h)$ is found when vectors with the same h are counted to appropriate bins.

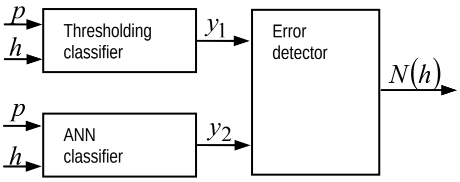

Fig. 2. Generated error detection unit

Multi-layer Perceptron Classifier

For numerical modeling of the given training set the two-layer perceptron is introduced:

$$y_k = g^{(2)}\left(\sum_{j=1}^{M} w_{kj}^{(2)} g^{(1)}\left(\sum_{i=1}^{d} w_{ji}^{(1)} x_i\right)\right); \tag{6}$$

where M - number of hidden neurons, $g^{(1)}$ - the transfer function of hidden layer, $g^{(2)}$ - the output layer's transfer function, $\vec{w}$ - the layer weights matrix.

The quantitative characteristics of analyzed objects are evaluated through MLP. Structural layout is presented in fig. 3, while construction of non-linear discriminative function is of following form:

$$z(\vec{x}, \vec{w}) = \sum_{i=1}^{N} w_i \varphi_i(\vec{x}). \tag{7}$$

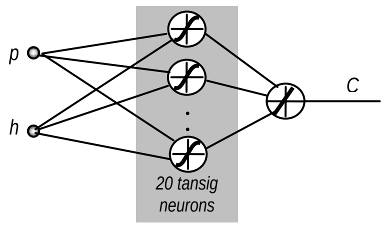

Fig. 3. Structural MLP layout

Respectively, individuals are classified as following, i.e. healthy and ill.

The set of ANN inner parameters $\vec{w}$ are modified when difference between systems' output values $y'(\vec{w}, \vec{x})$ and target values is minimal:

$$|y(\vec{x}) - y'(\vec{w}, \vec{x})| < \varepsilon, \tag{8}$$

where ε - the satisfactory training error limit.

Employing network training, the backpropagation algorithm was applied with the experimentally rated training parameters: maximum epochs – 2000, error limit – 0.017, hidden layer neurons number – 20. The trainscg function was applied for optimizing the weights of each neuron according to particular training error function.

Radial-basis Functions Classifier

Optimizing the discern among classes, i.e. healthy and ill, we provide the fitting of RBF network, which adapts its weights optimally (in reference of interpolation theory) according to the distribution function hidden in the training set:

$$z(\vec{w},\vec{x}) = \sum_{j=1}^{M} w_{kj} \exp\left(-\frac{\vec{x}^T \Sigma^{-1} \vec{x}}{2}\right) + w_{k0}\ , \qquad (9)$$

where M - radial-basis functions count, which is lower than probable input values count, w_{kj} - the weight for k-th target vector and j-th radial-basis function, Σ^{-1} - inverse covariance matrix.

The created RBF model consists of the first layer's weights (the exponential function parameters) identified by optimization methods from training vectors, while the second layer's weights are evaluated as the linear equation's assertion:

$$\vec{W}^T = \Gamma^+ \vec{T}\ ,\ (\Gamma)_{nj} = \gamma_j\left(\vec{x}^n\right), \qquad (10)$$

where Γ^+ - pseudoinversion of matrix Γ, $\vec{T}$ - the vector of target classes for input vector $\vec{x}^n$, γ_j - the Gaussian function derived from (9), $n = 1...N$, N - the quantity of input vectors, $j = 1...J$, J - the first layer's RBF quantity.

The optimal designed radial-basis function width is 20 and maximal count of neurons – 20, when obtaining minimal error of the network.

RBF and MLP Performance Comparison

Incorporation the stability of results (average and variance of 1000 experiments), adaptation to training set, generalization of the training set, qualitative evaluation of class reflection characteristics is applied for qualitative and quantitive analysis when comparing the classification differences in threshold classifier and MLP vs RBFN for detection of the tometrical measurement error.

Table 1. Comparison of Stability Results MLP vs RBF

MLP			RBF		
h, μm	p, mmHg	O	h, μm	p, mmHg	O
524	17,8182	10			
550	17,8182	18			
555	19,7097	66	555	19,7097	1000
560	20,2909	322	560	20,2909	1000

The comparative stability characteristics of experimental results are presented in table 1. While running RBF network for the explored relation, there had been identified two equal error vectors for all thousand experiments, consequently, the average is equal to those detected vectors and variance is zero. The increasing non-linear error detection frequency function is observed when the MLP was adapted for training set for each scalar h. In concluding remarks, it should be noted that the detected vectors are same in except of their detection frequency, the average is equal to those detected vectors by MLP and variance is zero.

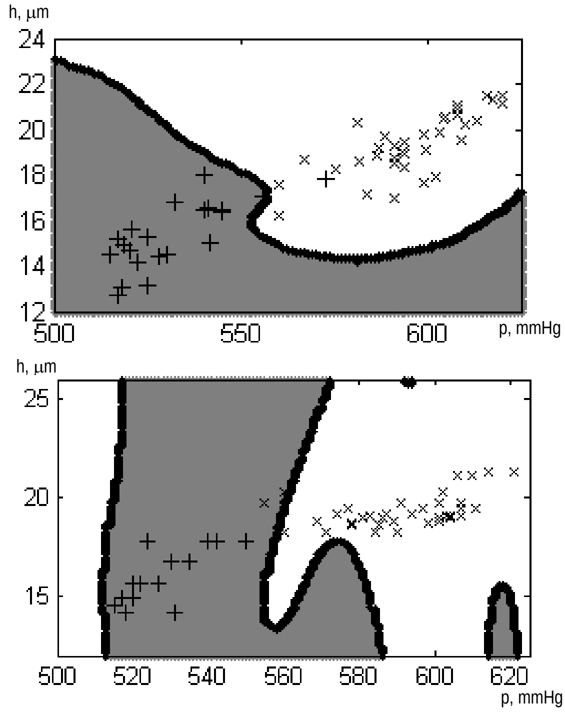

Fig. 4. Discriminative fields and function founded by MLP (top) and RBF (bottom) and the test set

The h interval obtained by RBF network is narrower than that obtained by MLP, though RBFN determines identical results for all experimental cycles and the stable error function had been observed. While adapting MLP for evaluated expression, the detection is not concluded for more than 50% of experimental loops for the reason, that the MLP redesigns the training data on each experimental cycle, as a result the increasing non-linear function is observed for those loops where the error has been detected.

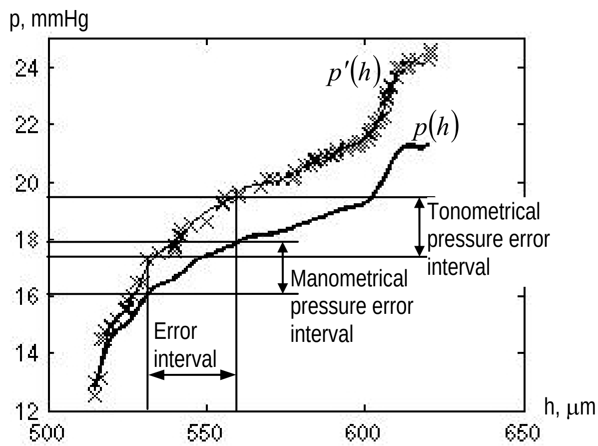

Fig. 5. IOP vs CCT approximation by RBF ANN and intervals of errors

Both ANNs underadapts to training set in the created system, thus showing that the learning parameters are optimal and the calculated discriminative surfaces cover the experimental continuum. The discriminative curve simulated by RBFN is identical and desirably optimal for every training cycle; the discriminative function obtained by MLP is not stable and the optimum is not achieved on every training cycle (Fig. 4). Optimal adoption to the training set is observed for RBF and MLP when investigating the created discriminative functions.

The qualitative and quantitive comparison directs to the conclusion that the RBFN is preferable in comparison with MLP: tonometrical measurement error is detected in the central part of IOP vs CCT curve (Fig. 5). These errors are edge conditioned subjects and present the minority of the test set matrix.

Conclusions

Applying the differences among the results of two classifiers: threshold and multi-layer perceptron classifier - tonometrical IOP error detection function was variable; threshold and radial-basis function classifier – tonometrical eye pressure error detection function was constant. In both cases, error has been identified in the central part of IOP vs CRS curve, i.e. edge conditioned subject values, which are minority of the test data. The RBF network compared with the MLP, optimally redesigns training set and learns faster, thus these concepts are the key ones in disease autonomic diagnostic system.

Analysis provided by authors, i.e. the influence of the central cornea thickness to tonometrical measurements error elimination, applying the radial-basis function classifier vs multi-layer perceptron classifier when evaluating the reliability of the IOP readings via GAT. The created system embodied the optimal synergy among artificial neural networks and the biosubject targeting the minimization of erroneous diagnosis in daily clinician practice.

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I. Sliesoraityte, V. Paukstaitis, V. Sliesoraitiene. Detection of the Tonometrical Measurements Error Adapting the Radial Basis Function Method Versus Multilayer Perceptron // Electronics and Electrical Engineering.- Kaunas: Technologija, 2006.– No. 3(67).– P. 77–80.

The values of eye pressure as well as the values of other parameters of the biological environment vary within a wide range, whereas the amplitude of variation depends on the age, the sex, adjacent diseases, medicines, exposure to allergens, and etc. The computation of the accurately measured eye pressure is the positive perspective of the system for diagnosing the autonomous disease. This research targets to create the system, which models the detection of tonometric measurment error. Modeling the target relations (IOP vs CCT) thresholding classifier and radial-basis function classifier versus multi-layer perceptron classifier was applied.. By numerical experiments, we have proved that the discrete model applied is adequate to the modeling of the expression being analyzed and that the optimal synergy of artificial neural networks and the biosubject is realized with the purpose of minimizing the frequency of diagnostical mistakes in the everyday activities of the clinician. Ill. 5, bibl. 3 (in English; summaries in English, Russian and Lithuanian).

И. Слесорайтите, В. Паукштайтис, В. Слесорайтене. Определение погрешности тонометрических измерений при помощи метода радиальных базисных функций в сравнении с многоуровневым перцептроном // Электроника и электротехника. – Каунас: Технология, 2006. – №. 3(67). – С.77–80.

Значения глазного давления, как и значения других параметров биологической среды, колеблются в широком диапазоне, в то время как амплитуда колебания обусловливается возрастом, полом, смежными болезнями, медикаментами, подвергаемости аллергенам и др. Вычисление точного измеряемого глазного давления – положительная перспектива системы диагностирования автономной болезни. Цель исследования – создание системы в ходе моделирования выраженного определения погрешности тонометрических измерений. Для моделирования измеряемого глазного давления с учетом влияющих зависимостей мы адаптировали разностный метод порогового классификатора и радиальных базисных функций в сравнении с многослойным перцептроном. Численными экспериментами мы доказали, что примененная дискретная модель адекватна моделированию анализируемого выражения, а при помощи созданной системы с целью минимизации частоты диагностических ошибок в ежедневной работе клинициста осуществляется оптимум синергии искусственных нейронных сетей и биосубъекта. Ил. 5, библ. 3 (на английском языке; рефераты на английском, русском и литовском яз.).

I. Sliesoraitytė, V. Paukštaitis, V. Sliesoraitienė. Tonometrinių matavimų paklaidos detekcija, taikant radialinių bazinių funkcijų metodą lyginant su daugiasluoksniu perceptronu // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2006.– Nr. 3(67).– P. 77–80.

Akispūdžio vertės, kaip ir kitų biologinės terpės parametrų, svyruoja plačiame diapazone, kai svyravimo amplitudė yra sąlygojama amžiaus, lyties, gretutinių ligų, medikamentų, alergenų ekspozicijos ir kt. Tikslaus išmatuojamo akispūdžio apskaičiavimas – teigiama autonominės ligos diagnozavimo sistemos perspektyva. Tyrimo tikslas – sukurti sistemą, kai išraiška modeliuojama tonometrinių matavimų paklaidos detekcija. Išmatuojamo akispūdžio įverčiams įtaką darančioms priklausomybėms modeliuoti, adaptavome slenkstinio klasifikatoriaus ir radialinių bazinių funkcijų skirtuminį metodą lyginant su daugiasluoksniu perceptronu. Skaitiniais eksperimentais įrodėme, kad taikytas diskretinis modelis yra adekvatus analizuojamos išraiškos modeliavimui, o sukurta sistema, siekiant minimizuoti diagnostinių klaidų dažnį kasdieniame klinicisto darbe, įgyvendinamas dirbtinių neuroninių tinklų ir biosubjekto sinergijos optimumas. Il. 5, bibl. 3 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).