The Application of Genetic Algorithms in the Biological Medical Diagnostic Research

Xi Wang

Software College
Nanyang Normal University
Nanyang, 473061 China
E-mail: nanyangwangxi@163.com

Received: February 18, 2016 **Accepted: November 10, 2016**

Published: December 31, 2016

Abstract: *In this paper, a genetic algorithm is used to determine the Mean Corpuscular Volume (MCV) as the optimal decision-making criterion for anemia caused by iron deficiency based on the diagnostic test of patients with such anemia. On the premise of attaining maximum sensitivity and specificity for the cost, this paper studies the impact of the cost ratio of the optimal decision-making criteria and compares the mathematical derivation and binominal model method, so as to discuss the application of the optimal diagnostic criteria in the genetic algorithm and provide a practical study method for the diagnostic test.*

Keywords: *Genetic algorithm, Biomedicine diagnostic analysis, Sensitivity and specificity, Optimal diagnostic criterion.*

Introduction

The diagnostic test is a common and important method for guiding clinical diagnosis of disease. If a certain index has been improved to have a diagnostic value assigned to a certain disease, the optimal decision-making level of the index can be determined. The optimal decision-making criteria requires that both sensitivity and specificity be optimized. As for the diagnostic test, an increase in sensitivity will reduce the specificity as the two aspect conflict [18]. How to determine the optimal decision-making criteria of a diagnostic test by utilizing a genetic algorithm is the focus of this study.

In 1975, Lusted published an influential academic paper in the journal Science, stating that the Reveuver Operating Characteristics (ROC) curve is an ideal tool in research to evaluate the diagnostic test value. In statistical methods in diagnostic medicine, the ROC curve has many advantages such as being fit for the binominal model curve free from the influence of prevalence rate. Furthermore, it has the inherent capability to distinguish a disease and non-disease condition based on the influence of the disease frequency spectrum and patient characteristics, which covers a larger area of the ROC curve, and the application value is higher [8]. The ROC curve is a visible expression of the accuracy, and the decision-making variables can be marked on the curve, including all possible decision-making criteria, that do not relying on the measuring unit of the test results. The application of the curve to determine the best decision-making criteria of a diagnostic test is currently a widely recognized method. However, the information of the curve has not so far been fully utilized as only some of sample sensitivity and specificity calculation results and the software analyzing results are used for the selection of optimal decision-making criteria, or some researchers consider only the intersection of the sensitivity and the specificity as the optimal decision-making point regardless of the non-uniqueness of the optimal solution of sensitivity and specificity. Thus, there are some limitations in practice [3].

It is relatively reasonable to define the optimal decision-making criteria of a diagnostic test as the value at the curve point with the minimum average influence on the economy and health (or cost) [6]. Two assumptions are provided to obtain the optimal decision-making criterion: (1) treatment is provided for ones who have disease in place of those who do not have disease; (2) whether to undergo treatment is decided by the test result of the positive ones rather than the negative ones that are given with treatment.

In practical use, the optimal decision-making criteria relies on the costs of test implementation and test results. The costs of test implementation include the implementation technology cost, business cost, and cost of influence of complications on health caused by the diagnostic test, while the costs of test results include the true-positive result cost, false-positive result cost, true-negative result cost, and false-negative result cost [1, 10, 11, 22]. The costs can be estimated based on the reviews of patients, doctors, insurance companies as well as the social expectations. The cost cannot be neglected for determining the optimal decision-making criteria of diagnostic tests although little attention from researchers has been given to the cost in practice [7, 12, 15]. The optimal decision-making criteria can be resolved through the mathematic derivation or binominal model method in application. Although mathematic derivation will lead to highly accurate results, it is not easy for medical researchers to master the method, and the binominal model method is also difficult to complete as the actual data cannot satisfy the binominal distribution [2].

Materials and methods

Characteristics of multi-objective optimization

(1) In most cases, the Pareto optimal solution, other than single-objective optimal solution, exists in multi-objective matters, and it is a solution set including all "not bad" solutions [9].

(2) If the multi-objective matter has an optimal solution, the solution must be a Pareto solution instead of other solutions, thus the Pareto optimal solution is the solution set suitable for multi-objective matters.

(3) In general, a Pareto optimal solution is a gather. The final decision about an actual problem shall be made according to the degree of awareness of the problem and the preference of the decision maker. One or some solution of the Pareto optimal solution set will be selected as the optimal solution of the multi-objective optimization matter. Therefore, the first and essential step for solving multi-objective matter is to obtain as man Pareto optimal solutions as possible [5, 13, 21].

Mathematic model of multi-objective optimization

The expression of the mathematic model of multi-objective optimization is as follows:

$$\begin{cases} V_{\max} = \max f(x), f(x) = \left[f_1(x), f_2(x), \cdots, f_k(x) \right]^{\mathrm{T}} \\ s.t. \quad x \in X \\ \qquad X \in R^m \end{cases}. \tag{1}$$

MOP (Multi-objective Optimization Problem) matter consists of m decision-making variable parameters, k objective functions and n constraint conditions (m, k and n refers to the amount), $V_{\max}$ refers to the largest possible sub-objective of the vector-objective function $f(x)$,

$X \in R^m$ is the constraint set of multi-objective optimization model, and x is the practicable value range of the decision vector [17].

Data

In order to determine the diagnostic standard for iron deficient anemia patients via Mean Corpuscular Volume (MCV), 100 dubious iron deficient anemia patients are set as the study objectives, and the marrow diagnosis is set as the as the golden standard. According to the golden standard, 34 patients with anemia belong to the case group while the remaining 64 belong to the non-case group, so the prevalence rate of the samples is 34%. The MCV of the patients is shown in Table 1.

Table 1. 100 cases of suspected patients with iron deficient anemia MCV Results

The diagnosis of bone marrow	**Bone marrow**	**Blood tests – the MCV**													
Case group	66	61	66	69	72	72	73	74	74	74	75	78	78	78	78
		78	77	77	79	79	80	80	81	82	82	82	83	83	83
		82	83	83	83	82	84	84	84	84	84	85	84	84	85
		87	88	88	88	89	88	87	85	85	85	85	86	86	86
		96	95	95	95	94	94	98	100	102	102				
Non-case group	35	53	58	59	62	68	69	72	73	73	73	74	75	75	75
		76	76	76	77	77	78	78	77	77	79	79	81	80	80
		85	85	86	86	88	88	90							

The performance is evaluated by the sensitivity (*Se*) and the specificity (*Sp*) [4, 20], False-positive rate and Youden's index:

(1) Sensibility $Se = \frac{a}{a+c}$.

(2) Specificity $Sp = \frac{d}{d+b}$.

(3) False-positive rate $FPR = 1 - Sp$.

(4) Youden's index $YI = Se + Sp - 1$.

As shown in Table 2, the sensitivity, specificity and Youden's index are the accuracy indexes for diagnosing the test itself. In order to determine whether increasing the target number can improve search precision, the following two indexes associated with specificity and sensitivity are increased.

Table 2. Diagnostic test decision matrix

Diagnostic test	**"Gold standard"**		**Total**
	Cases	**Not the case**	
Positive	*a*	*b*	*a* + *b*
Negative	*c*	*d*	*c* + *d*
Total	*a* + *c*	*b* + *d*	*n*

(5) Sum of sensitivity and specificity *sum* = *Se* + *Sp*.

(6) Product of sensitivity and specificity $prod = Se \times Sp$.

Curve fitting

The curve models of sensitivity and specificity are established, with the Youden's index, sum of sensitivity and specificity and product of sensitivity and specificity to MCV and ROC (Receive Operating Characteristic) curve model. Calculate u_{se} conversion value from the binomial distribution according to the sample sensitivity,

$u_{se} = probit\ (1 - Se)$,

and establish a curve model of MCV to u_{se} conversion value. The evaluation and selection of model fitting effect decide the coefficient and residual plot.

Optimization method with cost considered

The Upstream costs for test implementation are recorded as C_0, including the test technologies, business costs and health costs caused by test complications. Costs of test results include: C_{TP} (cost of true positive result), C_{FP} (cost of false positive result), C_{TN} (cost of true negative result) and C_{PN} (cost of false negative result). Their appearing probabilities are adopted as the weight of cost, therefore, the total average cost of a test is:

$$C = C_0 + P_{TP}C_{TP} + P_{FP}C_{FP} + P_{TN}C_{TN} + P_{FN}C_{FN}\,, \tag{2}$$

$$C = Se\ p\left(C_{TP} - C_{FN}\right) + \left(1 - sp\right)\left(1 - p\right)\left(C_{FP} - C_{TN}\right) + pC_{FN} + \left(1 - p\right)C_{TN}\,, \tag{3}$$

where, $Se = f(1 - Sp)$ is the ROC curve model, P being the "morbidity rate", i.e., prior probability. From Eq. (3), it can be seen that the cost of a test depends on the test sensitivity and specificity, and prior probability of the disease and consequences caused by test decisions [16].

The purpose of a diagnostic test is to determine the optimal decision-making criteria on the premise of the minimizing total costs. Therefore, the differential of C to $(1 - Sp)$ must be calculated, and the derivative of se to $(1 - Sp)$ is calculated by setting the derivative to be 0, as follows:

$$slope = \frac{1 - p}{p}\frac{C_{FP} - C_{TN}}{C_{FN} - C_{TP}}\,. \tag{4}$$

Slope is the slope at the best working point of the ROC curve, in which

$$CR = \frac{C_{FP} - C_{TN}}{C_{FN} - C_{TP}}$$

is referred to as the cost ratio.

The best decision point does not depend on the test cost, but only depends on the costs of test results. It is often very difficult to estimate the cost of a diagnostic test. However, here only the cost ratio is needed; i.e., the ratio between the difference of *FP* and *TP* costs and the difference of *FN* and *TP* costs, thus reducing the complexity of the problem.

(1) Mathematical derivation and root-finding methods

The derivation of ROC curve equation is determined as $Se = df(1 - Sp)$. If the tangent point is the best working point, then the derivative is equivalent to Eq. (4),

$$df\left(1-sp\right)=slope\,. \tag{5}$$

The root of Eq. (5) obtains the specificity (*Sp*) of the best working point, then *Sp* is plugged into the ROC curve equation to calculate the sensitivity (*Se*).Then the best working point on the ROC curve – ((1 – *Sp*), *Se*) is obtained [14, 19].

The se and spare plugged into the curve equations of sensitivity and specificity to MCV to resolve the optimal decision values of MCV.

(2) Binomial model method

In the living example, the decrease in MCV may cause anemia. A case group and a non-case group are set. The specificity and sensitivity of the best working point on a ROC curve are:

$$Se=probnorm\left(\frac{a-b\sqrt{a^2+\left(1-b^2\right)\ln\left(slope/b\right)}}{1-b^2}\right), \tag{6}$$

$$Sp=1-probnorm\left(\frac{ab-b\sqrt{a^2+2\times\left(1-b^2\right)\ln\left(slope/b\right)}}{1-b^2}\right). \tag{7}$$

Slope is the tangent slope of the best working point calculated according to the cost. Plug *Se* and spare the curve equations of sensitivity, while specificity and u_{se} conversion value to MCV resolve the optimal decision values of MCV respectively.

(3) Multi-objective genetic algorithm and parameter settings

Convert Eq. (5) into

$$abs\left(df\left(1-Sp\right)-slope\right)=0\,. \tag{8}$$

The derivation of slope is calculated by the equation with two methods; the minimum cost ratio and deviation of ROC curve is 0. The genetic algorithm is expected to minimize the deviation with 0. As the procedure used is to obtain the minimum of a function, the results will be inverted. The deviation is defined as:

$$constraint=-abs\left(df\left(1-Sp\right)-slope\right). \tag{9}$$

The equation is regarded as an objective function of the multi-objective genetic algorithm.

On the ROC curve, any straight line equation can be expressed as:

$$\begin{aligned} &Se = intercept + slope\left(1 - Sp\right),\ slope > 0 \\ &intercept = Se - slope\left(1 - Sp\right). \end{aligned} \tag{10}$$

When the straight intercept is the largest, the straight line is the tangent of the ROC curve. The slope in Eq. (10), is calculated with Eq. (4) and the straight line is of the tangent of the best working point. Eq. (10) is regarded as the second objective function of the multi-objective genetic algorithm. Therefore, considering the cost, the objective function of the multi-objective genetic algorithm is:

$$\begin{cases} V - \max\ f\left(Se, Sp\right) = \left[intercept,\ constraint\right]^{\mathrm{T}} \\ s.t. \quad Se,\ Sp \in \left[0,\ 1\right] \end{cases}. \tag{11}$$

The Pareto set of the best working point ((1 – *Sp*), *Se*) on the curve is obtained by using the multi-objective genetic algorithm.

Plug *Se* and *Sp* in the curve equations of sensitivity and specificity to MCV to resolve the optimal decision values of MCV respectively.

Five multi-objective genetic algorithms are used to search the Pareto solutions and eight Pareto solutions are given respectively by each of these approaches. The initial population of the genetic algorithm is 100; crossover probability is 0.90; mutation probability is 0.05; evolution algebra is 100.

Results and discussion

Various cut-off points of MCV are taken to calculate the sensitivity, specificity, false-positive rate, false-negative rate, Youden's index, sum of sensitivity and specificity and product of sensitivity and specificity and use conversion values of diagnostic test. The results are shown in Table 3.

Table 3. 100 cases of patients with iron deficient anemia MCV various cut-off points of sensitivity, specific degrees

MVC cut-off point	*Se*	*Sp*	*FPR*	Youden's index	Sum	Product	Use
52	0.0001	1.0000	0.0000	0.0000	1.0000	0.0001	-3.2154
53	0.0236	1.0000	0.0000	0.0241	1.0232	0.0215	-1.1233
54	0.0548	1.0000	0.0000	0.0252	1.0525	0.0515	-1.2355
55	0.0588	0.9856	0.0154	0.1024	1.0365	0.0526	-1.0322
56	0.0254	0.9858	0.0165	0.1520	1.0369	0.0525	-1.0061
57	0.1178	0.9254	0.0165	0.1682	1.0524	0.1123	-1.0214
58	0.1758	0.9102	0.0541	0.2541	1.0658	0.1145	-0.9696
59	0.1458	0.9352	0.0625	0.2695	1.0789	0.1174	-0.9252
60	0.1456	0.9351	0.0958	0.2825	1.0748	0.1125	-0.8583
61	0.6254	0.8878	0.0958	0.2915	1.0858	0.1425	-0.8150
62	0.5255	0.8986	0.1023	0.2021	1.0959	0.1456	-0.8982
63	0.2546	0.8457	0.1065	0.2021	1.1252	0.1485	-0.9584
64	0.2688	0.8325	0.1253	0.2021	1.1236	0.1498	-0.6582

65	0.3546	0.8314	0.2536	0.2265	1.1245	0.2103	-0.5856
66	0.3254	0.8252	0.2598	0.2625	1.1256	0.2163	-0.3262
67	0.4125	0.82454	0.2685	0.2695	1.1369	0.2175	-0.3653
68	0.4141	0.82325	0.2698	0.2895	1.3625	0.2199	-0.3652
69	0.4250	0.82125	0.2714	0.2925	1.3541	0.2912	-0.2446
70	0.5123	0.82102	0.2742	0.2925	1.3589	0.2196	-0.1238
71	0.5125	0.82014	0.2753	0.2529	1.2502	0.3021	-0.0213
72	0.6484	0.82453	0.2769	0.3256	1.2036	0.3125	0.0000
73	0.6858	0.85125	0.2789	0.2262	1.2427	0.3069	0.0742
74	0.7455	0.84251	0.2796	0.1625	1.2858	0.3169	0.1426
75	0.7852	0.83626	0.3025	0.1365	1.3024	0.3658	0.2522
76	0.7365	0.83610	0.4102	0.1399	1.3620	0.3655	0.6235
77	0.7623	0.82154	0.5021	0.1021	1.3021	0.3698	0.7145
78	0.8501	0.82015	0.5123	0.1362	1.0366	0.3782	1.0251
79	0.8214	0.81456	0.5236	0.0925	1.0329	0.3795	1.1235
80	0.8689	0.81256	0.5365	0.0928	1.0952	0.4012	1.1396
81	0.8982	0.72515	0.5456	0.0985	1.0685	0.4123	1.2858
82	0.9102	0.72151	0.5569	0.0925	1.0548	0.4256	1.5265
83	0.9254	0.6254	0.6251	0.0369	1.0369	0.4603	1.5485
84	0.9269	0.6201	0.6352	0.0365	1.0364	0.4714	1.8586
85	0.9548	0.5241	0.6857	0.0365	1.2054	0.4758	1.8282
86	0.9856	0.5362	0.6958	0.0457	1.0236	0.4853	1.8484
87	0.9869	0.4215	0.7154	0.0546	1.2054	0.3021	1.8569
88	1.0000	0.4102	0.7521	0.0546	1.2856	0.3695	1.8588
89	1.0000	0.4003	0.7695	0.0569	1.1629	0.3625	1.8752
90	1.0000	0.3202	0.7958	0.0574	1.1649	0.3652	1.8769
91	1.0000	0.3251	0.8145	0.0485	1.1362	0.3698	1.9263
92	1.0000	0.3012	0.8585	0.0412	1.1036	0.3548	1.9485
93	1.0000	0.2858	0.8789	0.0326	1.2039	0.2698	1.9496
94	1.0000	0.2715	0.8920	0.0352	1.3026	0.2458	2.0524
95	1.0000	0.26254	0.9254	0.0325	1.1020	0.2758	2.0698
96	1.0000	0.1032	0.8365	0.0314	1.1825	0.2958	2.1263
97	1.0000	0.0625	0.9584	0.0320	1.1325	0.5658	2.2657
98	1.0000	0.0352	0.9656	0.0201	1.2014	0.1025	2.3561
99	1.0000	0.0123	0.9685	0.0102	1.2658	0.1235	2.4596
100	1.0000	0.0323	0.9789	0.0120	1.2688	0.0365	2.5698
101	1.0000	0.0023	0.9895	0.0100	1.2515	0.0325	2.7456
102	1.0000	0.0012	0.9958	0.0020	1.2302	0.0215	2.8965
103	1.0000	0.0003	1.0000	0.0000	1.2302	0.0210	2.9214
104	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	2.9563

Curve fitting

According to the data in Table 3, the curve fitting for MCV is carried out with sensitivity, specificity, Youden's index, sum of sensitivity and specificity and product of sensitivity and specificity, and the fitting for sensitivity and false positive rate (1 – *Sp*) are carried out into a ROC curve model. The results are shown in Table 4 and the graph and residual plot are shown in Figs. 1-12. The fitting effects of six curve models are good; R^2 is greater than 95%, and the residuals are distributed randomly around zero.

Table 4. The MCV and sensitivity, specific degree of fitting curve equation

		Curve model name	R^2
1	Sensitivity	Logistic model: $Se = a/(1 + b\exp(-c\text{MCV}))$ $Se = 1.03256/[1 + 1695525.36\exp(-0.18325\text{MCV})]$	0.9985
2	Specific degrees for the MCV	Sinusoidal fit: $Sp = a + b\cos(c\text{MCV} + d)$ $Sp = 0.50251 + 0.5225632\cos(0.071523\text{MCV} + 20.2325)$	0.9815
3	Index of the MCV	Sinusoidal fit: $YI = a + b\cos(cx + d)$ $YI = 0.14254 + 0.1254524\cos(0.130214\text{MCV} - 4.021523)$	0.9485
4	Degree of sensitivity and the MCV	Sinusoidal fit: $sum = a + b\cos(cx + d)$ $sum = 1.145445 + 0.14256\cos(0.13625\text{MCV} - 4.36025)$	0.9658
5	Degree of sensitivity to product for the MCV	Sinusoidal fit: $prod = a + b\cos(c\text{MCV} + d)$ $prod = 0.195852 + 0.203255\cos(0.142515\ \text{MCV} - 4.92456)$	0.9685
6	Sensitivity to the false positive rate	Weibull model: $Se = a - b\exp(-c(1 - Sp)^d)$ $Se = 1.152545 - 1.123654\exp(-2.022355(1 - Sp)^{0.825412})$	0.9987
7	MCV for sensitivity, specific degrees	Quadratic: $\text{MCV} = 75.254 + 78.251Se - 51.254Se^2 - 66.257Sp + 47.145Sp^2$	0.9898
8	MCV to u_{se}	Quadratic: $\text{MCV}_{se} = 76.254 + 8.545u_{se} + 0.2415u_{se}{}^2$	0.9814

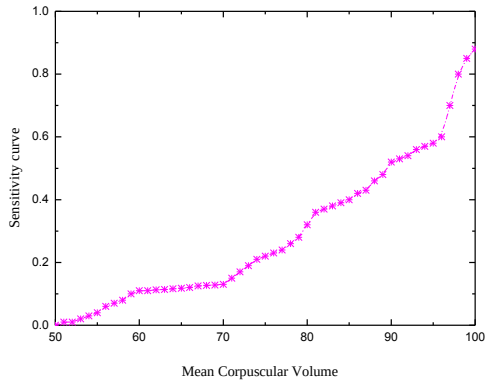

Fig. 1 MCV and sensitivity curves

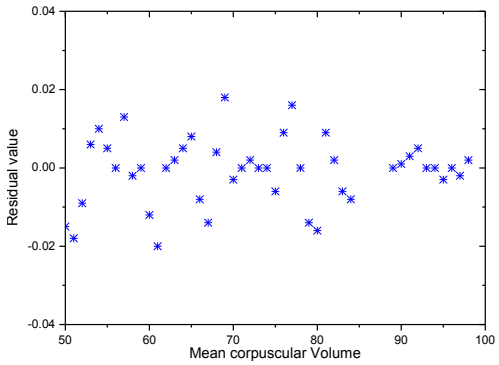

Fig. 2 MCV and sensitivity residual value

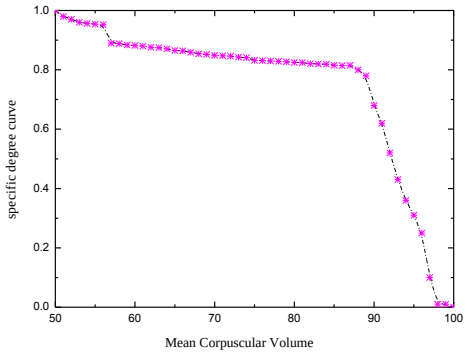

Fig. 3 MCV and specificity curve

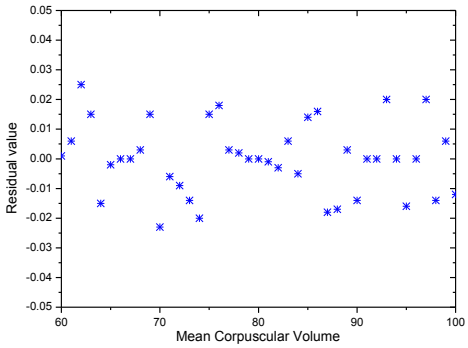

Fig. 4 MCV and specificity residual value

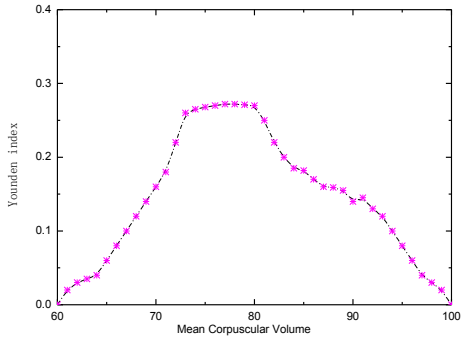

Fig. 5 MCV and the Youden's index curve

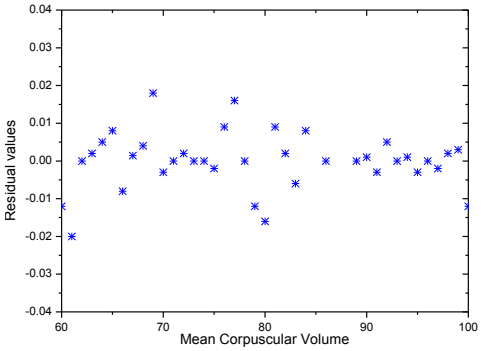

Fig. 6 MCV and Youden's index residual values

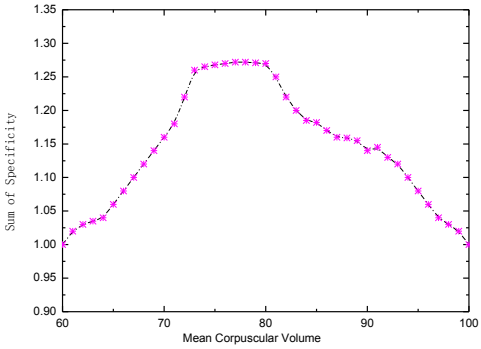

Fig. 7 MCV and sensitivity degree of specific curve

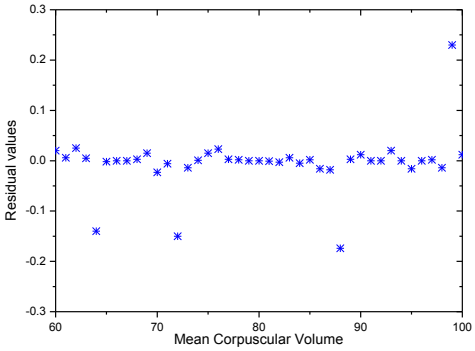

Fig. 8 MCV and specificity residual values

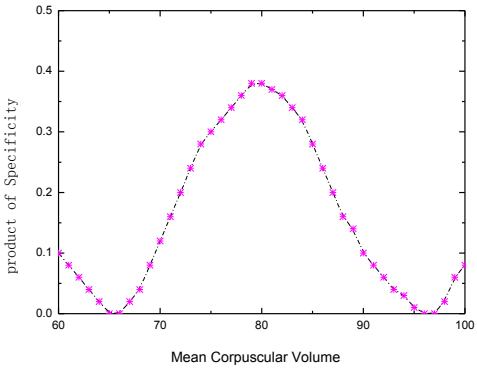

Fig. 9 MCV and sensitivity degree product curve

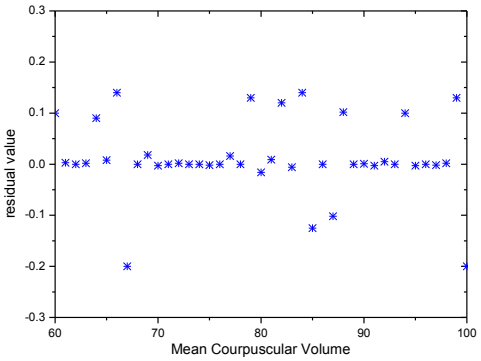

Fig. 10 MCV and sensitivity degree product residual values

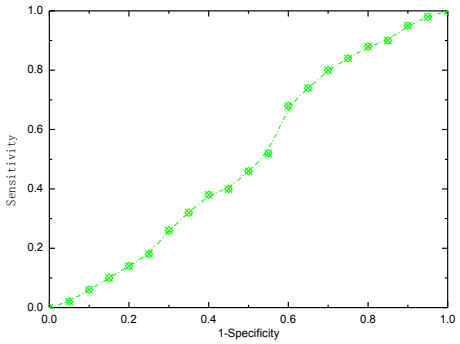

Fig. 11 MCV ROC curve

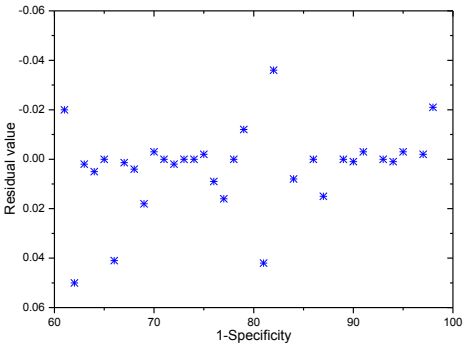

Fig. 12 ROC curve residual value

Direct solution of intersections

Fig. 13 shows that the MCV value at the intersection of sensitivity and specificity curves is about 80, when the sensitivity and specificity is about 65%.

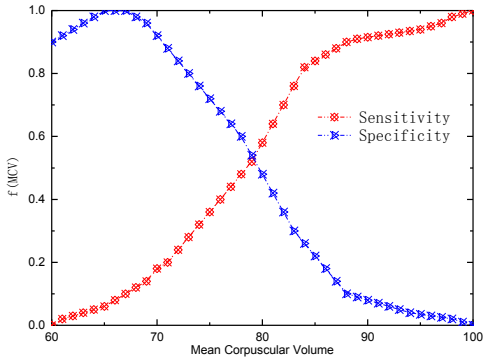

Fig. 13 MCV and sensitivity curve contrast MCV and specific curve

The two curve equations fit with sensitivity and specificity:

$$Se = \frac{1.03265}{1+169254.2\exp\left(-0.185456\text{MCV}\right)}, \tag{11}$$

$$Sp = 0.524535 + 0.523558\cos\left(0.0172564\text{MCV} + 20.362545\right). \tag{12}$$

The intersection coordinate is obtained with a mathematical method,

MCV = 80.80(*ft*), *Se* = *Sp* = 63.69%.

Conclusion

From the practical application of optimization, the genetic algorithm is an ideal random search method, having solved the selection problem of optimal decision-making criteria for a diagnostic test and has feasibility and practicability. For two conflicting objective optimization problems of sensitivity and specificity, a multi-objective genetic algorithm can quickly resolve the optimal decision-making criteria with the sensitivity and specificity as the objective functions without considering the cost.

References

1. Aalaei S., H. Shahraki, A. Rowhanimanesh, S. Eslami (2016). Feature Selection Using Genetic Algorithm for Breast Cancer Diagnosis: Experiment on Three Different Datasets, Iranian Journal of Basic Medical Sciences, 19(5), 476-482.
2. Adeli M., N. Bigdeli, K. Afshar (2013). New Hybrid Hepatitis Diagnosis System Based on Genetic Algorithm and Adaptive Network Fuzzy Inference System, 21st Iranian Conference on Electrical Engineering (ICEE'13), 1-6.
3. Anastasio M. A., H. Yoshida, R. Nagel, R. M. Nishikawa, K. Doi (1998). A Genetic Algorithm-based Method for Optimizing the Performance of a Computer-aided Diagnosis Scheme for Detection of Clustered Microcalcifications in Mammograms, Medical Physics, 25(9), 1613-1620.

4. Bhoi A. K., K. S. Sherpa, B. Khandelwal (2015). Classification Probability Analysis for Arrhythmia and Ischemia Using Frequency Domain Features of QRS Complex, International Journal Bioautomation, 19(4), 531-542.
5. Davidsen S. A., M. Padmavathamma (2015). Multi-modal Evolutionary Ensemble Classification in Medical Diagnosis Problems, International Conference on Advances in Computing, Communications and Informatics, 50, 369-70.
6. Ibrahim A. O., S. M. Shamsuddin, N. B. Ahmad, S. N. Qasem (2013). Three-term Backpropagation Network Based on Elitist Multiobjective Genetic Algorithm for Medical Diseases Diagnosis Classification, Horticultura Brasileira, 10(4), 348-356.
7. Jennane R., A. Almhdie-Imjabber, R. Hambli, O. N. Ucan, C. L. Benhamou (2010). Genetic Algorithm and Image Processing for Osteoporosis Diagnosis, 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 5597-5600.
8. Karegowda A. G., A. S. Manjunath, M. A. Jayaram (2011). Application of Genetic Algorithm Optimized Neural Network Connection Weights for Medical Diagnosis of Pima Indians Diabetes, International Journal on Soft Computing, 2(9), 89-96.
9. Kumar P. S., D. Anand (2016). A Computational Intelligence Method for Effective Diagnosis of Heart Disease Using Genetic Algorithm, International Journal of Bio-science and Bio-technology, 8(2), 363-372.
10. Lazli L., B. Mounir, A. Chebira, K. Madani (2011). Connectionist Probability Estimators in Hmm Using Genetic Clustering Application for Speech Recognition and Medical Diagnosis, International Journal of Digital Information & Wireless Communications, 1(1), 14-31.
11. Lee K. K., C. H. Han (2008). Medical Diagnosis Problem Solving Based on the Combination of Genetic Algorithms and Local Adaptive Operations, Maternal & Child Health Care of China, 14(2), 193-206.
12. Liang H., Z. Lin, R. W. McCallum (2000). Application of Combined Genetic Algorithms with Cascade Correlation to Diagnosis of Delayed Gastric Emptying from Electrogastrograms, Medical Engineering & Physics, 22(3), 229-234.
13. Maiorana A., F. Barbetti, A. Boiani, V. Rufini, M. Pizzoferro, P. Francalanci, F. Faletra, C. G. Nichols, C. Grimaldi, J. de Ville de Goyet, J. Rahier, J. C. Henquin, C. Dionisi-Vici (2014). Focal Congenital Hyperinsulinism Managed by Medical Treatment: A Diagnostic Algorithm Based on Molecular Genetic Screening, Clinical Endocrinology, 81(5), 679-688.
14. Mantzaris D., G. Anastassopoulos, A. Adamopoulos (2011). Genetic Algorithm Pruning of Probabilistic Neural Networks in Medical Disease Estimation, Neural Networks, 24(8), 831-835.
15. Özçift A., A. Gülten (2013). Genetic Algorithm Wrapped Bayesian Network Feature Selection Applied to Differential Diagnosis of Erythemato-squamous Diseases, Digital Signal Processing, 23(1), 230-237.
16. Park Y. J., B. C. Kim, S. H. Chun (2006). New Knowledge Extraction Technique Using Probability for Case-based Reasoning: Application to Medical Diagnosis, Expert Systems, 23(1), 2-20.
17. Sanz J., A. Fernández, H. Bustince, F. Herrera (2010). A Genetic Algorithm for Tuning Fuzzy Rule-based Classification Systems with Interval-valued Fuzzy Sets, 2010 IEEE International Conference on Fuzzy Systems (FUZZ), 23(3), 1-3.
18. Sanz J., M. Pagola, H. Bustince, A. Brugos, A. Fernández, A. Herrera (2011). A Case Study on Medical Diagnosis of Cardiovascular Diseases Using a Genetic Algorithm for Tuning Fuzzy Rule-based Classification Systems with Interval-valued Fuzzy Sets, Advances in Type-2 Fuzzy Logic Systems, 78, 9-15.

19. Sanz J. A., M. Galar, A. Jurio, A. Brugos, M. Pagola, H. Bustince (2014). Medical Diagnosis of Cardiovascular Diseases Using an Interval-valued Fuzzy Rule-based Classification System, Applied Soft Computing, 20(20), 103-111.
20. Spasova V., I. Iliev, G. Petrova. (2016). Privacy Preserving Fall Detection Based on Simple Human Silhouette Extraction and a Linear Support Vector Machine, International Journal Bioautomation, 20(2), 237-252.
21. Vally D., C. V. Sarma (2015). Diagnosis Chest Diseases Using Neural Network and Genetic Hybrid Algorithm, International Journal of Engineering Research & Applications, 5(1), 20-26.
22. Wang X. H., B. Zheng, Y. H. Chang, W. F. Good (1999). Optimizing the Feature Set for a Bayesian Network for Breast Cancer Diagnosis, by Using Genetic Algorithm Techniques, Proceedings of SPIE – The International Society for Optical Engineering, 3661, 1574-1580.

Xi Wang, M.Sc.
E-mail: nanyangwangxi@163.com

Xi Wang received her Bachelor degree in Computer and Information Engineering College from Henan Normal University and Master degree in Water and Electricity and Digital Engineering College from Huazhong University of Science and Technology, China, in 2003 and 2007, respectively. Since 2009, she is a lecturer at Nanyang Normal University. Her research interests include computer application and complex networks.