Tuning the Parameters for the Decision Making System in Order to Define Athlete's Aerobic and Anaerobic Thresholds

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Abstract: In this work we have managed to find parameters for defining athlete's aerobic and anaerobic thresholds. Thresholds which are of vital importance for top athletes. It is shown how differential evolution and different similarity measures has been used to tune computational model for threshold definitions. From our results it is obvious that the use of right parameter values for this kind expert system is of vital importance.

Keywords: Aerobic, Anaerobic, Threshold, Fuzzy Similarity, Differential Evolution

1. Introduction

The paper presented here is partially based on the work done in one diploma thesis [1] by Mika Hempil for the Lappeenranta University of Technology. During that work was developed a computational model which was met to define athlete's aerobic and anaerobic thresholds [2], [3]. That work was left partially unfinished. Especially the parts which includes comparison of different similarity measures and selection of right weights for computational model were left undone. Partly this was due the fact that data which was measured from the athlete's was collected from three different sources which used different measuring methods and was in that reason heterogeneous. Data used in this article has been collected only one source and is homogeneous in that sense.

Aerobic and anaerobic threshold is of vital importance for top athletes. Due the reason that their workout will be more efficient and can be more focused to different parts of stamina if thresholds are known. Basic aerobic stamina is improved with workouts when pulse won't exceed aerobic threshold. Aerobic speed stamina on the other hand is improved when pulse stays between these thresholds. Finally maximal aerobic stamina is improved when pulse is over anaerobic threshold.

This paper will show that by using differential evolution with aggregation closely related to the GOWA type (alias generalized ordered weighted averaging) [4] of measures a significant improvements and differences can be achieved to the prediction results estimated by our computational model.

2. Basis of the computational model

First we had the measurement data which came from the Research Institute for Olympic Sports in Finland. We also had the following criteria set by experts for choosing the thresholds.

In case of aerobic threshold criteria have been following ones:

1) Pulse is about 40 beat per minute below maximal pulse.
2) Content of lactic acid in capillary blood begins to raise.
3) Content of lactic acid in capillary blood is about 1.0-2.5 mmol per liter.
4) Ventilation begins to raise from beginning level.
5) Relative amount of oxygen in respiration air reaches its maximum.
6) Ventilation equivalent for oxygen is lowest.
7) Lactic acid divided by consumption of oxygen is lowest.

In case of anaerobic threshold criteria have been following ones:

1) Pulse is about 15 beat per minute below maximal pulse.
2) Content of lactic acid in capillary blood is about 2.5-4.0 mmol per liter.
3) Content of lactic acid in capillary blood begins to raise radically.
4) Ventilation equivalent for carbon dioxide changes radically.
5) Ventilation equivalent for oxygen begins to raise radically.
6) Relative amount of oxygen in respiration air begins to drop.

3. Basic model

In this section it is shown how differential evolution and different fuzzy logic based measures for comparison can been used to tune computational model for threshold definitions.

3.1. Differential evolution

Our computational model for finding right weights is using a differential evolution [5]. Differential evolution is a simple population based stochastic function minimizer. Idea of differential evolution is to iterate each member of population and compare its value to trial members value. Better member stays for next iteration. Evolution strategy defines the way how trial member is generated.

Here differential evolution tries to minimize the value of objective function with trial members values. The objective function is the total difference between thresholds from experts and thresholds defined by similarity used here for

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all learning data set. Finally DE gives us the weights for measures which have been fuzzified from the measurement data which comes from the Research Institute for Olympic Sports in Finland. Basic action of our differential evolution is demonstrated in the figure 1.

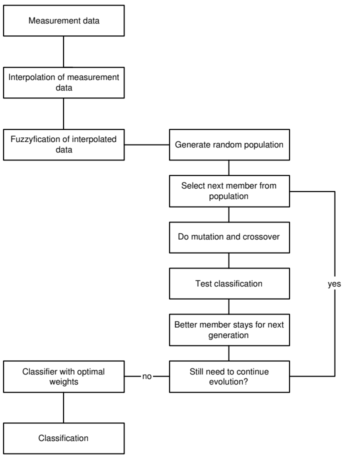

Fig. 1. Simplified computational model for DE

We used linear interpolation to interpolate measurement data along pulse. Various different interpolation methods were tried but they gave significantly poorer results.

Fuzzification has been done by using the interpolation of measurement data and by using membership functions, which have been Gaussian, triangular and trapezoidal. These are chosen to imitate experts judgement as a grade of certainty with corresponding data.

3.2. Measures for comparison

Comparison measure used is a combination of generalized mean presented by [6] and fuzzy equivalence relation based on the parameterized Łukasiewicz implication. We are seeking parameters that will give us the maximal similarity compared to values set by experts. In equations below weights and membership values has been normalized to values between $[0, 1]$. First we define a measure that is based on parameterized Łukasiewicz equivalence with generalized mean:

$$S_{\omega A}\left(P_A, P_i\right) = \left[\sum_{i=1}^{n} \omega_i \left(\sqrt[p]{1 - \left|\mu_A^p\left(P_A\right) - \left(\mu_{A_i}^{p_i}\left(P_i\right)\right)^p\right|}\right)^m\right]^{\frac{1}{m}} \tag{1}$$

, where $S_{\omega A}\left(P_A, P_i\right)$ is the total similarity between all fuzzified criteria for the corresponding data. Membership values are marked as μ and $\mu_A\left(P_A\right) = 1$ since it comes from expert. Index i shows the number of criteria that we are testing. Parameters are p, m and p_i. Since $\mu_A\left(P_A\right) = 1$, parameter p reduces out from our equations. This gives us the following two equations:

$$S_{\omega Aet}\left(P_{Aet}, P_i\right) = \left[\sum_{i=1}^{n} \omega_i \left(\mu_{Aet_i}^{p_i}\left(P_i\right)\right)^m\right]^{\frac{1}{m}} \tag{2}$$

for aerobic threshold and

$$S_{\omega Ant}\left(P_{Ant}, P_i\right) = \left[\sum_{i=1}^{n} \omega_i \left(\mu_{Ant_i}^{p_i}\left(P_i\right)\right)^m\right]^{\frac{1}{m}} \tag{3}$$

for anaerobic threshold.

4. Tuning the Model Parameters

The classifier uses following parameters: weights, p-values and m-value. These parameters were tuned to optimize classification. Optimization was done by differential evolution algorithm, which is described above.

At first we tuned only weights and achieved fairly good results, but after adding p_i-values and m-value denoting generalized mean to classifier results got slightly better. In case of anaerobic threshold tuning had no such significant meaning as in case of aerobic threshold.

Differential evolution seemed to be quite efficient to our application. Good results were gained after few thousand evolution.

4.1. Development of mean error along evolution steps

Figures 2 and 3 show that differential evolution reaches good solution rather fast. The solution is in this case mean error of classification with current training data set.

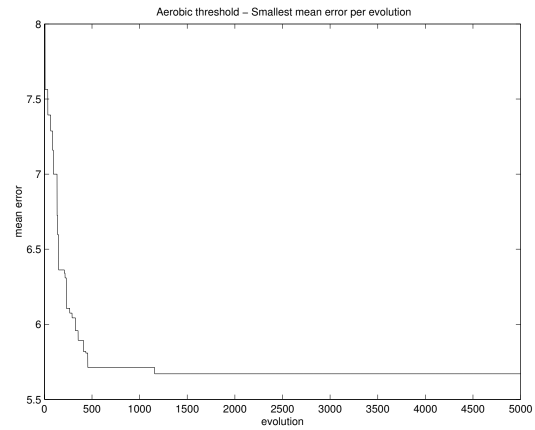

Fig. 2. Mean error development for aerobic

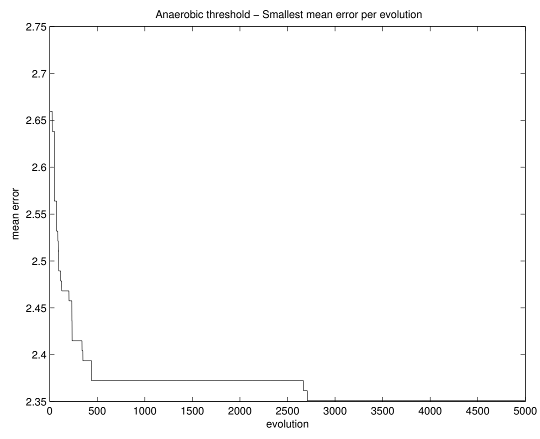

Fig. 3. Mean error development for anaerobic

4.2. Tuned parameters for classifier

Following parameters are for aerobic threshold classifier:

Table 1. Classifier parameters, aerobic

i	$\mathbf{w_i}$	$\mathbf{p_i}$	m
1	3.1394	9.4039	0.2307
2	45.0996	3.0604	
3	25.7102	4.7183	
4	18.4844	0.6633	
5	0.2418	0.6976	
6	7.2322	6.0769	
7	0.0925	5.6312	

Following parameters are for anaerobic threshold classifier:

Table 2. Classifier parameters, anaerobic

i	$\mathbf{w_i}$	$\mathbf{p_i}$	m
1	0.0967	9.3537	0.4517
2	33.4295	9.7802	
3	23.6398	3.0888	
4	6.9080	0.8098	
5	34.5696	2.8369	
6	1.3564	0.1598	

5. Results

Next we are considering statistical effects of parameters in similarity to the final predictions of thresholds.

Following is a summary statistics from the calculations with three different mean measures, arithmetic, geometric and harmonic with and without weights. In our newest model we used individual parameter p_i for different membership values and generalized mean. Following notations has been used in tables 3 and 4. Expert, is a heart beat value which is coming from the expert. A, G and H illustrate the corresponding average and NO means that no weights has been used. Final means our newest model. We used a test called multiple range test to test that is Fisher's least significant difference (LSD) procedure.

* denotes a statistically significant difference.

Table 3. Multiple Range Tests (LSD), aerobic

expert	-	anode	*13,894
expert	-	ade	2,12583
expert	-	gnode	*22,351
expert	-	gde	*21,9272
expert	-	hnode	*7,82119
expert	-	hde	*5,40397
expert	-	final	1,6755
anode	-	ade	*-11,7682
anode	-	gnode	*8,45695
anode	-	gde	*8,03311
anode	-	hnode	*-6,07285
anode	-	hde	*-8,49007
anode	-	final	*-12,2185
ade	-	gnode	*20,2252
ade	-	gde	*19,8013
ade	-	hnode	*5,69536
ade	-	hde	3,27815
ade	-	final	-0,450331
gnode	-	gde	-0,423841
gnode	-	hnode	*-14,5298
gnode	-	hde	*-16,947
gnode	-	final	*-20,6755
gde	-	hnode	*-14,106
gde	-	hde	*-16,5232
gde	-	final	*-20,2517
hnode	-	hde	-2,41722
hnode	-	final	*-6,1457
hde	-	final	*-3,72848

Table 4. Multiple Range Tests (LSD), anaerobic

expert	-	anode	1,2649
expert	-	ade	0,84106
expert	-	gnode	*59,5099
expert	-	gde	*59,5099
expert	-	hnode	0,509934
expert	-	hde	0,145695
expert	-	final	0,298013
anode	-	ade	-0,423841
anode	-	gnode	*58,245
anode	-	gde	*58,245
anode	-	hnode	-0,754967
anode	-	hde	-1,11921
anode	-	final	-0,966887
ade	-	gnode	*58,6689
ade	-	gde	*58,6689
ade	-	hnode	-0,331126
ade	-	hde	-0,695364
ade	-	final	-0,543046
gnode	-	gde	0
gnode	-	hnode	*-59,0
gnode	-	hde	*-59,3642
gnode	-	final	*-59,2119
gde	-	hnode	*-59,0
gde	-	hde	*-59,3642
gde	-	final	*-59,2119
hnode	-	hde	-0,364238
hnode	-	final	-0,211921
hde	-	final	0,152318

The results from our computational model shows that our newest model with individual parameter values and generalized mean improving the results in most of the cases. Furthermore there were no statistically significant difference from the values estimated by the expert for the case of aerobic threshold. In case of anaerobic threshold the results were all along very good except in the case when we used geometric mean.

6. Conclusions

Here in this work we have managed to find parameters for defining athlete's aerobic and anaerobic thresholds. Thresholds which are of vital importance for top athletes. We showed that finding the right parameters is very important in order to make this kind of expert system to work appropriately. Especially aerobic threshold was very sensitive for right parameter values. Anaerobic threshold was more stable for the differences of parameter values, except that obviously geometric average should not been used. Weights had significant difference in all cases for results.

In the future we are going to develop a working application which will calculate the athlete's aerobic and anaerobic thresholds by using the measurement data from the laboratory testing.

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