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CLASSIFICATION WITH ARTIFICIAL IMMUNE SYSTEMS

Małgorzata Kuchta, Andrzej Sokołowski

Silesian University of Technology, Faculty of Mechanical Engineering
Konarskiego 18a, 44-100 Gliwice,
Poland

ABSTRACT
The classification with artificial immune systems (AIS) is the main problem discussed in the paper. First, academic type of tasks was analysed. The tests were to reveal classification performance of AIS, first of all. In the second step of the conducted research, cutting tool wear classification during multi-spindle drilling is discussed. Here, an algorithm for multi-class classification is proposed. The obtained results are compared to other approaches. Namely, the results are compared to those obtained with artificial neural networks and fuzzy logic reasoning.
Keywords: artificial immune systems, classification, cutting tool wear diagnostics

1. INTRODUCTION

More and more often technical science takes inspiration from nature in the form of artificial intelligence methods. Among others, artificial immune systems (AIS) are ones of the approaches that attract researchers, recently. Artificial immune system is metaphor of biological complex immune system, which can discover and grow its qualifications by learning and experience. Due to its complexity, AIS apply only selected mechanisms that can be described with mathematical formulas. Typically, artificial immune systems can be applied while conducting optimization, anomaly detection or classification. For example, the anomaly detection has been studied in [2] and several problems has been revealed in this case.

The above mentioned classification with AIS is the main problem discussed in the paper. It should be emphasised the presented research reflects continuation of the research presented in [3]. First, academic type of tasks was analysed. For such tasks, the solutions are known, so one can easily assess performance of the tested methods. Different shapes of classes boundaries were considered, e.g. circle, ellipse or kidney-like. The tests were to reveal classification performance of AIS, first of all. Also, possibility of automatic determination of AIS parameters was studied, e.g. the relationship between NAT values and dispersion of points representing a certain class was investigated.

In the second step of the conducted research, cutting tool wear classification during multi-spindle drilling is discussed. Here, an algorithm for multi-class classification is proposed. The obtained results are compared to other approaches. Namely, the results are compared to those obtained with artificial neural networks and fuzzy logic reasoning.

2. CLASSIFICATION SYSTEM

The Rlais algorithm (e.g. [1]) has been applied in the research. This algorithm can be characterised in many different ways and, therefore, the most important features are recalled here. Namely, it uses set of B-cells to create immune memory. Next, it applies cloning, mutation of B-cells and mechanism of removing non-effective cells. Creation of immune memory reflects the preliminary immune system response, while the classification (intruder recognition) is related to the secondary immune response (Figure 1).

Creation of immune memory - *p* set based on Rlais algorithm

↓

Computation of fit factor *d(a,p)* of memory cells and antigen that represents an element to be classified /the fit factor is described with formula (1)/

↓

Comparison of fit factor with user defined NAT parameter

$d(a,p) \le NAT$ ↓ → Self element

↓ $d(a,p) > NAT$ → No-self element

Figure 1. Classification algorithm

$$d(a,p)=\sqrt{\sum_{i=1}^{n}(a_i-p_i)^2} \tag{1}$$

where: *d(a,p)* – fit factor

a – vector representing antygen

p – vector representing memory cell (antibody)

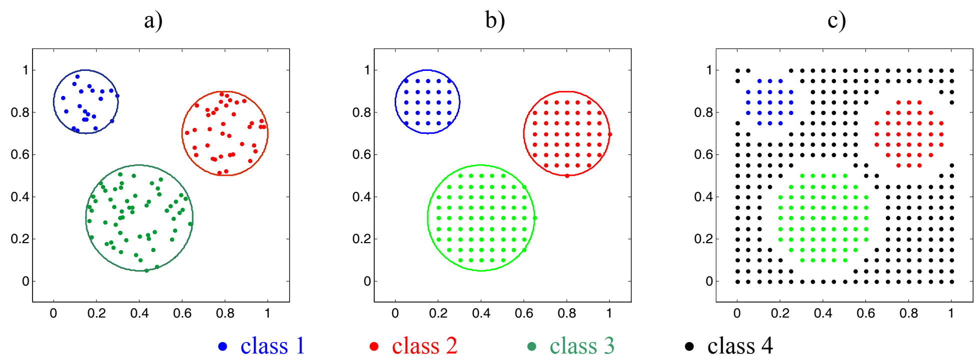

Figure 2. Example of data applied; a) training data with randomly generated points; b)training data with evenly generated points; c) testing data

Creation of three sets of immune memory representing classes: 1, 2 & 3

↓

Classification based on the three sets – three classifiers

↓	↓	↓
Classification by one classifier	Classification by more than one classifier	No classification
↓	↓	↓
Point belongs to class 1 or 2 or 3	Classification error	Point belongs to class 4

Figure 3. Structure of classification system

As it was mentioned in the introduction, the first step of the research was based on the generated data. An example of applied data is shown in Figure 2. The classification of points in 2D space into three classes was of our interest in this case. The points were randomly or evenly generated and, then, the points inside the user-defined circles were considered as representatives of the analysed classes. It should be underline that data applied for training represented three classes. However, classification to four classes was considered, i.e. if no-classifier responded to introduced point, the classification to the fourth class was assumed (Figure 2c).

Conventional immune classifier allows classification to two classes only (self or no-self element). Therefore, an algorithm for multi-class classification has been proposed in the research conducted. The algorithm is shown in Figure 3 and selected results obtained with the algorithm are shown in Figure 4.

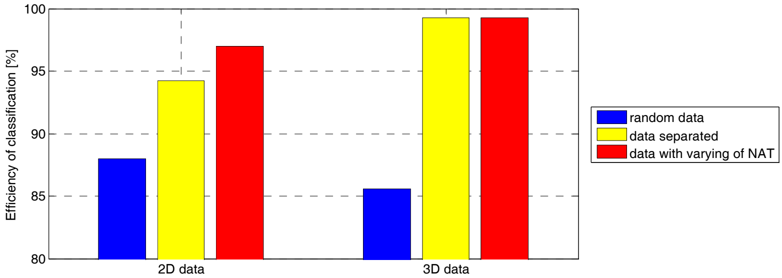

Figure 4. Classification efficiencies obtained for different approaches

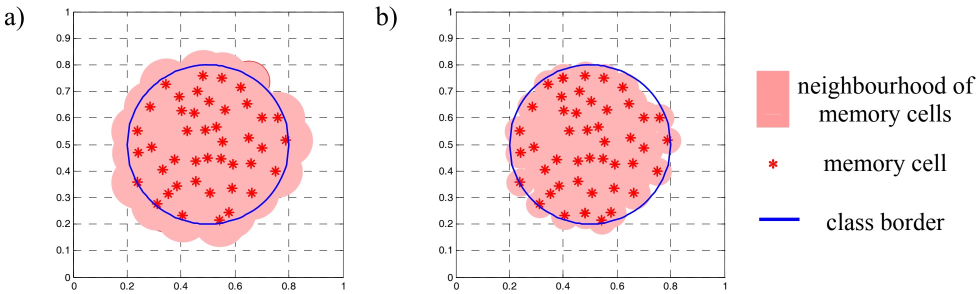

Figure 5. Representation of classes obtained with constant (a) and varying (b) NAT values

The results shown in Figure 4 reveal substantial differences in the classification efficiency (classification performance). First of all, relatively low efficiency has been obtained while analysing the data representing randomly generated points (random data). In this case misclassification occurred for testing points placed near the class border. This could be expected because random generation of the points causes that the separation of the classes can be relatively difficult. Thus, in the next step of the research second data set was generated. Here, the points were evenly distributed and the points placed near the class border were removed from testing data (Figure 2b and c). Such an approach allowed obtaining much more satisfying results (Figure 4 – data separated).

The above discussed reason of relatively low classification performance is not the only one. The second reason is related to the way of building immune memory. An example of immune memory is shown in Figure 5a. The memory defines an area in which points are considered to belong to the analysed class. As it can be noticed, the area over-crosses the user-defined class border. The over-crossing depends on NAT parameter value, i.e. it is becoming higher with increasing NAT value. In the presented research, variation of NAT values has been suggested. Varying NAT value is applied for all points for which the distance to the centre of the class is higher than the half of maximal distance calculated in this way. The NAT value assigned to these points is of 50% of original value. The proposed approach allowed increasing the classification efficiency, again (Figure 4). The explanation of this case can be found in Figure 5b based on the above discussion.

3. CLASSIFICATION OF CUTTING TOOL WEAR DURING MULTI-SPINDLE DRILLING

The approach described in the previous part of the paper has been tested with the data collected during multi-spindle drilling (e.g. [4]). The main goal of the research was to develop drill wear diagnostic system. The three classes of drill wear were considered, i.e. “fresh” drills, partly worn and worn drills.

During the experimental procedure 6 sensors were applied and 24 sensor features were calculated. Together with workpiece material and feed value, 26 quantities defined input vectors. Finally, application of data selection methods led to several sub-sets of data, i.e. sub-sets of vectors with different number of inputs.

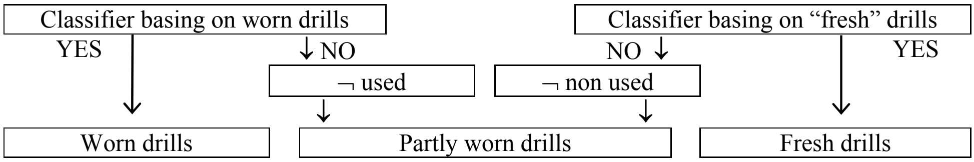

Figure 6. Classification system for drill wear estimation

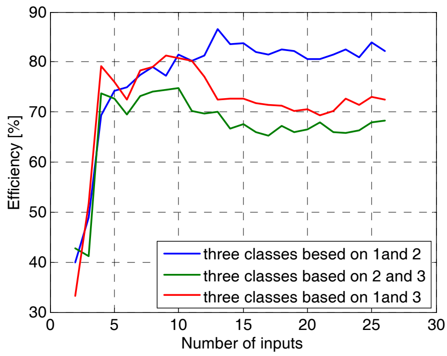

Figure 7. Classification efficiency achieved for different number of inputs

In order to perform classification to three classes, two drill states were used in the training phase. One of possible classification systems is shown in Figure 6.

The data representing “fresh” and worn drills served as a base for developing two classifiers. Then, the classifiers were applied to classify the testing data. In this stage, the partly worn drills were pointed at, when none of classifiers responded to the input vector.

The results of the conducted simulations are shown in Figure 7. As it can be noticed, the three approaches have been tested. In each case, data representing the two drill states was applied, as it is described above. In Figure 7, the description of simulations is organised as follows: denotations 1, 2 and 3 correspond to “fresh”, partly worn and worn drills, respectively. The discussion of the obtained results is presented in the summary of the paper.

4. SUMMARY

The general assessment of the obtained results can be done from different points of view. First of all, the classification efficiency above 80% can be considered satisfying. Such efficiency was obtained with data representing “fresh” and partly worn drills which is considered very desirable since knowledge on two classes is required to be able to perform classification to three classes. From other hand, there are no rules that could be helpful in deciding which class can be omitted during training. Thus, this feature of artificial immune systems may be useless in many cases, unfortunately.

Regarding the obtained classification efficiency, it seems to be reasonable to recall results of application other artificial intelligence methods. The system based on neural network has classified drill wear with performance of 95% while system based on Mamdani fuzzy logic with performance above 90% depending on number of inputs (e.g. [4]). This suggests further research and development of classifiers basing on artificial immune systems.

5. REFERENCES

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