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Negative Selection Inspired Machine Learning Approach for Damage Detection

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ABSTRACT

The fault detection of dynamics systems is of great importance when it comes to ensuring safety and increasing their performance. The present paper uses the concept of the natural immune systems and takes the advantage of its major characteristics like evolution and trainability for fault detection purposes. In the presented approach, first, both negative and clonal selection methods are used in order to improve the rate of convergence. Second, the generated population is compared to the members of memory cells (as the set of best samples of overall population) that results in a more efficient local search and faster convergence. Finally, the obtained results from the artificial immune system (AIS) are compared to the genetic algorithm (GA). The simulation results indicate that the proposed approach shows a higher accuracy in terms of identifying the location and intensity of the fault in the system under study.

Keywords: Machine Learning, Fault Detection, Genetic Algorithm

1. INTRODUCTION

The common structures, such as bridges and buildings, play an important role in our life. Dynamic systems are widely used in this civil structures and machines. There have been attempts to model these complexities and their dynamics [1], [2], [3]. Maintaining safe and reliable structures is important to the well-being of all of us. The sudden failure of structures that is occurred because of cracks during the operation could be very dangerous.

Damage detection in structures is one of the research topics that have received growing interest in research communities [4], [5]. Numerical techniques including finite element method (FEM) and finite volume method (FVM) are widely used to study the failure behavior of solids and structures. More recently, the meshless peridynamic method gains popularity among researchers for failure analysis of engineering structures involving faults such as cracks. Yaghoobi and Chorzepa [6] employed peridynamics to analyze the fracture behavior of cementitious composites. Furthermore, the effect of fiber reinforcement on the fracture behavior of cementitious composites is studied using peridynamics by Yaghoobi and Chorzepa [7]. Along with these methods, other methods such as Wavelet Spectral Finite Element (WSFE) has been developed in order to simulate dynamic behavior of structures. Khalili et al. [8], [9] developed WSFE-based UEL to simulate the wave propagation in composite structures for SHM purposes. The novelty of their work is implementing the WSFE-based elements in Abaqus. This method overcomes to the drawbacks of spectral elements in modeling complex features. These newly developed elements also has been used to create baseline data in wave propagation based SHM [10] and proved its efficiency. A similar approach can be utilized to characterize damage development in a metallic or composite structure [11], [12], [13]. In recent years, AIS method has been considerably employed and adapted to solve optimization and classification problems in various fields such as optimization problems and damage diagnosis of the structures [14], [15]. Selective and adaptive features of AIS allow algorithm to evolve its antibodies towards the goal of defined problem [16], [17], [18], [19], [20].

While a number of damage detection and localization methods have been proposed, in this paper, a novel damage diagnosing method based on AIS has been developed, which incorporates several major characteristics of the natural immune system. The damage patterns are represented by feature vectors that are extracted from the structure’s dynamic response measurements. In our method the possible changes in the natural frequencies of the structure are utilized as feature vector. The selective and adaptive features of the proposed algorithm allow the AIS to evolve its antibodies towards the goal of minimizing the described cost function. The proposed framework is studied through a benchmark dynamic system. Different scenarios of the faulty conditions are generated via changing parameters of the system. Then, the classification and detection of theses faulty scenarios are carried out by two machine learning methods. In this paper, one of the components of the dynamic system is assumed to be variable as an indicator of fault in the associated system. For this purpose, a limited number of samples with different or possibly equal values for the variable components is generated by defining a parameter called fault intensity. Setting different values to the variable components translates to a new set of fault intensities.

The gathered data from setting different values to the system components forms the training and testing data for artificial immune system (AIS). As the next step, the performance of the trained algorithm in classification and detection of the test data is studied by defining a measure of relativity of test data to various fault classes. The objective is to quantify the ability of the AIS algorithm in fault detection and classification.

2. MEASURE OF AFFINITY

In order to detect and classify the fault, similarities between data needs to be quantified in the training part. To this end, the closeness and similarity of each data point to different fault classes is measure by defining a measure of affinity. There are various ways to define such affinity parameter like finding the Euclidean distance between two feature vectors.

In the present work, the feature vectors are consisted of strings of 0 and 1. A threshold is defined for each value in the feature vector, the corresponding element in the feature vector is 1 if their value is greater or equal to the defined threshold, and otherwise, it will be zero. The set of training (antibody) and test (antigen) data are then decoded into a binary feature vectors.

In the proposed setting, the affinity is obtained as the number of bits that two feature vector have in common that is obtained by the operator XOR.

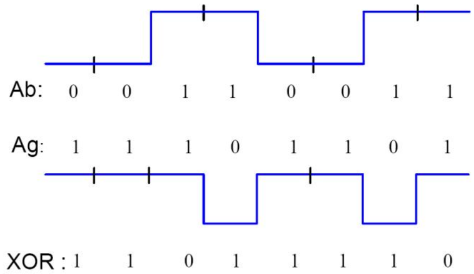

Figure 1. Implementing the operator XOR to obtain measure of affinity

As shown in Figure 1, the affinity between the given antibody (ab) and antigen (ag) is equal to 2.

3. AFFINITY-BASED FAULT DETECTION APPROACH

As described in the previous section, the feature vectors are consisted of binary strings. This leads to similarity of the antibodies that can cause incorrect fault detection and/or classification. Hence, the methods that perform based on continuous update of the data extracted from the system can mitigate these errors.

The main concept the behind the proposed algorithm is to vary the decoding thresholds at each run and generate new set of binary feature vectors. Then, the affinity between antibodies and antigens are calculated for different threshold values. Each test data belongs to a class that has the highest affinity measure with the feature vectors in that class of fault. The aforementioned procedure continues until each test data has the highest affinity with only one of the feature vectors from the training set. The proposed approach is compared to the genetic algorithm to assess its performance.

4. AIS METHOD FOR FAULT DETECTION

In this section, an artificial immune system algorithm is developed with respect to the feature vector extraction method described in the previous section. Within the AIS framework and terminology, the thresholds are generated by the algorithm as part of antibodies. The objective function is sum of all the maximum affinity measures for each test data in affinity matrix divided by number of test data. Each pick in the objective function represents an antigen of the immune system where antibodies are generated according to them to finally obtain the desired response.

Parameters of the Artificial Immune System

The list of the parameters of the artificial immune system is listed below:
Antigen: Test data containing of natural frequencies of the dynamic system for different fault intestines.
Antibody: Feature vectors representing the natural frequencies of the training data.
Fitness: Affinity measure between antibodies and antigens that indicates of an antibody is acceptable or not.
Affinity: Number of similar bits in two feature vectors
Offspring: Generated antibodies from the parent antibodies.
Memory cell: A set of antibodies with high fitness measures.
Negative selection: Act of removing new antibodies that are already too similar to the members of memory cell.
The proposed AIS algorithm is shown below.
1. Initialize of the parameters

2. Generate the random population
3. Expand the main population by proliferation of the each population member by $n_c - 1$ where n_c is the proliferation number
4. Use the mutation method for the generated population (except the main population)
5. Assessment of the population with respect to the objective function
6. Choose the best member of each group for generating new population
7. Obtain the correct solutions and save them in the memory cell
8. Use the negative selection method
9. Repeat the steps 3 to 9 until the results converge or number of iterations exceeds the maximum number of iterations.

5. MODELING OF A MASS AND SPRING SYSTEM

In order to evaluate the effectiveness the of the proposed fault detection approach, a there degree of freedom spring mass system is molded as shown in Figure 2. The parameters of the dynamic system are m1=200kg, m2=800kg, m3=200kg, k1=7e6N/m, k2=7e6 N/m and k3=7e6N/m.

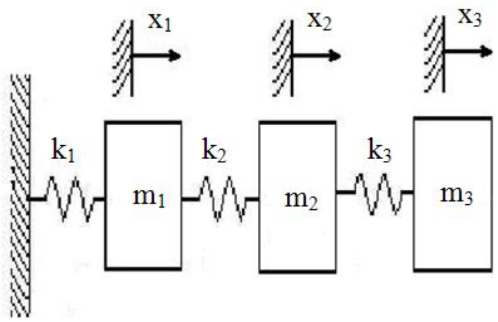

Figure 2. A 3-DOF system of mass and spring

The governing equation can be written as

$$M\ddot{x} + Kx = 0$$

where

$$[M] = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix}$$

And

$$[K] = \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ -k_2 & k_{2+}k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix}$$

By solving the eigenvalue and via the following equation, we obtain the natural frequencies of the system.

$$\left[[K] - \omega^2[M]\right]\{\bar{X}\} = \{0\}$$

The obtained natural frequencies of the system are used construct the feature vectors for our fault detection purpose.

5.1 Generating the Feature Vectors by Changing the System Parameters

The stiffnesses of the springs k_1, k_2 and k_3 are considered to be the changing parameters of the system. By changing these parameters, various faulty conditions are simulated. Table 1 represents the assigned values to the stiffness of the springs and their associated fault intensity.

Table 1. Different assigned stiffness values and their fault intensity.

Intensity	k_1	k_2	k_3
0	7000000	7000000	7000000
0.05	6650000	6650000	6650000
0.1	6300000	6300000	6300000
0.15	5950000	5950000	5950000
0.2	5600000	5600000	5600000
0.25	5250000	5250000	5250000
0.3	4900000	4900000	4900000

As it can be seen in Table 1, six fault intensities are chosen for each spring that sums up to 19 classes including the faulty and intact cases. To have a better indication of faulty conditions, the natural frequencies are extracted for each class. Table 2 shows the fault intensities and their associated natural frequencies.

Table 2. Natural frequencies and their associated fault intensities.

	Intensity	ω_1	ω_2	ω_3
Safe	0	57.1129	207.935	275.6831
k_1	0.05	56.321	207.6178	272.897
	0.1	55.4767	207.2694	270.1143
	0.15	54.5745	206.8855	267.3388
	0.2	53.608	206.4611	264.5751
	0.25	52.57	205.9905	261.8288
	0.3	51.4519	205.4671	259.1061
k_2	0.05	56.4593	207.9171	271.837
	0.1	55.7569	207.8966	267.9462
	0.15	55	207.8731	264.01
	0.2	54.1822	207.8455	260.0279
	0.25	53.2955	207.813	255.9997
	0.3	52.3308	207.774	251.9254
k_3	0.05	57.1129	207.935	275.6831
	0.1	57.0818	202.9757	275.418
	0.15	57.047	197.852	275.1822
	0.2	57.007	192.557	274.971

	7	3	4
0.25	56.9632	187.0829	274.7821
0.3	56.9123	181.4172	274.6112

As explained before, the natural frequencies construct the feature vectors that are used for fault detection and classification.

6. SIMULATION RESULTS

The proposed fault detection algorithm is examined through generating some test data. The fault intensities are chosen to include different scenarios. Six data points and their associated intensities and associated natural frequencies are shown in Table 3.

Table 3. Fault intensities and natural frequencies for different test data

	Fault situation	**Intensity**	ω_1	ω_2	ω_3
Test# 1	**k1**	0.35	50.2435	204.8832	256.4146
Test# 2	**k2**	0.22	53.8362	207.8332	258.4222
Test# 3	**k3**	0.02	57.1009	205.9707	275.5732
Test# 4	**k1**	0.001	57.0976	207.9289	275.6273
Test# 5	**k2**	0.2	54.1822	207.8455	260.0279
Test# 6	**k1+k2**	0.1+0.1	54.2376	207.1786	262.2219

A Monte Carlo method is used to run the algorithm starting from different points. The results for 100 runs are shown in Tables 4 and 5. It should be mentioned that these tables show the bests results for each Monte Carlo run.

Table 4. Best thresholds values

Best limit		
ω_1	ω_2	ω_3
57.0508	206.95	263.3418

Table 5. Affinity matrix for the best values of the objective function in AIS method

	Test# 1	**Test# 2**	**Test# 3**	**Test# 4**	**Test# 5**	**Test# 6**
Safe	0	1	2	3	1	1
k1	1	2	1	2	2	2
	1	2	1	2	2	2
	2	1	2	1	1	1
	2	1	2	1	1	1
	3	2	1	0	2	2
	3	2	1	0	2	2
k2	1	2	1	2	2	2
	1	2	1	2	2	2
	1	2	1	2	2	2
	2	3	0	1	3	3
	2	3	0	1	3	3
	2	3	0	1	3	3

k3	1	0	3	2	0	0
	2	1	2	1	1	1
	2	1	2	1	1	1
	2	1	2	1	1	1
	2	1	2	1	1	1
	2	1	2	1	1	1

The main measure for fault detection and classification is set to be the sum of affinity measures of each antibody with other antibodies. In this example, the iteration is considered 400 and population size is set 200. Hence, since the maximum affinity measure is 3, therefore, the maximum possible value of this measure would be 240000.

Table 6. Sum of affinity measure of each antibody with other antibodies for AIS method

	Test#1	**Test#2**	**Test#3**	**Test#4**	**Test#5**	**Test#6**
Safe	145124	172893	236043	239500	175262	174995
k1	168894	195063	215905	216730	197386	198765
	182738	207363	203605	202886	209686	212609
	197737	221138	189830	187887	223461	226726
	210712	230567	177673	174912	229172	231867
	221537	227742	167524	164087	226347	228592
	233145	218658	155936	152479	216717	216984
k2	169806	197575	213007	215818	199944	199677
	184574	212343	198323	201050	214712	214445
	200224	227993	182783	185400	230362	230095
	209862	237631	173291	175762	240000	236735
	216082	235979	167185	169372	233610	230629
	222117	228720	160204	162113	226351	223648
k3	148087	168086	234174	230717	170409	173674
	134889	154888	216940	213483	157211	160476
	115197	135196	194072	190615	137519	140784
	98439	118438	174264	170807	120761	124026
	93925	113924	166794	163337	116247	119512
	95697	115696	165014	161557	118019	121284

After assessing the result in Table 6, two highest values are chosen for each test data. If these values are closer than a predefined threshold, 5000 in this case, the fault intensity would be between these two data points. This threshold is assigned based the training data. The results associated with the proposed AIS based fault detection algorithm are shown in Tables 7 and 8.

Table 7. Identified values for location of fault by AIS method.

	Test# 1	Test# 2	Test# 3	Test# 4	Test# 5	Test# 6
lt situation	k1	k2	safe	safe	k2	k2
		k2	k3			k1

Table 8. Identified fault intensities by AIS method

	Test# 1	Test# 2	Test# 3	Test# 4	Test# 5	Test# 6
Intensity domain	0.3	0.2	safe	safe	0.2	0.2
		0.25	0.05			0.2

6.1 Fault Detection using Genetic Algorithm

For the sake of comparing our approach with other machine learning algorithms, we implement the genetic algorithm as one of the powerful optimization methods. The feature vectors are obtained as described in the previous sections. In this algorithm, we also obtain the optimum thresholds for natural frequencies to get the best objective function. The population size and number of iterations are set to 200 and 400, respectively. The associated result are shown in tables 9 to 13. Also, Table 14 compares the success of each method in detecting the fault for each test data.

Table 9. Best threshold values.

Best limit		
ω_1	ω_2	ω_3
57.053	207.2848	262.3769

Table 10. Affinity matrix for the best values of objective function by GA

	Test# 1	Test# 2	Test# 3	Test# 4	Test# 5	Test# 6
Safe	0	1	2	3	1	0
k1	1	2	1	2	2	1
	2	1	2	1	1	2
	2	1	2	1	1	2
	2	1	2	1	1	2
	3	2	1	0	2	3
	3	2	1	0	2	3
k2	1	2	1	2	2	1
	1	2	1	2	2	1
	1	2	1	2	2	1
	2	3	0	1	3	2
	2	3	0	1	3	2
	2	3	0	1	3	2
k3	1	0	3	2	0	1
	2	1	2	1	1	2
	2	1	2	1	1	2
	2	1	2	1	1	2
	2	1	2	1	1	2
	2	1	2	1	1	2

Table 11. Sum of affinity measures of each antibody with other antibodies in GA method

	Test#1	Test#2	Test#3	Test#4	Test#5	Test#6
Safe	2676	81798	162445	239123	82337	8360
k1	102484	137778	107237	139869	138293	108168
	145075	95759	149256	97278	96274	150759
	156917	85181	159834	85436	85696	161731
	158206	85018	159297	84147	85075	161064
	236761	161071	82252	5592	161128	236355
	239146	160500	79885	3207	159993	233970
k2	80533	159655	85188	161820	160194	86217
	80878	160000	84889	161475	160539	86562
	81658	160780	84131	160695	161319	87342
	159738	238860	6129	82615	239399	163364
	161218	237990	4637	80665	237451	161872
	162399	236681	5646	79356	236142	162881
k3	80643	3813	237530	160852	4328	80363
	154052	77222	163077	86399	77737	153772
	154305	77475	161838	85160	77990	154025
	154342	77512	161581	84903	78027	154062
	155415	78585	160432	83754	79100	155135
	155443	78613	160394	83716	79128	155163

Table 12. Identified location of fault by GA

	Test#1	Test#2	Test#3	Test#4	Test#5	Test#6
Fault situation	k1	k2	k3	safe	k2	k1
	k1	k2			k2	k1

Table 13. Identifies intensities of test data by GA

	Test#1	Test#2	Test#3	Test#4	Test#5	Test#6
Intensity domain	0.3	0.2	0.05	safe	0.2	0.25
	0.25	0.25			0.25	0.3

Table 14. Comparison of AIS and GA performance for 6 test data points.

		Test#1	Test#2	Test#3	Test#4	Test#5	Test#6
Safe	0			✓	✓		
k1	1						
	2						
	3						
	4						✓×
	5	×					×
	6	✓					
k2	1						
	2						
	3						
	4		✓			✓	✓×
	5		✓			×	
	6						
k3	1			✓			
	2						
	3						
	4						
	5						
	6						

GA Results
AIS Results
Same Results

✓	Correct Classification
✓×	Correct Detection
×	Incorrect Classification

The comparison with GA indicates that AIS show a higher performance as shown in Table 14. The AIS method correctly detects the location of fault in all of the test data while GA was not successful in test data number 3 and 6. In case of identifying the fault intensities, the AIS –based method was able to report the correct values for all the test data except data number 6. In contrast, the GA has obtained the correct data for just data number 2 and 4.

7. Concluding Remarks

The proposed method by proposing in new way to generate feature vectors allows for more accurate classification of various kinds of faults. In addition, by taking the advantage of successful feature of AIS algorithm like memory cells, the proposed approach is capable of adapting with changing conditions or new fault data by adding reshaping the memory cells when necessary. All in all, the AIS-based fault detection approach shows a better performance in detecting the fault and its intensities. The results indicate that with some revision to the method, it can be applied to more complicated dynamic system like cracked beam.

References

[1]. F. Abbasi and J. Mohammadpour, "Nonlinear model order reduction of Burgers' equation using proper orthogonal decomposition," in American Control Conference (ACC), Chicago, 2015.
[2]. S. W. Doebling, C. R. Farrar, M. B. Prime and D. W. Shevitz, "Damage Identification and Health Monitoring of Structural and Mechanical Systems From Changes in Their Vibration Characteristics: A Literature Review," Los Alamos National Laboratory, Los Angeles, 1996.
[3]. F. Abbasi, J. Mohammadpour, R. Tóth and N. Meskin, "A Bayesian approach for system identification of LPV systems with uncertain scheduling variables," in IEEE 54th Annual Conference on Decision and Control (CDC), Osaka, 2015.
[4]. B. Mohebbi, F. Abbasi, M. Ettefagh and H. Biglari, "Delamination diagnosis in composite beam using AIS and BGA algorithms based on vibration characteristics," in Optimization of Structures and Components, Berlin, Springer International Publishing, 2013, pp. 73-89.
[5]. M. M. Ettefagh, H. Akbari, K. Asadi and F. Abbasi, "New structural damage-identification method using modal updating and model reduction," Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, vol. 229, no. 6, pp. 1041-1059, 2015.
[6]. A. Yaghoobi and M. G. Chorzepa, "Fracture analysis of fiber reinforced concrete structures in the micropolar peridynamic analysis framework," Engineering Fracture Mechanics , vol. 169, pp. 238-250, 2017.

[7]. A. Yaghoobi and M. G. Chorzepa, "Meshless modeling framework for fiber reinforced concrete structures," Computers & Structures, vol. 161, pp. 43-54, 2015.
[8]. A. Khalili, R. Jha and D. Samaratunga, "Spectrally Formulated User-Defined Element in Conventional Finite Element Environment for Wave Motion Analysis in 2-D Composite Structures," European Journal of Computational Mechanics, DOI: 10.1080/17797179.2016.1253364, 2016.
[9]. A. Khalili, R. Jha and D. Samaratunga, "The Wavelet Spectral Finite Element-Based User-Defined Element in Abaqus for Wave Propagation in One-Dimensional Composite Structures," Simulation: Transactions of the Society for Modeling and Simulation International, DOI: 10.1177/0037549716687377, 2017.
[10]. A. Khalili, R. Jha and N. Jayakody, "Structural Health Monitoring of Skin-Stiffener Composite Structures Using WSFE-based User Defined Elements in Abaqus," in AIAA SciTech 2017, Grapevine, TX, 2017.
[11]. P. Gharghabi, P. Dordizadeh B. and K. Niayesh, "Impact of Metal Thickness and Field Shaper on the Time-varying Processes during Impulse Electromagnetic Forming in Tubular Geometries," Journal of the Korean Physical Society, vol. 59, pp. 3560-3566, 2011.
[12]. P. Gharghabi, J. Lee, M. S. Mazzola and T. E. Lacy, "Development of an Experimental Setup to Analyze Carbon/Epoxy Composite Subjected to Current Impulses," in Proceedings of the American Society for Composites: Thirty-First Technical Conference, VA, 2016.
[13]. P. Dordizadeh-Basirabad, P. Gharghabi, and K. Niayesh, "Dynamic Analysis of a Fast-acting Circuit Breaker (Thompson) Drive Mechanism," J. Korean Phys. Soc., vol. 59, p. 3547, 2011.
[14]. D. Dasgupta, "Advances in Artificial Immune Systems," IEEE Computational intelligence magazine, vol. 1, no. 4, pp. 40-49, 2006.
[15]. C. Z. B. Chen, "Artificial immune pattern recognition for structure damage classification," Computers and Structures , vol. 87, no. 21, p. 1394–1407, 2009.
[16]. J. Timmis, "Application areas of AIS: the past, the present and the future," Applied Soft Computing, vol. 1, no. 3, p. 191–201, 2008.
[17]. B. Mohebbi, F. Abbasidoust and M. Ettefagh, "Delamination detection in CFRP composite beam using modified AIS algorithm," in Innovations in Intelligent Systems and Applications (INISTA), 2012 International Symposium on, Trabzon, 2012.
[18]. F. Abbasi, A. Mojtahedi and M. M. Ettefagh, "Fault diagnosis using noise modeling and a new artificial immune system based algorithm," Earthquake Engineering and Engineering Vibration, vol. 14, no. 4, pp. 725-741, 2015.
[19]. J. Timmis, A. Hone, T. Stibor and E. Clark, "Theoretical advances in artificial immune systems," Theoretical Computer Science, vol. 403, no. 1, pp. 11-32, 2008.
[20]. M. Vakil-Baghmisheh, M. Peymani, M. Sadeghi and M. Ettefagh, "Crack detection in beam-like structures using genetic algorithms," Applied soft computing, vol. 8, no. 2, pp. 1150-1160, 2008.

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