EasyChair Preprint

№ 1279

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July 11, 2019

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Abstract. This paper proposes an algorithm for outline recognition in mobile robots, based on Clonal Selection algorithm, a machine learning technique of Artificial Immune Systems. The model is defined from the industrial process chain point of view, where a robot should recognize object outlines and transport them based on their geometric forms. This detection process should be also rotation and translation invariant. The robot is equipped with color sensors and laser sensors for classifying contours. The robot should have the capacity to recognize new objects, classifying those different from the existing ones. The results showed that the Clonal Selection Algorithm in a mobile robot generated antibodies for the correct classification of objects, regardless of their geometrical shape, either defined or undefined geometrical shapes, or even irregular shapes, and including objects with modified contours due to wear and tear, and white noise in the sensors. Therefore, whenever new objects were introduced to the chain process, the robot was successful trained to correctly classify them.

Keywords: Outline Recognition, Artificial Immune Systems, Clonal Selection Algorithm, Mobile Robots

1 Introduction

The application of object recognition for mobile robots increased in industrial environment, such as navigation [1], object detection or building [2]. In this way, the need for low-cost sensors has led to use lasers or sonar sensors to obtain characteristics from the object to be recognized, for example, edge detection for classifying objects [3]- [4]. In mobile robots, recognition systems need ability to adaption, robustness, and invariance to rotation and translation. In this way, evolutionary algorithms are commonly used in recognition systems, for example genetic algorithms for object recognition system in a dynamical environment [5], evolutionary algorithms applied to image segmentation [6], or emotion recognition [7]. Within the class of evolutionary algorithms, Artificial Immune Systems (AIS) present a kind of bio-inspired model

that adapts the capability of the human immune response in order to adapt the immunological response when there are different pathogens [8].

Artificial Immune Systems have been used in different industrial tasks, such as pattern recognition [9], cognitive models of behavior [10], or navigation [11]. Within the Artificial Immune Systems, Clonal Selection Theory establishes the idea that cells can recognize antigens, which are selected to proliferate [12]. In this context, different applications of Clonal Selection Algorithm have been applied in robotics, for example in UAV cooperation [13], trajectory planning in a robotic manipulator [14], coordination in swarm systems [15], or other applications data mining, medical application or classification [16]. One advantage of Artificial Immune Systems is their capacity to adapt to new conditions and their ability to learn online [17].

This paper proposes an Artificial Immune System model based on Clonal Selection Algorithm, applied to object recognition in mobile robots. For the recognition process, outline object information and Hu invariant moments are used, the latter are employed because they provide invariance in relation to the translation and the rotation of the object to be recognized. This immune model involves innate and acquired response; this model belongs to cognitive model where a multi-agent system must identify, classify, transport, and store objects. Robots have similar characteristics and can collaborate to the classification process. The model is validated in a 2D simulation environment.

This article is organized as follows. Section 2 presents the Clonal Selection Algorithm. Section 3 explains the stage conditions. Section 4 analyzes the immune model. Section 5 shows the experiment and. Finally, section 6 provides conclusions and future works.

2 Clonal Selection Algorithm

Understanding the AIS (Artificial Immune System) models involves knowing about the immune theories that inspired the AIS. In the case of the Natural Immune System, it has comprises two principal immune responses: the innate response and the acquired response.

The innate response is an innate immunity static barrier. This barrier is activated when a foreign agent (pathogen) enters the body. The innate response distinguishes between self cells and non-self cells in the body and attacks non-self cells. When non-self cells are detected, the innate system liberates proteins, called innate cells, that produce inflammation and fever [18].

As some pathogens have the capacity to avoid the innate response, vertebrates developed the acquired system. The acquired response anticipates mutations in the pathogen and then different mechanisms are activated to neutralize the pathogen attack. The antigens are molecules (usually proteins), on the surface of pathogens, and each antigen is composed of divisions called epitopes. The antigen is used to recognize the pathogen; for example, when phagocytic cells neutralize the pathogen, the phagocytes present the antigen of the specialized cells of the acquired system. B cells are specialized cells in the antigen presentation process; B cells interact with T cells, T cells

confirm the antigen, and B cells immediately begin a mutation and clonal selection process. When an antigen enters the body, it can be recognized by the immunoglobulins of B lymphocytes. If the antigen is recognized, the confirmation of T lymphocytes is necessary, and then the humoral response is activated. At this point, B cells are cloned and differentiated (cloned B cells with high affinity are cloned and reproduced again; B cells with low affinity are suppressed). T cells produce memory cells and plasma cells that generate immunoglobulins [19].

The clonal selection algorithm proposes that antigens and antibodies are presented as vector spaces. The affinity between antigens and antibodies are measured by a metric that provides a set of candidate solutions by selecting the best affinities in order to generate a new set of clones looking for antibodies with best affinities [20]. Figure 1 shows this process.

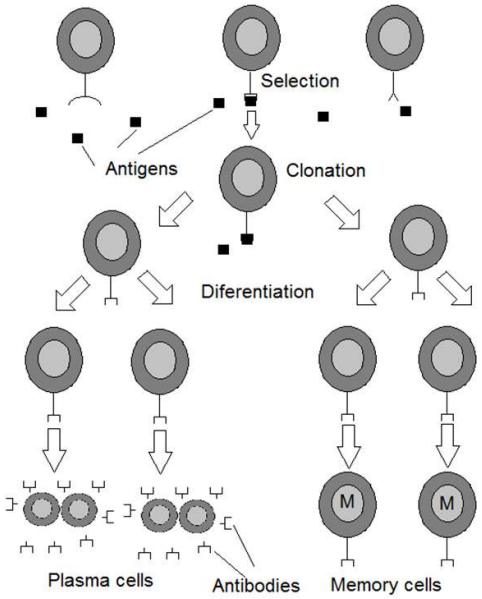

Fig. 1. Clonal selection theory.

3 Stage Conditions

Given a 2D environment, some geometrical objects must be recognized and classified by mobile robots for future transportation. For the experiment, Player Project is employed, a client-server platform, using TCP IP protocols, which provides an interface among sensors, actuators, and control response for robot control. Player Project includes a 2D simulator: Stage. This simulator provides drivers for sensors and robots, and it has the capacity to build different stages for simulations. This simulator sup-

ports C++ language. The stage is simulated in an industrial environment. Figure 2 shows an initial set of objects; these objects are called submarine, invader, phantom, circle, squarer, and triangle, respectively. They must be classified by a mobile robot.

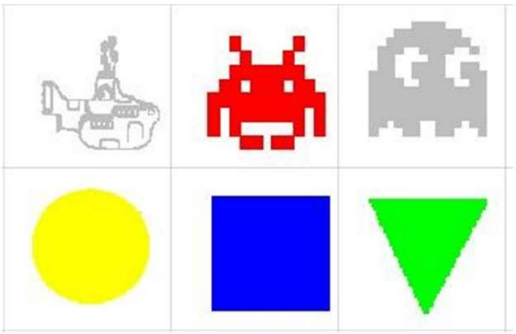

Fig. 2. Objects to be classified.

The robots have laser sensors and color sensors in their front. The laser sweeps the area, with 180 degrees around the robot, with a frequency of 180 samples per second; the range of the laser sensor is 8 meters. The laser returns a signal value corresponding to the distance of the object. For example, if there is an object two meters away, the laser returns a value of two. The clonal selection algorithm is used by the pattern recognition algorithm. Figure 3 shows the experiment stage. In this scenario, the robot looks for objects to be classified, so it must differentiate between the object (non-self objects) and walls or other robots (obstacles of the environment).

4 Object Recognition Based on Immune Model

4.1 Innate and Acquired Immune Model

The robot moves through the environment while looking for objects to be classified; it uses laser sensors and color sensors. First, the robot should distinguish between self objects (walls and other robots) and non-self objects (objects to be classified). For these works, an Artificial Immune System is proposed.

According to the theory of Innate Response, the innate system is activated when non-self pathogen is detected. When the robot detects an object using its laser sensors at a distance of 1.3 meters ahead, it will determine if that object must be identified or not, using the innate response. In this industrial stage, some environment conditions can be controlled. Consequently, self objects such as walls, obstacles, and other robots are black. Objects to be identified have different colors; these objects are considered non-self objects. The classification is made by color detection: if the color is black, the object will be considered a self object and then the robot continues the search.

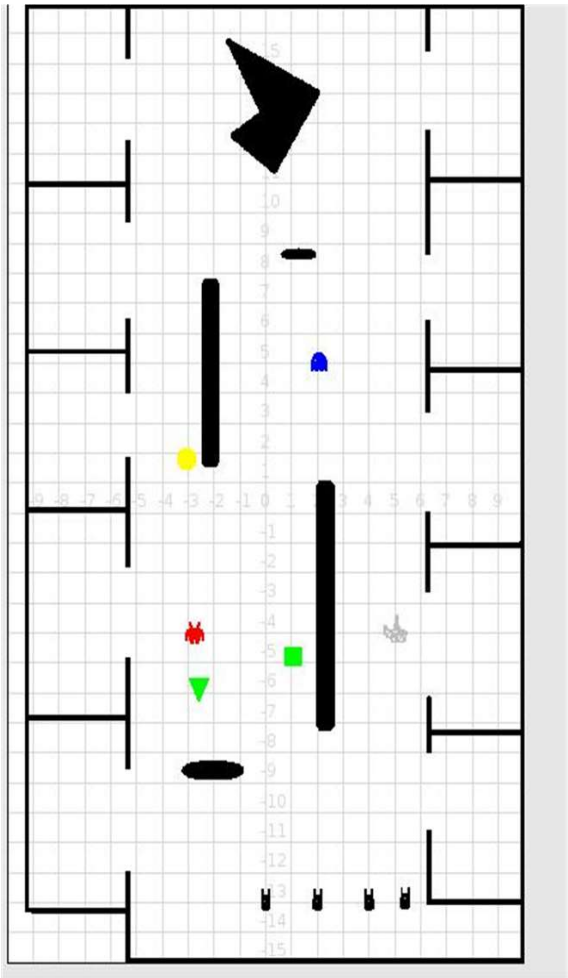

Fig. 3. Stage.

In the innate systems, macrophages can phagocyte the pathogens, applying the meta-phor in the innate model. The macrophage corresponds to the color sensor and the phagocytosis process corresponds to the transportation of the non-self object without any classification process different from color recognition. Section 2 has explained that macrophages can activate the acquired response through the antigen presentation process. Based on this concept, the macrophage shows the antigen to the ac-quired systems, and the acquired response attacks the pathogen identified. Subsequently, the laser sensor works as antigen presenting-cell. When the color sensor detects the object as a non-self object (color different from black), the robot follows the following steps:

- Robot goes into distance of 0.7 meters in front the object.
- Robot locates in front of the object using laser information of the right and left of center.
- Robot rotates 90 degrees in clockwise direction.
- Robot turns around the object. In this act, the left laser sensor that is located to 180 degrees of the X axis of the robot, takes information of the outline of the robot.

Figure 4 shows this process.

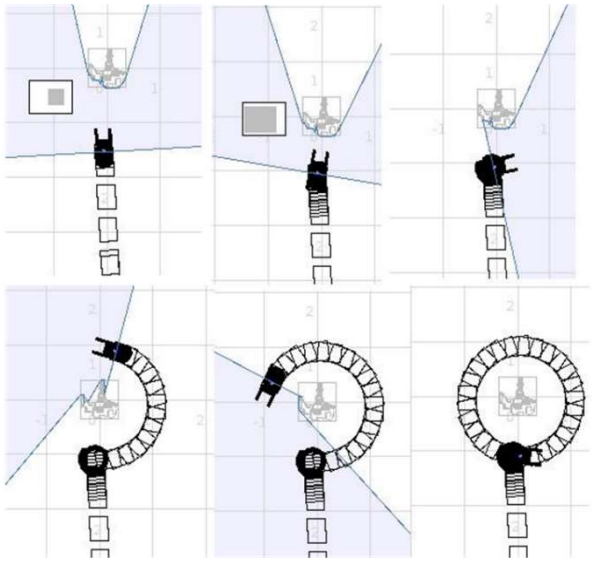

Fig. 4. Data acquisition for the classification process.

To acquire the antigen of the pathogen (non-self object to be transported), Hu invariant moments are used to obtain outline information on the object. The data obtained in the last process correspond to distance between the robot and the object. A set of the information contains between 150 and 200 different information vectors. The information on the object is translated to the outline of the object in a plane (x,y), by (1) in the axis X, and (2) in the axis Y.

$$Xc=l*\cos\theta-Xr \tag{1}$$

$$Yc=l*\sin\theta-Yr \tag{2}$$

Xc and Yc are the coordinates of the outline of the object, l is the distance between the object and the robot, θ is the angle between the front of the robot and the X axis, and Xr and Yr are the robot's coordinates. Figure 5 shows an example of the outlines obtained; these are triangle, invader, submarine, phantom, circle, and square, respectively.

The antigen is the vector that contains the Hu moments on the object to be identified. Each component of this vector corresponds to the epitope. The antibodies correspond to sets of Hu moments of the different objects previously obtained; these are used for the classification process. Each moment that composes each antibody is the paratope, in immunology paratope is defined as the region of the antibody that it used to recognize and grab the antigen [15]. The antigen is compared by a set of the antibodies stored in the robot by using equation (3).

$$Aa = K1|Mp1-Me1| + K2|Mp2-Me2| +\ldots + K7|Mp7-Me7| \quad (3)$$

Aa corresponds to error between the antigen and the antibody; this error represents the difference between antigens and antibodies. Mpn is the n paratope of Hu moments stored in the robot, Men is the n epitope of the antigen, and Kn is a n scaling factor. If Aa is lower than the U1 threshold, the object will be considered classified. If Aa is greater than U1 but lower than U2, the object will be considered indeterminate. Finally, if Aa is greater than U2, the object will be considered unknown.

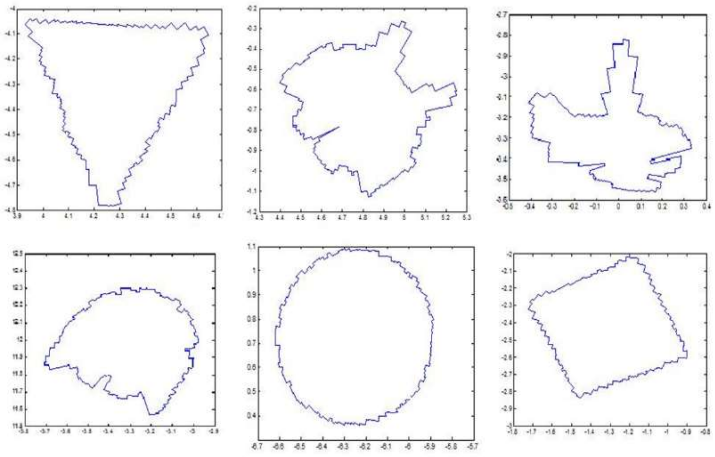

Fig. 5. Object outlines.

A set of antibodies is generated using the clonal selection algorithm. In case the error between the antibodies and the antigens is greater than U2, the pathogen will be considered unknown and the mechanism of generation of the set of antibodies using clonal selection algorithm will be activated. Table 1 shows the immunological metaphor. The set of antibodies stored inside the robot's memory corresponds to the immunological memory.

Table 1. Immunological metaphor.

Robotic System	Immune Inspiration
Object to Recognize	Pathogen
Hu Invariant Moments	Vector Antigen
Individual Moments	Epitope
Invariant Moments Stored in Robot	Antibodies
Individual Moments Stored in Robot	Paratope
New Object to Recognize	Antibodies Generation
Antibodies Stored in the Robot	Immunology Memory
Color Recognition	Innate Immune System
Outline Recognition	Acquired Immune System

4.2 Clonal Selection Algorithm

In order to identify an object, it is necessary to generate a set of antibodies for each object. To this end, the following Clonal Selection Algorithm is proposed:

1. A set of antigens is acquired for each pathogen (objects to be recognized). These are acquired in different directions of the object. In this process, the robot finds a non-self object in the environment (pathogen). Subsequently, the robot starts the process of antigen recognition; the agent repeats the process explained in Section 3 and shown in Figure 3. The antigen is composed of the vector of Hu invariant moments. On average, eight antigens are taken for most of the cases, rotating 23 degrees.
2. For each antigen acquired, one antibody is exactly cloned and created, which corresponds to a non-matured antibody. Each antibody is composed of the vector of Hu invariant moments.
3. The non-matured antibody is cloned in a determinate number of copies. There are ten clones for each non-matured antibody; these clones are similar to the original antibody.
4. Subsequently, each clone is muted. The mutation consists in randomly mutating each paratope ±25% of its value. Each paratope corresponds to each individual Hu invariant moment.
5. The error between the antibodies non-matured and their own clones mutated is calculated by solving for (3). The clones with error lower than 10% are selected as matured antibodies. These clones are included in the immunological memory of the acquired response.

5 Experiments and Results

5.1 Experiment 1

In the first experiment, ten different trajectories were performed for the six elements in order to extract their antigens by measuring the error with the non-matured antibodies acquired previously. The antibodies will be activated with errors lower than 50, this error is obtained by using equation (3), representing an absolute value of the comparison between antigens and antibodies. Table 2 shows the results obtained for each pathogen; the first column contains the object, the second column contains the numbers of antibodies with affinity lower than 50, and the third column contains the range of the errors. The error was obtained experimentally.

Table 2. Results obtained in experiment 1.

Object	Antibodies activated	Range of errors
Submarine	28 of submarine	From 8 to 42
	16 of triangle	From 18 to 50
Invader	28 of invader	From 8 to 47
	14 of circle	From 30 to 45
	1 of phantom	40
Phantom	36 of phantom	From 8 to 47
	2 of circle	From 46 to 49
	2 of square	From 46 to 48
Circle	20 of circle	From 1 to 10
	26 of invader	From 35 to 50
Square	22 of square	From 8 to 50
	1 of circle	45
Triangle	26 of triangle	From 5 to 46
	4 of submarine	From 30 to 50

In the case of the submarine, some trajectories were strongly critical because the error measured of the antibodies of submarine was similar to the triangle. In other cases of the submarine, antibodies of the triangle were activated, but submarine anti-bodies were more related. Only in four cases the most related antibody of submarine had an error lower than 20. For the invader, in all cases the best measured error was obtained with antibodies of invader, with an error lower than 20, except for two cases in which the errors measured were greater than 30. In the case of the phantom, in three cases the antibodies had an error lower than 20. For the circle, there is some similarity to the invader, but the error of the antibodies of the circle is strong, while the measures of the invader could be ruled out. The error of the square is convincing for the recognition; only one of other antibodies was selected, belonging to the circle, but the error obtained was not comparable with the error obtained by the square. The last case of

the triangle, the lowest error was not lower than 20 in five experiments, and in one case the error of the submarine was low, so the classification was incorrect.

5.2 Experiment 2

In order to obtain better results, the Clonal Selection Algorithm was activated and a set of matured antibodies was selected and included in the immunological memory of the agents. Once a new set of antibodies matured were trained, the conditions of experiment 1 were repeated, with ten different trajectories for each object. In this case, the antibodies activated had an error lower than 30 according to (3). Table 3 shows the results; the first column contains the object, the second column contains the numbers of antibodies cloned with an error lower than 30, and the third column shows the range of the value of errors. It is worth noting that the error was lower in experiment 2, because the matured antibodies had higher affinity with the antigens.

Table 3. Results obtained in experiment 2.

Objects	Antibodies cloned activated	Range of errors
Submarine	50 of submarine	From 4 to 30
Invader	100 of invader	From 8 to 30
	5 of circle	From 25 to 30
Phantom	40 of phantom	From 3 to 30
Circle	30 of circle	From 1 to 30
	5 of invader	From 27 to 30
Square	32 to square	From 7 to 30
Triangle	47 of triangle	From 2 to 27
	10 of submarine	From 17 to 29

In the experiments of the submarine, the antibodies of the triangle activated in experiment 1 were not activated in the new cases. The error of the antibodies selected in experiment 2 had an error lower than the error obtained in experiment 1. For the case of the invader, the errors of antibodies were lower without any doubt of the classification in all cases. For the phantom, the error values were always conclusive for the classification process; no antibodies for other pathogen were activated. In the case of the circle, although few antibodies of the invader were activated, the errors of the circle's antibodies were lower for all cases. In the experiments of the square, no other antibodies with different pathogen were selected. In all cases antibodies with errors lower than 30 were activated. For the triangle, in all cases the antibodies of triangle had robust performance, in the cases in which errors belonging to the submarine were activated, the lowest error belonging to the triangle was lower than 15, achieving correct classification in all cases.

5.3 Experiment 3

The circle, the square, and the invader were added in the environment, with noise in their outlines, as shown in Figure 6. Noise in the square is significantly higher than in the circle and in the invader. In two cases, antibodies of the square had affinity values around 70; these values were greater than U2, and the clonal selection algorithm was activated in order to train new antibodies for the new object. As for the circle and the invader, affinity values were lower than 20 (lower than U1); they were classified correctly.

Fig. 6. Pathogens mutated.

The mutation in square is higher than in circle and invader. Then the antigen of square mutated enough to be considered a different pathogen. Biologically, there are some viruses that can mutate their epitopes, so the antibodies cannot detect and neutralize the pathogen [21].

5.4 Experiment 4

Finally, Kohonen maps were developed for comparison. For the experiments the six objects considered in experiments 1 and 2 were used. For the training of the Kohonen map, the Hu invariant moments obtained in previous experiments were used; those correspond to the inputs of the network. The Kohonen Network was trained with 48 networks. Once the Kohonen Map was trained, each neuron was assigned to one object. To this end, equation (4), based on (3), was used.

$$A_a = K_1|M_{par}1-M_{nk}1| + K_2|M_{par}2-M_{nk}2| +\ldots + K_7|M_{par}7-M_{nk}7| \quad (4)$$

Aa corresponds to error or affinity between the neuron and the Immune System, the set Mpar corresponds to Hu moments used by the Immune System (antibodies), and the set Mnk corresponds to the weights of each neuron; constants K are similar to (3). Each antibody was compared with each neuron by evaluating their affinity based on (4). If Aa is lower than 30, the object associated to this antibody will be assigned to the respective neuron. In case the Aa values between the same neuron and different antibodies associated to different objects are lower than 30, the neuron will be considered not classifiable. A similar case is when all the Aa values of one neuron are greater than 30.

Finally, the neurons were assigned as follows: to submarine, 10 neurons; to invader, 8 neurons; to phantom, 5 neurons; to square, 13 neurons; to triangle, 7 neurons; to circle, 1 neuron; and finally, 4 neurons are unclassifiable. In order to compare the Kohonen network with the Immune System, robots were used in order to classify the six objects, with similar conditions as explained in experiment 1, using both classifiers. Ten experiments per classifier were conducted by each object; Table 4 shows the results.

Table 4. Results obtained in experiment 4.

Objects	**Antibodies activated.**	**Neurons activated.**
Submarine	10 of submarine	9 of submarine 1 of triangle
Invader	10 of invader	5 of invader 3 of phantoms 1 of submarine 1 non-classifiable
Phantom	10 of phantom	6 of phantom 2 of square 2 non-classifiable
Circle	10 of circle	10 of circle
Square	10 of square	5 of square 3 of phantom 1 of circle 1 non-classifiable
Triangle	10 of triangle	6 of triangle 2 of submarine 2 non-classifiable

6 Conclusions and Future Works

An Artificial Immune System was designed for classifying objects with a mobile orbot. This Immune System involved an innate response and acquired response. The innate response involved color detection, but not geometrical classification, which is used for acquired response.

For the acquired response, a set of antibodies was trained by a proposed Clonal Selection Algorithm. The antibodies showed robustness in case of noise in the classification. The noise was modeled as superficial deformation. The AIS was adaptable to new pathogens and their new antibodies generated were stored in the immunology memory of the robot.

Clonal Selection Algorithm was used for the maturation of antibodies by mutation and cloning. The performance of the acquired system classification, after maturing the clones, improved the affinity values of. A lower threshold for activation could also be assigned. When there were untrained antigens in the AIS, the immune system was

able to detect them as unknown pathogens, and a new set of antibodies was trained and stored in the immunological memory.

In future works Artificial Immune Systems will be proposed for machine learning applied to 3D object recognition using kinetic and real sense in mobile robots.

Acknowledgements. This work has been funded by "Decimotercera convocatoria interna para el Fomento de la Investigación - FODEIN 2019" at Universidad Santo Tomás, Bogotá Colombia, entlited "Mapeo, Localización Y Planeación De Trayectorias En Ambientes Interiores Aplicado A Robots Móviles Para Las Sedes De La Universidad Santo Tomás", project code: 1936005.

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