Implementando un Algoritmo Competitivo Imperialista para reducir marginalidad en un polígono de los más pobres en Chihuahua.

Implementing Imperialist Competitive Algorithm to reduce marginality in a poorest polygon in Chihuahuas

Carlos Alberto Ochoa Ortiz[1,2], José Alberto Hernández Aguilar[3] & Julio César Ponce Gallegos[4]

[1] alberto.ochoa@uacj.mx Maestría en Cómputo Aplicado, Universidad Autónoma de Ciudad Juárez, Ciudad Juárez, México
[2] Gerencia de Tecnologías de la Información, Instituto Nacional de Electricidad y Energías Limpias, Reforma 113, Palmira, Cuernavaca, Mor., México, CP. 62490.
[3] jose_hernandez@uaem.mx Facultad de Contaduría Administración e Informática, Universidad Autónoma del Estado de Morelos, Av. Universidad No. 1001, Col. Chamilpa, Cuernavaca, Mor., México, CP. 62209.
[4] jcponce@correo.uaa.mx Departamento de Ciencias de la Computación, Universidad Autónoma de Aguascalientes, Av. Universidad No. 940, Col. Ciudad Universitaria, Aguascalientes, Ags., México, CP. 20131.

PALABRAS CLAVE:

Algoritmo Competitivo Imperialista, Modelo reactive bajo incertidumbre, Modelado social.

RESUMEN

El Algoritmo Competitivo Imperialista (ACI) usa un sistema básico de conocimiento fuente para determinar las mejores situaciones bajo incertidumbre usando un modelo de países, cada uno relacionado al conocimiento observado en varios aspectos del comportamiento social. Este conocimiento está combinado para direccionar las decisiones de los agentes individuales para resolver problemas de optimización o en la solución de la distribución de recursos en diferentes comunidades. En la presente investigación, nosotros simulamos un modelo reactivo bajo incertidumbre para integrar estas diversas fuentes de conocimiento para dirigir la población del agente. Las diferentes fases de solución del problema emergen combinando el uso de estas fuentes de conocimiento y estas fases dan lugar a la aparición de roles individuales dentro de la población en términos de líderes y seguidores para cada país (grupo de agentes). Estos roles dan lugar a la salida de un grupo organizado o grupos organizados en nivel de población y grupos de conocimientos o conocimiento agrupado en el espacio de creencias sociales. Esta aplicación optimiza una función revalorizada en el diseño de problemas de modelado social, permitiendo ilustrar un mejor modelo reactivo bajo incertidumbre.

KEYWORDS:

Imperialist Competitive Algorithm, Reactive Model under uncertainty, Social Modelling.

ABSTRACT

The Imperialist Competitive Algorithm (ICA) use a basic system of knowledge source to determine the better situations under uncertainty using a model of countries, each one related to the knowledge observed in several aspects of social behavior. These knowledges are combined in order to direct the decisions of the individual agents to solve optimization problems or in the solution of distribute resources in different communities. In the present research, we simulated a reactive model under uncertainty to distribute energy resources in the Southwest Chihuahua using a reactive model under uncertainty to integrate these diverse sources of knowledge to direct the population of the agent. The different phases of solution of the problem emerge combining the use of these source of knowledge and these phases give rise to the appearance of individual rolls within the population in terms of leaders and followers to each country (group of agents). These rolls give rise to an exit of organized grouping or organized groups in the population level and knowledge groups or knowledge grouping in the social belief space. This application optimizes a function revalued in the design of problems of social modeled of social modeling, allowing illustrating a better reactive model under uncertainty.

Recibido: 5 de marzo del 2017 Aceptado: 16 de junio de 2017 Publicado: 30 junio de 2017

1 INTRODUCCIÓN

The search problem denominated: Distributed resources is represented as a reactive model under uncertainty, and is featured as a multiagent problem of general type and has been relatively studied, but it has not yet been adequately solved o addressed. The search problem using Imperialist Competitive Algorithm was introduced in [1] and included diverse countries' agents whose goal was to solve a "distribution problem" agent surrounding it by the four sides in a world of cells. This problem has been used to study phenomena such as coevolutionary competitiveness [2], multiagent strategies, and multiagent communication. The rest of this introduction describes some previous studies about last two phenomena that constitute the distribution problem. In [2] is used a reactive Model with a Fuzzy Logic Type-2 to develop a reactive group of stratagems or strategies of Distribution of resources and to demonstrate that a linear problem related with energy distribution (selecting a direction at random and to continue the direction for the rest of the game) was impossible to capture reliably because in the experiments o in the experiments because the linear necessity of energy avoids the movement place.

IMPERIALIST COMPETITIVE ALGORITHM

Imperialist competitive algorithm (ICA) is a new evolutionary optimization method that is inspired by imperialistic competition. It starts with an initial population like other evolutionary algorithms which is called country, which be of, type being colonized or being imperialist [11]. Imperialistic competition is the main part of proposed algorithm and causes the colonies to converge to the global minimum of cost function. This method is a new socio-politically motivated global search strategy that has recently been introduced for dealing with different optimization tasks [7].

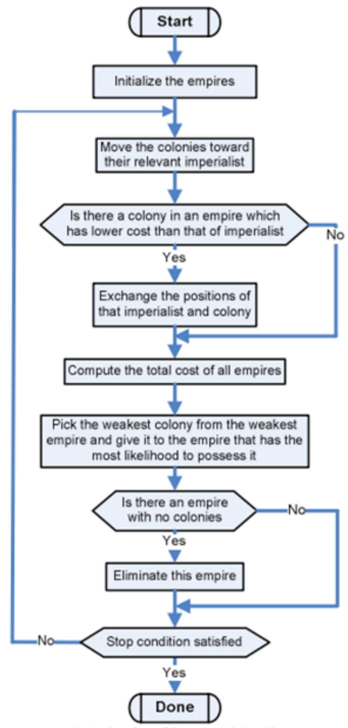

Figure 1 Flowchart of the Imperialist Competitive Algorithm [11].

Figure 1 shows the flowchart of ICA, where all countries are evaluated and some of the best countries are selected to be the imperialistic and the rest of them are named colonies of these [20]. Each country is identified by country i = [p1, p2, … , pNvar] where Nvar is the dimension of optimization problem [7]. The function value of each country is represented by floating point numbers. The cost or value of each country is obtained by the evaluation of the function f at the variables (p1, p2,..., pNvar). Therefore, we have [11]:

$$country = f(country) = f(p1, p2, \dots , pNvar) \qquad (1)$$

Is selected the imp N countries of the most powerful in the subset of empires. The remaining of the population will constitute the subset of colonies (col N) belonging to an empire. The initial empires are formed dividing the subset of colonies between imperialists based on their power level. To divide the subset proportionally is defined the following equation for normalizing the cost of an imperialist [20]:

$$Cn = CN - max(Ci) \qquad (2)$$

Where the cost of nth imperialist is Cn and CN is the cost, which is a normalized value. The power level of each imperialist can be obtained by:

$$p_n = \frac{C_n}{\sum_{i=1}^{Nmax} Ci} \quad (3)$$

After dividing colonies Cn between imperialists, the empire starts closing. The total power of an empire can be calculated by the power of imperialist country plus a percentage of power of its colonies as follow [7, 20]:

$$power\ n = cost(imperialists\ n) + e\ mean\{(cost(\ colonies\ of\ empires \quad (4)$$

Where n power is the total power (cost) of the nth empire and powern is a positive number less than 0.1.

Powerless empires will collapse in the imperialistic competition and their colonies will be divided among other empires as in [16]. After a while, all the empires except the most powerful one will collapse and all the colonies will be under the control of this empire [11], which is the answer of optimization problem.

Implemented methodology

The search problem denominated Imperialist Competitive Algorithm is a Multiagent problem of the general type and has been relatively studied, but it has not yet been adequately solved o addressed. The search problem Predator/Prey was introduced in [1] and included four predators' agents whose goal was to capture a "prey" agent surrounding it by the four sides in a world of cells. This problem has been used to study phenomena such as co-evolutionary competitiveness [6], [8], [13], multiagents strategies, and multiagents communication. The rest of this introduction describes some related works about last two phenomena that constitute the Predator/Prey problem. In [6] is used Genetic Programming (GP) to develop strategies of Predator to demonstrate that a linear prey (selecting a direction at random and to continue the direction for the rest of the game) was impossible to capture reliably because in the experiment or in the experiments, the linear prey avoids the movement place.

In [7] was studied a version of the Predator/Prey problem in which the predators could move or be allowed to move diagonally as well as orthogonally and the prey moved randomly. In [16] it was used reinforced learning, this research demonstrated that the agents cooperated to share "sensations and policies of learning" significantly perceivable for no cooperative agents in a version of the Predator/Prey problem. On the other hand, in [8] random clusters of a swarm and other types of collective movements of preys in an ICA were observed. Finally, in [15] it was studied a simple predator strategy that it does not communicate, in which the predators move to the nearest position of the capture, and demonstrate that this strategy is not at all right because the predators can block themselves trying to move to the same position of capture. In the same work, it was also presented another strategy, in which three predators transmitted all their sensorial information to a central predator agent that decides where all predators' resources search to conduct where the predators must move. This central strategy of a single agent was successful for 30 Imperialist Competitive Algorithms of the test, but perhaps the rank of successes would be too lower if the agents moved simultaneously instead of taking turns. This article uses an implementation that probably is more difficult for the predators that in the previous works since it uses Imperialist Competitive Algorithm to represent the agents. The characteristics of our framework are:

1. Algorithm configuration, each agent can move in four directions. The predators and prey cannot take shortcuts moving diagonally to other cells [7].

2. The speed is the same for all agents. The predators and prey are equal fast [6].

3. The movements of agents are simulated simultaneously. The simulation is made by iterations, each one represents one move of all agents in a determined time t (e.g. [15]) there is a certain uncertainty in anticipating the result of each movement. In addition, the movements of agents introduce potential conflict, example: two or more agents can try to move to the same cell.

4. The predators cannot see themselves or know their locations.

The information about themselves or their locations is essential to get captures, the predators must develop a form to represent its own information, that it is used a vector with positions of all the predators. The board (world) is represented by a graph with two dimensions that consist of 350 nodes (cells). Since the board has continuous representations, if an agent (predator or prey) is on the left side of the graph he will reappear in the right side of the graph, and a similar behavior is observed vertically. It is not allowed to any agent to occupy the same node in the next time. If two or more agents try to move to the same node, all the involved agents are blocked and they remain in their current positions. To initialize a test instance, the predators and the preys are placed randomly on diverse nodes using predetermined percentages. There is a board of evolution until all preys are captured, or until 5000 epochs or iterations have passed without change. Two strategies designed for the prey are used in the simulations. The prey chooses randomly o at random the next action to do for a set North (N), South (S), East (E), and West (W) using a uniform distribution at random or random uniforms distributions. The prey chooses at random o randomly a direction at the beginning of a movement and continues the entire scene in that direction. It has demonstrated that the linear prey can be difficult to capture, as mentioned in [6] and [14] because the prey does not remain located in the same area. In our simulations, we show a prey is more difficult to capture because the preys associated with marginal people and the predators move at the same speed.

2 Evaluation of the Imperialist Competitive Algorithm

2.1 Evaluating the predator strategies

A vector that stores the locations of each predator represents the behavior of each developed predator. According [20] the size C of the vector is a function of the number of possible observable states N states by the predator based on the stored information, and the number of actions b. The sensorial information available for the predators includes the rank and the reach of the prey, and the contents of the messages board (vector). The rank (measured in terms of distance of Manhattan) and the reach is discretized to Nrange=4 and Nbearing=8 sectors. The number of symbols in the message board is ml, where m is the number of predator agents is the chain size. This board can have Nmessages= 2ml possible messages. The total number of states that can be detected by the predator is, therefore, Nstate = Nrange *Nbearing *Nmessages. The actions include the movements {N, S, E, and W} and contain a chain of size 1 for each iteration. The number of bits required to represent the 4 movements is bmoves= 2. Therefore, the total number of actions is bactions= b moves+l. We determined the following equation associated with the communication of the predator with chains of size l within the equipment of m predators: Cml = bactions Nstates .

Figure 2.The southwest of Chihuahua is featured by a low HDI.

2.2 Modeling southwest Chihuahua related to energy resources

According to this research, there are 11 prey representations and 44 predator representations (Chihuahua people). Then, the board is represented by a graph (See Figure 3), in which the predators and the preys cross it. The preys require achieving a goal or achieving an agreement of movement, based on the type of societies that constitutes the board [9].

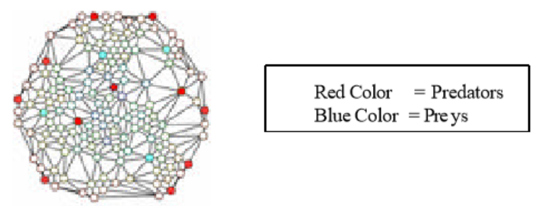

Figure 3. Representation in the graph of the predators and the preys.

2.2 Evaluating the performance of the developed predators.

The aptitude of each developed strategy is determined to prove it with 100 scenes randomly generated with diverse locations where the predators and the prey's agents begin. The maximum number of iterations by scene is 5000, after that, it is considered that the predators have failed. Since the initial population is generated randomly. It is very improbable that the first generations will be able to capture the prey. We tried to accelerate the evolution of the fit strategies. The strategies that remain at least near of the prey and can block its trajectory are rewarded. The fitness function fi of the individual i at the end of each iteration is calculated as follows [20]:

$$nc = 0, \quad fi = 0.4 / davg + 0.6\,(nb / NmaxT). \qquad (5)$$

Where Nmax represents the maximum number of cycles by scene, T the total number of scenes for each individual, nc is the number of captures, davg is the average distance of the predators towards the prey during the scenes, nb is the cumulative number of cycles in which the movements of the prey were blocked by an adjacent predator during T scenes. We follow the setup mentioned in [20], where Nmax = 500, T=100, and the performance of strategies of capture never can be greater than 1.

3 Complementary Method: ICA

The Imperialist Competitive Algorithm is a class of computer model derived from the evolutionary cultural process in nature [11]. The Imperialist Competitive Algorithm has three basic components: a population space, a beliefs space, and a protocol that describes how the knowledge is interchanged between the first two components [19]. The Imperialist Competitive Algorithm allows that the agents interact reciprocally in several ways using varied forms of reflective symbolic information of complex cultural systems. The basic cultural algorithm allows that the individuals communicate through a shared belief space. The shared space stores five basic types of information that can be shared cognitively or symbolically. The population space can support any computational model based on population, as genetic algorithms [2, 3], and evolutionary programming [4]. The Computer Diagram of the Imperialist Competitive Algorithm is shown in figure 3.

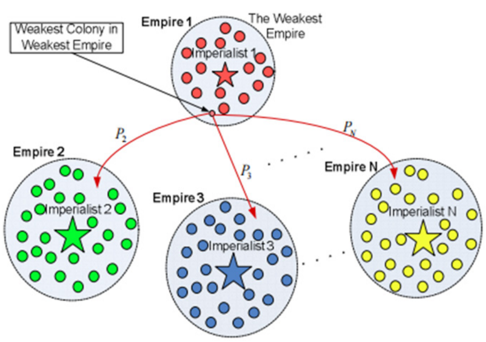

Figure 4. Solution of Imperialist Competitive Algorithm.

The Imperialist Competitive Algorithm has been studied in pattern problems proves, as well as successfully applied in diverse applications such as to model the agriculture evolution, the learning concept, the optimization of the function of real value [11] and in re-engineering of knowledge bases for the process of manufacture assembly, and to model based on agent's systems of price incentives.

They have also been used in the distribution of elements in a Diorama [9], obtaining a ranking in Eurovision, social simulation in an intelligent game [10], and compared with other techniques of swarm intelligence [10] among others. The Imperialist Competitive Algorithm is a dual system of inheritance which characterizes the evolution in human culture in the macro-evolutionary level that happens within the belief space and in the micro-evolutionary level, which happens in the population space. The knowledge produced in the population that is the space in the micro-evolutionary level is accepted for to pass to the belief space and to be used selectively to fit the structures of the generated knowledge. This knowledge can be used to influence the changes done by the population in the following generation.

4 Experiments for the developed Framework

A multiagent system, in which all the agents communicate between them simultaneously, is corresponding to a finite state machine for the linking of the sequences in the communication of the agents [20]. Thus, the development of a communication protocol for this multiagent system is equivalent to develop a finite state machine to solve the problem. The simulations demonstrate that the use of Imperialist Competitive Algorithm allows developing predators that can communicate in a superior way, which improves their possible performance because they develop "tactics" (see Table 1).

Table 1. The theoretical superior limit δU in the density of meaning and the average superior limit observed δU* for best predators N* is the average number of states in the developed multiagent. Shown here to be more explicit].

Predator	δU	δU^* against the linear prey	δU^* against the random prey	N*
Predator (0)	128			11
Predator (0→1)	64	38	10	16
Predator (1)	64	38.5	16	16
Predator (1→2)	32	19.75	10	87
Predator (2)	32	20	20	252

The table 1 shows that for most of the Imperialist Competitive Algorithms the developed agents are better than the superior limits of semantic density because the average number of states is greater than the superior limits of semantic density, as is shown in [18,19]. The Imperialist Competitive Algorithms where the superior limit observed in the semantic density δU* is greater than the number of states, are exactly such Imperialist Competitive Algorithms where a greater language (greater information on the message board) improved the performance in simulations. For example, δU* against a linear prey with chains of communication of length 1 is greater than the number of possible states, and in our simulations the increase in the communication size to a value of 2 improved the output of the capture.

5 Conclusions

By using the Imperialist Competitive Algorithm, we improved the understanding of its functionality to obtain the shift of the “better paradigm” o “best paradigm”, because we appropriately simulated the communities represented by agents, considering an approach to the relation that keeps their characteristics. This situation allowed us to understand the concept of “collaboration” with base in the determination of the acceptance function to interchange information between the same preys and their proposed location for the rest of them. The Imperialist Competitive Algorithm offers an alternative of long achieve for optimization problems and redistribution in Imperialist Competitive Algorithm problems [12]. Therefore, this technique provides an absolutely comprehensible outlook panorama to the represented cultural phenomenon [17]. When combining the two techniques it was allowed to include the possibility of generating experimental knowledge created by the community of agents to survive an attack. The use of a message board allows that the predators locate their positions and the reach of the preys. This help to the predators to organize the attacks establishing the concept of “tactics”, on the other hand the use of Imperialist Competitive Algorithm helped to the preys to reach a “consensus” of the movements to do, since they had to establish a movement adapted to the present scene, and to find the way to locate positions in where they can avoid attacks organized by the predators. In this sense, the “tactics” and the “consensus” are optimized providing to the prey a predator greater capacity to make decisions that is greater intelligence. This has been done with other techniques like Artificial Immune System (AIS) [5]. As future work, we will try the Artificial Immune System (AIS) because it can provide more intelligence to the agents [5]. The analysis of the level and degree of cognitive variation goes beyond phenotypic characteristics and they are mainly associated with similar attributes developed at the time [10].

References

1. Benda, M.; Jagannathan V. & Dodhiawalla, R.: On optimal cooperation of knowledge sources. Technical Report BCS-G2010-28, Boeing AI Center, Boeing Computer. (1985).

2. Fogel D. B.: An introduction to simulated evolutionary optimization. In IEEE Trans. On Neural Networks, vol. 5, num 1, pp 3-14. (1994)

3. Goldberg D.E.: Genetic Algorithm in Search, Optimization and Machine Learning. AddisonWesley. (1989)

4. Holland J. H. Application in Natural and Artificial Systems. MIT Press, Cambridge Massachusetts. (1975)

5. MacDonald Donald; Fyfe Colin: Strategy Selection in Games Using Co-Evolution Between Artificial Immune System. (2004)

6. Haynes, T.: Evolving behavioral strategies in predator and prey. IJCAI-95 Workshop on Adaptation and Learning in Multiagent Systems. (1995)

7. Korf, Richard E.: A simple solution to pursuit games. In Working Papers of the 11th International Workshop on Distributed Artificial Intelligence. (1992)

8. Nishimura, S. & Ikegami T.: Emergence of collective strategies in an Imperialist Competitive Algorithm model. Artificial Life, 3(4): 243-260. (1997)

9. Ochoa A. et al.: Baharastar – Simulador de Algoritmos Culturales para la Minería de Datos Social. In Proceedings of COMCEV'2007. (2007)

10.Ochoa A. et al.: Una comparativa de la Inteligencia Grupal desde la perspectiva del Cómputo Evolutivo CIICC'08; Cuernavaca; México. (2008)

11.Reynolds, R. G. & Saleem, S. M.: The Impact of Environmental Dynamics on Cultural Emergence. Perspectives on Adaptions in Natural and Artificial Systems. Oxford University Press, 253-280. (2005)

12.Reynolds, R et al. Optimization Problem Solving using Imperialist Competitive Algorithms and Imperialist Competitive Algorithm. CIG 2006: 119-125. (2006)

13.Savill, N. & Hogeweg, P.: Evolutionary stagnation due to pattern-pattern interactions in a coevolutionary predator-prey model. Artificial Life, 3(2): 81-100. (1997)

14.Steels, Luc: Self-organizing vocabularies. In Proceedings of Alife V. (1996)

15.Stephens, L. & Merx, M.: The effect of agent control strategy on the performance of a day pursuit problem. In Proceedings of the 10th International Workshop on DAI. (1995)

18 Esmaeil Atashpaz-Gargari, Caro LuImperialist Competitive Algorithm: Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. IEEE Congress on Evolutionary Computation 2007: 4661-4667

19 Mahdi Bashiri: Optimal scheduling of distributed energy resources in a distribution system based on imperialist competitive algorithm considering reliability worth. Neural Computing and Applications 25(3-4): 967-974 (2014)

Acerca de los autores


Carlos Alberto Ochoa Ortiz (BSc 1994 – Eng. Master 2000, Ph.D. 2004 at CICATA at Instituto Politécnico Nacional, México, Postdoctoral Researcher 2006 at University of Campinas (UNICAMP), Brazil and Industrial Postdoctoral Research 2008 at Centro de Innovación Aplicada en Tecnologías Competitivas (CIATEC - CONACYT). He has participated in the organization of different international congresses like HAIS, HIS, ENC, and MICAI. His research interests include Evolutionary Computation, Natural Processing Language, and Social Data Mining; he is part-time professor at the Social Science department at Juarez City University. He is a member of the National System of Researchers Level 2 in Mexico (SNI).


José Alberto Hernández Aguilar. He finished his Doctorate thesis in 2007 at Universidad Autónoma del Estado de Morelos (UAEM) and received his Ph.D. degree in 2008. He obtained a Master of Business Administration degree, Cuma Sum Laude in 2003 at Universidad de las Americas (UDLA), A.C. He has a B.S. in Computers Engineering at Universidad Nacional Autónoma de México. Since 2010, he is a full-time professor at the accounting, management and computer sciences School at Universidad Autónoma del Estado de Morelos. His areas of interest are Databases, Artificial Intelligence, Online Assessment Systems, Data Mining and Marketing Research. He has participated in the organization of different international congress like HIS and MICAI.


Julio César Ponce Gallegos. He received the B.S. degree in computer system engineering from the Universidad Autónoma de Aguascalientes in 2003. He received the M.S. degree in computer sciences from the Universidad Autónoma de Aguascalientes in 2007, and the Ph.D. Degree in computer sciences from the Universidad Autónoma de Aguascalientes in 2010. He is currently a full-time professor in the Universidad Autónoma de Aguascalientes. He is author and coauthor of several international papers and book chapters in Computer Sciences related fields. His research interests include Evolutionary Computation, Data Mining, Software Engineering and Learning Objects. He has participated in the organization of different international congress like HIS and MICAI. He is a member of the National System of Researchers Candidate level.