# A Fuzzy Logic Fish School Model

Juan Carlos González, Christianne Dalforno, Remo Suppi, and Emilio Luque

Computer Architecture and Operating System Department (CAOS)
University Autonoma of Barcelona, Spain
{jgonzalez,chris}@caos.uab.es,{remo.suppi,emilio.luque}@uab.es

**Abstract.** This paper summarizes our work on fuzzy modeling for an Individual-oriented Model (IoM). Our model is particularly geared toward simulating the movement of fish schools, derived from the model by Huth and Wissel. The background and motivation for the problem as well as a description of biological model are given here. A fuzzy logic implementation is discussed based on the mathematical model proposed. Finally, the experiments performed to demonstrate that our model represents the real behavior of fish schools. Keywords: Fuzzy Logic, Individual-oriented Models (IoM), Fish School.

**Keywords:** Fuzzy Logic, Individual-oriented Models (IoM), Fish School.

## 1 Introduction

Individual-oriented Models (IoM) were created to solve to the limitations imposed by models based in a population that use differential equations, for example to explain the behavior of a group of individuals.

In IoM the unit of the system is the individual, so the group's heterogeneity can be represented through the differentiated behavior of each individual. Therefore, "individuals are the building blocks of ecological system. The properties and behavior of individuals determine the properties of the systems they compose" [1]. The system is not directly modeled as a globally integrated entity, individuals are autonomous.

In [2] many examples of IoM applications are given and the author outlines the importance of this kind of model for researches where the individuals' interactions are important to accurately represent the group's features. "Organisms get together and form populations and societies, have properties none of which can be explained by properties of the individual organism alone" [3].

We chose the simulation of fish schools as a case study. Some kinds of fish present the characteristically behavior of being together for a long time maintaining a self-coordinated movement without the presence of leaders [4]. This behavior caught the attention of the biologists interested in investigating this kind of formation.

The April 2007 issue of National Geographic [5] presents an overview of the situation of worldwide fishing. In fact, fish consumption has been growing and, in approximately 50 years, fishing went from about 30 million tons to nearly 100 million tons.

One of the species that has been suffering a lot due to an increase of its consumption is blue tuna. The situation of this specie is so critical that the International Commission for the Conservation of Atlantic Tunas (ICCAT), responsible for managing the reserves

G. Allen et al. (Eds.): ICCS 2009, Part I, LNCS 5544, pp. 13–22, 2009.

of blue tuna, was created. Equilibrium between commercial interests and preservation of the species must be found. Thus current research works focus their interest in fish behavior, reproduction, development and exploration. There are some models that represent the behavior of these populations [6], [7], [8]. The one used in this work is an Individual-oriented Model (IoM) [4]. This kind of model represents the behavior of a group by applying some rules to a group of individuals interacting among each other.

Our general interest is the application of fuzzy logic (FL) to simulations based on IoM. Within fish school simulations several models have been developed using conventional mathematical modeling as in [9], [10]. We use the fuzzy approach to achieve an alternative way of modeling. Also, by using fuzzy logic we odd a degree of uncertainty, which is present in reality, to the model.

In this work we start by using the biological model described in [4]. This biological model defines the behavior of each fish as a consequence of its interaction with four selected neighbors. A fish changes its reaction direction according to its neighbor's proximity. So in each simulation step each fish will shift to new position and direction in the simulation space. A qualitative scheme is defined through fuzzy modeling for represent the biological model. A systems behavior described in a natural language can be interpreted using this kind of scheme.

This paper is organized as follows. In section 2, we present the necessary background on the biological model that describes the fish interaction schemes. In section 3, we describe our implementation of the fuzzy model. We describe the experimentation made in section 4 and conclude the paper in section 5.

## 2 The Biological Model

Fish schools are one of the most common social groups in the animal kingdom. Many fish species are organized in groups without a hierarchical structure. These schools show a high level of synchronization in short and long periods of time. Therefore, the movement of a school of fish presents highly parallel orientation.

The biological model implemented in this work is based on an IoM developed by Huth and Wissel [4]. This model defines the behavior of a fish school representing simple rules to be applied to each individual. So the behavior of individuals and their interaction is what determines the dynamics of the group.

The organization of schools is based on a passive communication; the patterns of detection are their eyes and lateral line. Each fish observes the movement of its neighbor using its eyes and or its lateral line. Only in special situations do other senses take part in the communication.[11]

### 2.1 Interaction Areas

Each fish in the group changes its direction at each time step. This new direction depends on the position and direction of a fixed number of neighbors. So the influence of a neighbor depends on its relative position. We distinguish three different influences: attraction, parallel orientation and repulsion [4]. Fig. 1 shows three areas for each influence. These areas are bounded by three concentric circles and anything outside of R3 is considered the search area which has no influence in interaction. Additionally, the region defined by angle ω determines the null vision area or DA (Dead Area).

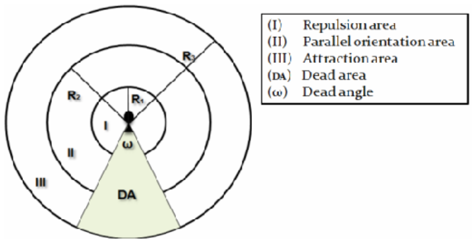



**Fig. 1.** Interaction Areas

Fish reaction depends on the area in which a neighbor is positioned. The areas are determined by the radii R1, R2, R3 and the dead angle ω. Typical values for these radios are: 0.5BL, 2BL, 5BL (Body length) and 30º respectively.

Repulsion occurs when the chosen neighbor is in range I. When two fish are very close, they tend to change their course to avoid collision. A neighbor found in range II influences the fish to move in parallel with it. It is a way to maintain a regular distance between them that is a parallel orientation situation. When a neighbor in range III is chosen, it attracts the fish to it. The attraction reduces the distance between fish maintaining the group's cohesion. Finally, the DA is the area behind the individual where no neighbors can be perceived.

The final reaction of the fish will be a combination of each reaction to the selected fish. When there are no neighbors in these areas, the fish starts looking for neighbors by swimming in random directions [7].

## 3 Fuzzy Model of the Fish School

The importance of our model is the use of qualitative modeling based on fuzzy logic. With the use of fuzzy logic is possible to approximate reasoning based on vague or incomplete knowledge. Therefore, there is nothing vague or fuzzy about fuzzy logic. It is natural and simple mathematics, which allows handling vague on difficult to specify information or. The utility of fuzzy sets lies in their ability to model uncertain or ambiguous data, so often seen in real life [12].

### 3.1 Fuzzy Structure

Fuzzy inference system (FIS) consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface [13]. A FIS with five functional blocks is shown in Fig 2.

FIS operation is described as follows. The crisp input is converted into fuzzy by using a fuzzification method. After fuzzification the rule base is formed. A rule base containing a number of fuzzy IF/THEN rules and a database which defines the membership functions of the fuzzy sets used. The rule base and the database are jointly referred to as the knowledge base. A decision-making unit which performs the inference operations on the rules. Defuzzification is used to convert a fuzzy value to a real world value which represents the output.

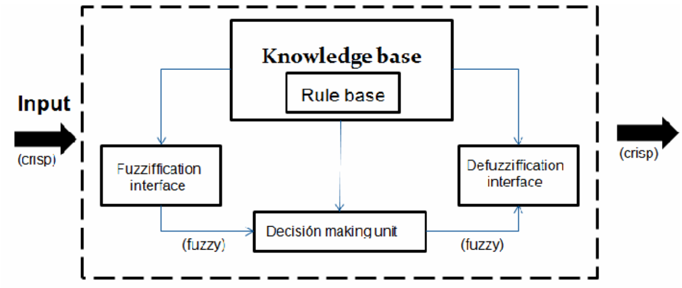



**Fig. 2.** Fuzzy Inference System

### 3.2 Model Structure

Our model consists of a fish school that moves inside an area where each fish is a unit of the system. The interaction between the fish results in the movement of the group. We define the area as a finite bidimensional space limited by an imaginary borders, where these borders also represent an external influence on the fish. To simulate movement, we have taken the location of each fish represented by x and y coordinates. The fish's speed and direction are considered.

Our model is derived from the model [4], described in section 2. We have made some assumptions which describe the interactions among individuals, as well as the numerical data that this has taken. First, it is necessary to mention the assumptions extracted from the biological model for each fish in order to explain how we are implementing it using fuzzy logic. These assumptions involve the behavior patterns that depict the movement of the fish school. Therefore, every fish:

– Selects its neighbors according to certain remote regions.
– Calculates the reaction to each of its neighbors or the external influence.
– Calculates the final effect based on the influence of all the reactions with its neighbors.
– Calculates a new position.

Starting from these assumptions we built a number of fuzzy systems to represent the model. Hence, we implemented three fuzzy systems; Proximity, Reaction and Aggregation. For these systems some variables such as position and orientation were defined and used. Within fuzzy logic these variables are called universe of discourse and they are represented by fuzzy sets.

### 3.3 Fuzzy Systems Description

We started by building a single fuzzy system; Proximity. This first system helped us represent how the fish identifies the distance to its neighbor. Therefore, we determined proximity as a fuzzy system to find the relative position with respect to its neighbor. By getting the position of an individual, the position of its neighbor and the orientation of the individual.

We took three variables for this system; the x and y distance and orientation. We defined distance as the gap that separates a fish from its neighbor taking into account the x and y axes. Orientation is the variable in which we can represent how the fish recognizes its nearest neighbors according to its area of vision. Also we determined if a fish has a neighbor located in the region of null vision (Dead area) or not. The output variable of the system is the consequence, of three input variables and gives proximity as a result.

Once a fish recognizes its four most nearby neighbors according to proximity, we built another fuzzy system called Reaction. This system represents the response of fish to the influence given by its neighbors in accordance with interaction zones. As a result, we have variables related with the orientation of its neighbor and itself. Hence, the output of this system represents the rotation a fish is able to do.

We also included an influence given by an external agent. This agent is an imaginary border that limits the area. Hence, if a fish is found very near to the border, it assumes the reaction of repulsion, which is a similar situation to when the fish has a neighbor in the zone I, i.e., it will change the orientation in order not to touch the border.

Once we have the four influences, there is a relation between them. In order to depict this, we built a third fuzzy system named Aggregation. Our scheme allows finding the final slew that the fish must do due to influences. This is done by linking pair of influences until the four reactions. Here, the influences are taken as vectors. i.e., our fuzzy system is implemented as a sum of vectors but the values are approximated. System output permits to determine a new position and orientation for each fish.

Now that the fuzzy systems have been defied, we describe the knowledge base that is the main part of the FIS used to build fuzzy systems. As we mentioned in section 3.1, the knowledge base is formed by a Rule base and a database, where the membership functions and the rules of all the system are establish.

**Knowledge base.** In all fuzzy sets, we determined a set of the fuzzy rules which involves behavior patterns of whole system according to assumptions mentioned above. Then using the knowledge of the biological system, we built a database in which we defined the membership functions of each fuzzy set. This is used in the process of fuzzification. The purpose of fuzzification is to map the inputs from a set of features to values from 0 to 1 using a set of input membership functions thus forming the fuzzy sets. Figure 3 shows the membership functions of each input for the Proximity fuzzy system. There are three inputs and an output: distance X, distance Y, orientation and proximity. These input membership functions represent fuzzy concepts such as “near” or “far,” “very to the left” or “very to the right,” “northwest” or “northeast”. We included in this system; 8 fuzzy sets to represent the distance variables, 4 sets for orientation variable and 7 sets for proximity variable.

Once we defined all fuzzy sets, we continue to describing the rules. Each rule is formed by a precedent and a consequent. The precedents express an inference or inequality and the consequent is how it can be inferred, and represents the output. Therefore the sentence which an FIS relates and consistent in rules, is given by: IF precedent, THEN consequent. The number of rules of a system depends of the equation 1, which follows:

$$\#Rules = \#FS_1 \_ \#FS_2 \_ \#FS_3 \_ \ldots \#FS_n \quad (1)$$

Where FS is the amount of fuzzy sets of a variable and n is the number of variables. We built 256 rules on Proximity system so we formed the base of the knowledge. E.g., one of these rules is: “If Distance X is *Far Behind* AND Distance Y is

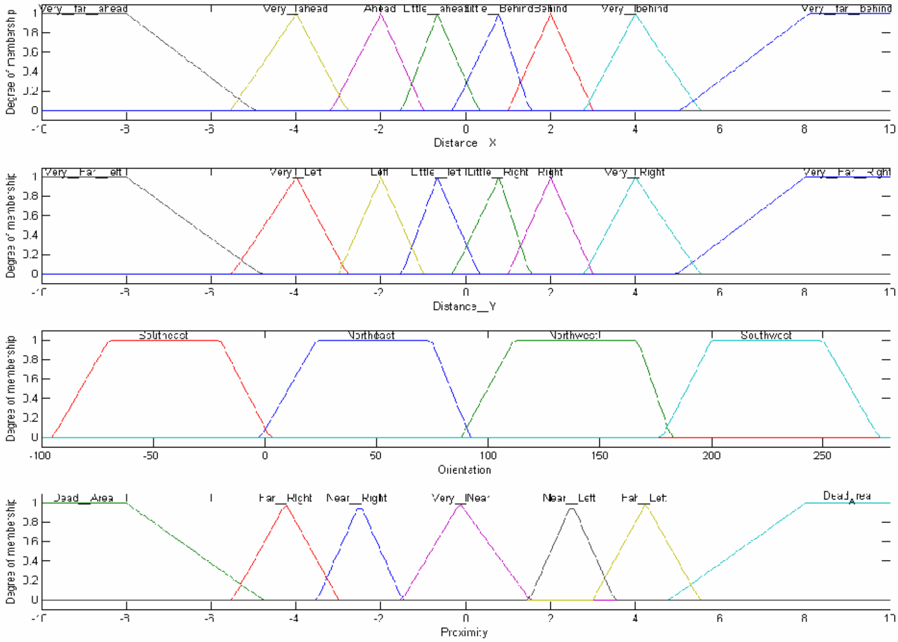


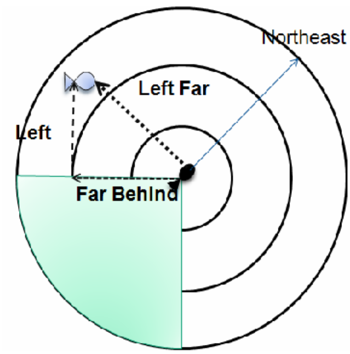
**Fig. 3.** Membership Functions to Proximity system

*Very Left* THEN Proximity is *Far to the Left*". This rule is represented in the figure 4 and it abstracted of Rule base of Proximity system. The same figure shows as is choose this rule starting of a rule sets. Figure 4a shows how a fish calculates the proximity with its neighbor and figure 4b shows how a rule is used to select an output given certain inputs.

The Reaction fuzzy system is represented by fuzzy sets with request to the orientation and rotation. Within orientation, we have stretched the sets used on previous system; we now have 12 fuzzy sets. It means, the fish have 12 directions in which it can be facing. Figure 5 shows the orientation divided fuzzy sets. These fuzzy sets have a range from –90º to 270º. Also, a rotation variable is used as the system output. Here, we built 9 fuzzy sets to depict several turns. These sets can have linguistic variables such as: "Very large positive turn,""Large positive turn," "Medium positive turn," "Short positive turn," "null turn" similarly for "negative turn". These fuzzy sets have a range from –90º to 90º.

Finally, on the Aggregation fuzzy system uses the output variables as its inputs. Hence, we utilized the same fuzzy sets.

In terms of the rules, we built the rules based on the relationship of the four influences. But it should be noted that we relate these in pair of influences to produce a final effect. This is made in order to have a feedback system but with few variables. E.g., we compare two reactions as "large positive turn"' and "short negative turn". The union of these two reactions result another reaction. Then we compare the third reaction to this new reaction and then with the forth, similarly.




(a) Scheme proximity

| Distance X / Distance Y | | Orientation | | | |
|---|---|---|---|---|---|
| | | Northeast | Northwest | Southdwest | Southdeast |
| Far behind | Little Right | Dead Area | Left far | Left far | Dead Area |
| | Little left | Dead Area | Left far | Left far | Dead Area |
| | Right | Dead Area | Left far | Left far | Left far |
| | Left | Left far | Left far | Left far | Dead Area |
| | Very Right | Dead Area | Dead Area | Dead Area | Dead Area |
| | Very Left | Dead Area | Dead Area | Dead Area | Dead Area |
| Behind | Little Right | Dead Area | near | near | Dead Area |
| | Little left | Dead Area | near | near | Dead Area |
| | Right | Dead Area | Left far | Left far | Left far |
| | Left | Left far | Left far | Left far | Dead Area |
| | Very Right | Dead Area | Left far | Left far | Left far |
| | Very Left | Left far | Left far | Dead Area | Left far |

(b) Rule sets

**Fig. 4.** Proximity Fuzzy system

These sets are used to built rules according to interaction zones as well as the external influence. Therefore, according to this influence we designed a set of rules that represent a turn.

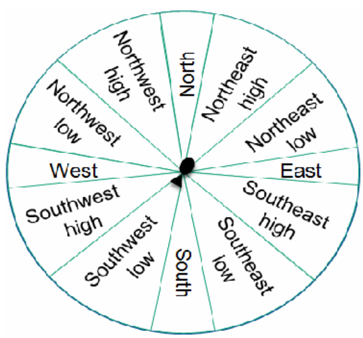



**Fig. 5.** Fuzzy sets of Orientation

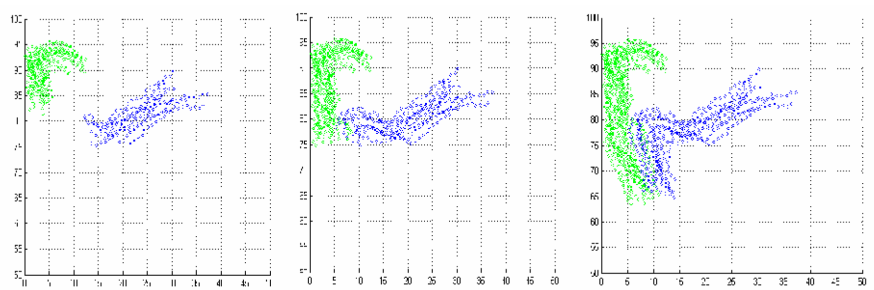
Finally, we defuzzify the output to obtain the new position of the fish that is calculated with the current position and final orientation. This process is repeated for each individual fish.

## 4 Experiments and Results

The correct functioning of the model can be analyzed at two levels. One aspect is to verify that our simulated fish will reproduce certain typical maneuvers. [14]. the second aspect is a measure of certain parameters of the global structure. These two ways of experimentation have been from the work presented by Huth and Wissel [4].

At a group level we compared the typical behavior of a real fish school with our simulation. This experiment is intended to describe the merging of two similar schools. When two schools meet in open water, the new swimming direction appears to be approximately the resultant vector of the two original tracks. In our experimentation we used two groups of 15 fishes for each shoal.

The result is shown in the Figure 6. Then of 10 steps of simulation, there are formed two schools. After 20 more iteration, the two schools are met and later they form an only school with same orientation.



(a) After 20 iterations (b) After 40 iterations (c) After 60 iterations

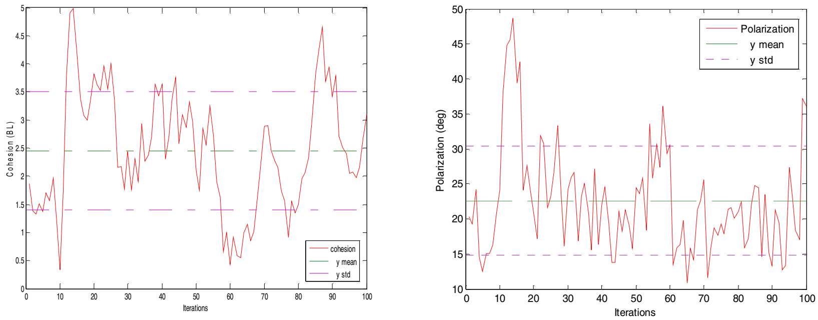
**Fig. 6.** Simulation of the merging of two schools

Also, the global structure of fish schools can be measured by two quantities: the nearest neighbor distance *nnd* and the polarization *p*. The nearest neighbor distance characterizes the typical distances in a school. It is defined as the average of the distance of every fish to its nearest neighbors. Typical values from the literature are around of 0.5-2 body length (BL).

The polarization characterizes the intensity of orientation in the school. The polarization is defined as the average of the angle deviation of each fish to the mean swimming direction of the school. Schools with a high parallel orientation have polarization values between 10º and 20º.

A fish school with 15 individuals during 100 iterations was simulated to measure cohesion and polarization. These parameters are shown in the Figures 8a and 8b. From those parameters we calculate the mean and standard deviation of all iterations. In this simulation the means are 2.4 BL in cohesion and 22.2 en polarization. These results are found within of the typical values. Our simulations show variations on the cohesion and polarization of fish school along the time due to uncertainty given by the fuzzy sets. These results were what we expected.

We can see in the Fig.8a the cohesion of the group along of 100 iterations what it show some time steps in which the group presents compactness or high cohesion ($\sigma$<2BL) and low cohesion ($\sigma$ > 4BL), e.g. Between 10$^{th}$ and 15$^{th}$ iteration the school presents low cohesion and at same time a confuse grade ($\rho$>60). This confuse behavior is due that the school is influenced by external agents as in this case the border (see Figure .6a).




(a) Cohesion (b) Polarization

**Fig. 7.** Parameters measurement of the Fish School movement

## 5 Conclusions

In this work we proposed the usage of fuzzy modeling to develop Individual oriented models aiming to give some uncertainty to the individual behavior. As a case study we worked with fish schools behavior, an example of a biological system that has many known models cited in the best references but none using fuzzy logic. Hence, we assume that the way the fish realizes the distances between each other has been simulated and their decisions based on that data are not exact.

Our implementation is based in a biological model that that defines a set of general rules that we extended to a more detailed one. We built several fuzzy systems to represent this rules set: a system of proximity, a system of reaction and aggregation. These systems together represent the orientation of the fish school. To validate our simulator we proceeded in the same way that other authors have done: we compared the simulation results with the results of the original model [4].

The implementation using MATLAB did not present good performance, requiring a lot of time to simulate big populations. So, most of the time simulating we worked with few individuals to test and refine the simulator. Some studies show that the parallelization of the simulator can improve the system performance a lot [15],[16]. In future work we intend to parallelize this simulator to improve speed up and scalability. We are currently working on this version to extend the model to represent a more detailed system taking into account the presence of other species, predators and vegetation.

## References

1. Grimm, V.: Individual-based modeling and ecology 4, 541–550 (2005), `http://jasss.soc.surrey.ac.uk`
2. Breckling, B., Middelhoff, U., Reuter, H.: Individual-based models as tools for ecological theory and application: Understanding the emergence. Ecological Modeling 194, 102–103 (2006)

3. DeAngelis, D.L., Rose, K.A.: Which individual-based approach is most appropriate for a given problem? In: DeAngelis, D.L., Gross, L.J. (eds.) Individual- Based Models and Approaches in Ecology, pp. 67–87. Chapman & Hall, London (1992)
4. Huth, A., Wissel, C.: The simulation of the movements of fish schools. J. Theor. Biol. 156, 365–385 (1992)
5. Montaigne, F., Warne, K., Carroll, C.: Crisis mundial de la pesca. National Geographic 20 (2007)
6. Anderson, J.: A stochastic model for the size of fish schools. Bull. Fish 8, 109–132 (1980)
7. Aoki, I.: Internal dynamics of fish schools in relation to inter-fish distance. Bull. Jap. Soc. Scient. Fish. 48, 1081–1088 (1984)
8. Parrish, J., Viscido, S., Grunbaum, D.: Self-organized fish schools: an examination of emergent properties. Biol. Bull. 196, 397–454 (2002)
9. Niwa, H.S.: Self-organizing dynamic model of fish schooling. J. Theor. Biol. 171, 123–136 (1994)
10. Hubbard, S., Babak, P., Sigurdsson, M.K.: A model of the formation of fish schools and migrations of fish. Ecological modeling 174, 359–374 (2004)
11. Shaw, E.: Schooling fishes critique and review. Devlopment and Evolution of Behaviour, 452–480 (1970)
12. Zadeh, L.: Itoward a theory of fuzzy systems. Aspects of network and system theory 8, 469–490 (1971)
13. Sivanandam, S., Smathi, S., Deepa, S.: Introduction to fuzzy logic using matlab, vol. 1, pp. 118–121. Springer, Heidelberg (2007)
14. Pitcher, T.J., Wyche, C.J.: Predator avoidance behavior of sand-eel schools: why schools seldom split. In: Noakes, D.L.G., Lindquist, B.G., Helfman, G.S., Ward, J.A. (eds.) Predators and Prey in Fishes, vol. 54, pp. 193–204. The Hague, Junk (1983)
15. Mostaccio, D., Dalforno, C., Suppi, R., Luque, E.: Distributed simulation of large-scale individual oriented models 2, 59–65 (2006), `http://journal.info.unlp.edu.ar`
16. Dalforno, C., Mostaccio, D., Suppi, R., Luque, E.: Increasing the scalability and the speedup of a fish school simulator. In: Gervasi, O., Murgante, B., Laganà, A., Taniar, D., Mun, Y., Gavrilova, M.L. (eds.) ICCSA 2008, Part II. LNCS, vol. 5073, pp. 936–949. Springer, Heidelberg (2008)