# BOIDS WITH A FUZZY WAY OF THINKING

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## Abstract

The increase of the processing power of personal computers in the last decade resulted in a notable progress of the artificial animal (animat) construction and simulation field. Regardless of the achieved results the coding of an animat's behavior can, to someone unfamiliar with physics of motion and robotics, seem like pure witchcraft. Not to mention the wealth of ethological knowledge required regarding the behavior of the animal that is being modeled. In this article we suggest the use of fuzzy logic as the basis of an animat's decision about its next step. We hypothesize that by using linguistic programming based on common sense unclear and even partially contradictory knowledge of the animal's behavior, we can achieve comparable if not even better simulation results than with the classical crisp implementation. The following article presents an investigation of our theories on the case of a boid – a special type of animat – limiting itself on the boid's urge of alignment with its flockmates.

## Key Words
fuzzy logic, behavioral animation, flock, bird, boid, animat

## 1. Flocks of Birds

In nature there exists a phenomenon of unity. People gather in schools, stadiums, at the sea-side or walking down the streets. On a smaller scale and in a more sociological point of view the most common group of people – part of which almost every one of us is – is a family. Most of the time we can speak about people's choice or free will when forming groups, but not always. A simple look down the window tells us that people moving about in the streets do form groups but in most cases unwillingly. What about animals? We know of different animal species that can survive mostly because they form groups. Examples of them are schools of fish, herds of sheep, and last but not least flocks of birds.

Researchers have answered the question "why animals form groups" – to survive – namely for higher chances of finding food, for limiting its encounters with predators [1], etc. However the question "how animals form groups" is still an open area of research.

Two researchers have focused their attention on humans from our initial discussion. More precisely they have investigated the behavior of pedestrians. In their study they propose a set of internal motivations named social forces as the basis of an individual's choice of its next step [2]. Returning to the animal kingdom, there is a lot of ethological literature available about fishes. This abundance of literature is the primary reason that there was substantial work done in the simulation of fish behavior. One study [3] presents a complete perception, behavior and locomotion simulation of fish. Another study [4] investigates the use of evolved sensory controllers to produce schooling behavior. In the presented artificial world with hazards and food, prey and predator fish are coevolving. The study showed that predators are of key importance as a means of encouraging prey to school [4]. To continue in the animal kingdom, one researcher even worked on the problem of a shepherd herding sheep into a pen by coercing [5].

But the paper which most researchers find as the origin of all subsequent work was Craig Reynolds's study of bird behavior [6]. His primary reason was a believable procedural computer animation of bird flocking. He constructed an artificial bird that makes the decision of its new heading and speed of flight based on three simple rules referred to as steering forces, and named it *a boid*. When observing a group of boids moving through an environment one can sense a strong resemblance to the characteristic behavior of a group of birds. In the study Reynolds also states that his algorithm applies equally well to the simulation of herds and schools [6].

Reynolds, as well as most of the researchers that followed him, used mathematical formulas as approximations of their linguistically formulated rules (see Table 1). We understand that Reynolds's primary motive was a procedural model but we still find the use of mathematical approximations and crisp numerical data contradictory. Firstly, it is hardly imaginable that animals have the ability to sense crisp values (e.g. distance, predator presence, obstacle presence, etc.) from their environment. Secondly, it is also hardly imaginable that

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they have the ability to execute accurate numerical or geometrical calculations. In the following paper we suggest the use of fuzzy logic as the basis of the boid's decision process.

In section two we give a formal definition of Reynolds's boid model and present the background of the steering forces. In section three we present the fuzzy logic implementation of one of the steering forces and conclude by comparing the two implementations.

## 2. Birds vs. Boids

Reynolds modeled the boid as an object moving in a three dimensional environment, with its motion being governed by the laws of geometrical flight [6]. At this point it is enough if we say that these laws represent the tendency of a moving object to stay in motion, its inability to exceed a certain velocity even if continually accelerating and the consideration of a finite amount of available energy. The boid is therefore specified by its position in space, heading and speed of flight, maximal achievable speed and available force. To correctly simulate bird flocking, Reynolds introduced three rules named steering forces (Table 1), by means of which every boid chooses its new heading and speed. For a more detailed explanation of the boid model background it is advised to consult Reynolds's studies [6,7].

| **Description of steering force** |
|---|
| 1. Collision Avoidance: avoid collision with nearby flockmates. |
| 2. Velocity Matching: attempt to match velocity with nearby flockmates. |
| 3. Flock Centring: attempt to stay close to nearby flockmates. |

Table 1: Reynold's steering forces.

Let us define the boid model formally. From the point of view of the boid, the processing of its decision takes place in discrete time steps, whereas from the point of view of the flock it takes place in parallel. Since Reynolds does not give a formal definition of the boid we based our definition on the animat [8,9] model. The later is based on the Moore automaton [10] model.

**Definition 1:** Animat A is a special Moore automaton $A = < \mathbf{X}, \mathbf{Q}, \mathbf{Y}, \delta, \lambda, \boldsymbol{P}, \boldsymbol{S}, B >$, where $\mathbf{X}$, $\mathbf{Q}$, and $\mathbf{Y}$ are finite non-empty sets representing the input alphabet, the internal states and the output alphabet respectively. $\boldsymbol{P} = (P_1,\ldots,P_k)$ is a vector of perception functions $P_i$: $\mathbf{X} \times \mathbf{Q} \rightarrow \mathrm{P}(\mathbf{R}\times\mathbf{Q})$, $i = 1,..,k$. $\boldsymbol{S} = (S_1,\ldots,S_l)$ is a vector of steering functions $S_j$: $\mathrm{P}(\mathbf{R}\times\mathbf{Q})^k \times \mathbf{Q} \rightarrow \mathbf{F}$, $i = 1,..,l$ and $B$: $\mathbf{F}^l \times \mathbf{Q} \rightarrow \mathbf{Q}$ is a mapping called the behavior function. $\lambda$: $\mathbf{Q} \rightarrow \mathbf{Y}$ is a mapping called the output function, $\delta$: $\mathbf{X} \times \mathbf{Q} \rightarrow \mathbf{Q}$ is a mapping called the transition function and is defined with three stages eq. (1).

$$\begin{aligned} \delta(x,q) &= B\left(\left(f_1,\ldots,f_l\right),\ q\right), \\ f_j &= S_j\left(\left(\mathbf{N}_1,\ldots,\mathbf{N}_k\right),\ q\right),\ j=1,\ldots,l, \\ \mathbf{N}_i &= P_i\left(x,\ q\right),\ i=1,\ldots,k. \end{aligned} \tag{1}$$

Let us explain the definition a little more informally. Consider a finite non-empty set of animats – the environment $\mathbf{E}(t) = \{A_1,\ldots,A_n\}$. Every animat $A_i$, $i = 1,\ldots,n$ is modeled as a finite state machine, more precisely as a special Moore automaton. The animat's decision of its next step takes place in discrete time steps and is based on its internal state and the state of the environment. Therefore at any discrete time step $t$ the animat is in state $q(t) \in \mathbf{Q}$ emitting the output $\lambda(q(t)) \in \mathbf{Y}$ and according to its current state $q(t)$ and the current state of the environment $\mathbf{E}(t)$ the animat processes its next state $q(t+1) \in \mathbf{Q}$, assumes it and starts emitting the output $\lambda(q(t+1))$. The three stage method used to process the animat's next state – see eq. (1) – tries to imitate one of the more widely adopted theories about the behavior of animals, where every action is the result of perception of certain signals present in the environment and satisfaction of personal goals. Every perception function $P_i$ ($i = 1,\ldots,k$) therefore represents a selector of relevant information, whereas every steering function $S_j$ ($j = 1,\ldots,l$) represents one personal goal. The behavior function $B$ represents the animat's wish to approximately optimize the satisfaction of all of his personal goals.

**Definition 2:** Boid B is an animat where the vector of perception functions is defined as $\boldsymbol{P} = (P_f)$, the vector of steering functions is defined as $\boldsymbol{S} = (S_s, S_a, S_c)$ and the behavior function is defined as $B_{pa}$. The boid's state at a discrete time step $t$ is $q(t)$ as defined in eq. (2), where $p(t) \in \mathbf{R}^d$ $(d = 2,3)$ is the boid's position in space, $v(t) \in \mathbf{R}^d$ $(d = 2,3)$ is the boid's velocity (heading and speed of flight), $r$ is the boid's radii of perception, *fov* is the boid's field of view, $m$ is the boid's mass, *maxs* is the boid's maximal achievable speed and *maxf* is the boid's available force.

$$q(t) = \left(p(t),\ v(t),\ r,\ fov,\ m,\ maxs,\ maxf\right). \tag{2}$$

Let us again explain the definition informally. Consider a boid flying through a crowded sky. To fly in a flock it needs to consider at least its nearby flockmates, namely their position, heading and speed. The term nearby addresses the boid's perception, which is in our case modeled with the perception function $P_f$. Its formal definition is given in [9], but at this time it is enough if we say that it selects from the environment $\mathbf{E}(t)$ only the set of boids B that are in the observed boid's field of view $q_{fov}$ and in its radii of perception $q_r$. We shall name this set the observed boid's flockmates and address it with $\mathbf{N}_f$. More precisely the set $\mathbf{N}_f$ is a set of pairs $(s_B, q_B)$ where $s_B$ is the significance and $q_B$ is the state of the observed boid's flockmate B. The significance decreases with the square of distance. The three steering functions $S_s$, $S_a$ and $S_c$ represent the three steering functions (Table 1), namely separation, alignment and cohesion [7]. Their detailed formal definitions are given in [9]. In this paper we shall concentrate only on the alignment steering function, which shall be presented in the next section. At this point let us just say that every steering function based on the observed boid's flockmates $\mathbf{N}_f$ calculates the force needed for the desired change of heading and speed of the observed boid. In the final stage of eq. (1) these forces are combined using the behavior function $B_{pa}$, whose formal definition can be found in [9].

## 3. Boids with Fuzzy Thoughts

In the previous section we gave a condensed overview of the classical crisp boid model. In this section we shall implement one of the boid's steering forces using fuzzy logic. Simulation showed [9] that the alignment steering function has the highest influence on the boid's ability to flock. Its foremost purpose is to match the speed and heading of flight with the nearby flockmates (Table 1) and its most significant quality is its predictive collision avoidance. In other words, if a boid does a good job matching velocity with its nearby flockmates, it is unlikely that it will collide with any of them any time soon [6].

The alignment steering function is defined with eq. (3), where $\mathbf{N}_f$ are the observed boid's flockmates. It depends only on the velocities of the observed boid's flockmates and ignores their position. The vector $q_v$ is therefore the observed boid's velocity vector and $s_{\mathrm{B}}$, $q_{\mathrm{B}v}$ are the significance and velocity vector of the observed boid's flockmate B. The velocity vector gives the relative position changes per coordinate axis in the Cartesian coordinate system and therefore codes the heading and speed of a boid.

$$S_a\left(\mathbf{N}_f, q\right) = \left( \frac{1}{\left|\mathbf{N}_f\right|} \sum_{\left(s_{\mathrm{B}}, q_{\mathrm{B}}\right) \in \mathbf{N}_f} \left( q_v + s_{\mathrm{B}} \left( q_{\mathrm{B}_v} - q_v \right) \right) \right) - q_v . \quad (3)$$

We think that a real bird can not sense the crisp value of a flockmates heading and speed, but it can sense only a relative difference between their headings and speeds. We shall address the relative heading difference with a linguistic variable *Hd* and code it with three linguistic values LEFT, SAME and RIGHT (Fig. 1). Similarly we shall address the relative speed difference with a linguistic variable *Sd* and code it with three linguistic values SLOWER, SAME and FASTER (Fig. 2). For reasons of similarity with the original definition of the alignment steering function – eq. (3) – we shall represent the significance of the observed boid's flockmate $s_{\mathrm{B}}$. with a linguistic variable named *SIG* and code it with two linguistic values LOW and HIGH (Fig. 3).

Let us now declare two linguistic variables *Hc* and *Sc*, which represent the desired heading and speed changes respectively. We shall code them with the same linguistic values as we used to code the linguistic variables *Hd* and *Sd* (Fig.1, 2). Than the following list of rules represents the fuzzy alignment steering function:

if (*Hd* is SAME) then *Hc* is SAME,
if (*Sd* is SAME) then *Sc* is SAME,
if (*SIG* is LOW) and (*Hd* is RIGHT) then *Hc* is SAME,
if (*SIG* is HIGH) and (*Hd* is RIGHT) then *Hc* is RIGHT,
if (*SIG* is LOW) and (*Hd* is LEFT) then *Hc* is SAME,
if (*SIG* is HIGH) and (*Hd* is LEFT) then *Hc* is LEFT,
if (*SIG* is LOW) and (*Sd* is SLOWER) then *Sc* is SAME,
if (*SIG* is HIGH) and (*Sd* is SLOWER) then *Sc* is SLOWER,
if (*SIG* is LOW) and (*Sd* is FASTER) then *Sc* is SAME,
if (*SIG* is HIGH) and (*Sd* is FASTER) then *Sc* is FASTER.

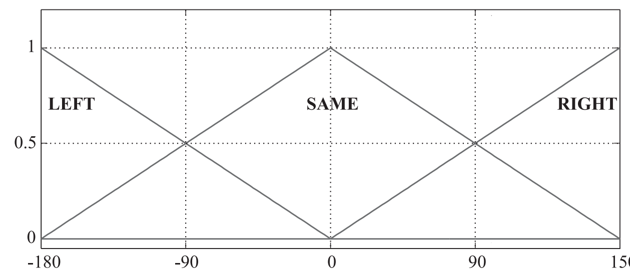

Fig. 1: Linguistic variable *Hd* membership functions.

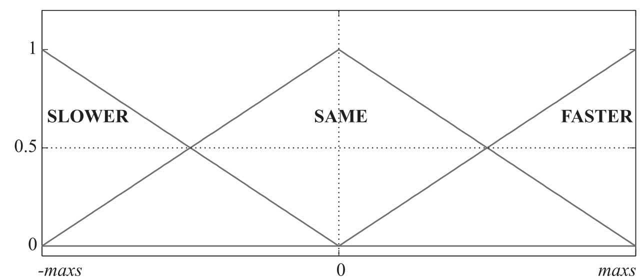

Fig. 2: Linguistic variable *Sd* membership functions.

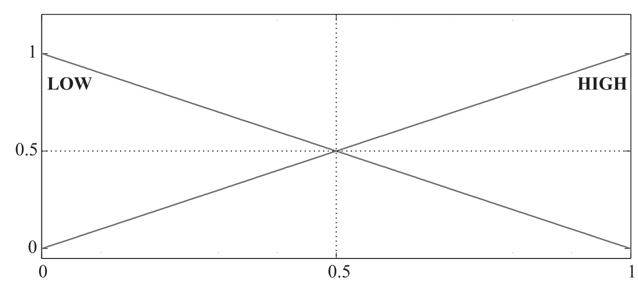

Fig. 3: Linguistic variable *SIG* membership functions.

## 4. Results and Discussion

The previous section has presented a fuzzy logic implementation of the alignment steering function. In the following section we shall investigate the influence of its use on the boids' flocking behavior.

Let us begin by comparing the graphs of the crisp and fuzzy alignment steering functions (Fig. 4). The vector at point ($x$, $y$) of each graph presents the alignment steering force in the case when the observed boid is at point ($x$, $y$) heading away from the centre with speed *maxs* and its only flockmate is at location (0,0) heading in the positive $y$ direction with speed *maxs*. From the two graphs it can be seen that even with a simple set of fuzzy logic rules a remarkable similarity can be achieved. Let us emphasize that we did not use fitting or other forms of automatic generation of the fuzzy logic rules.

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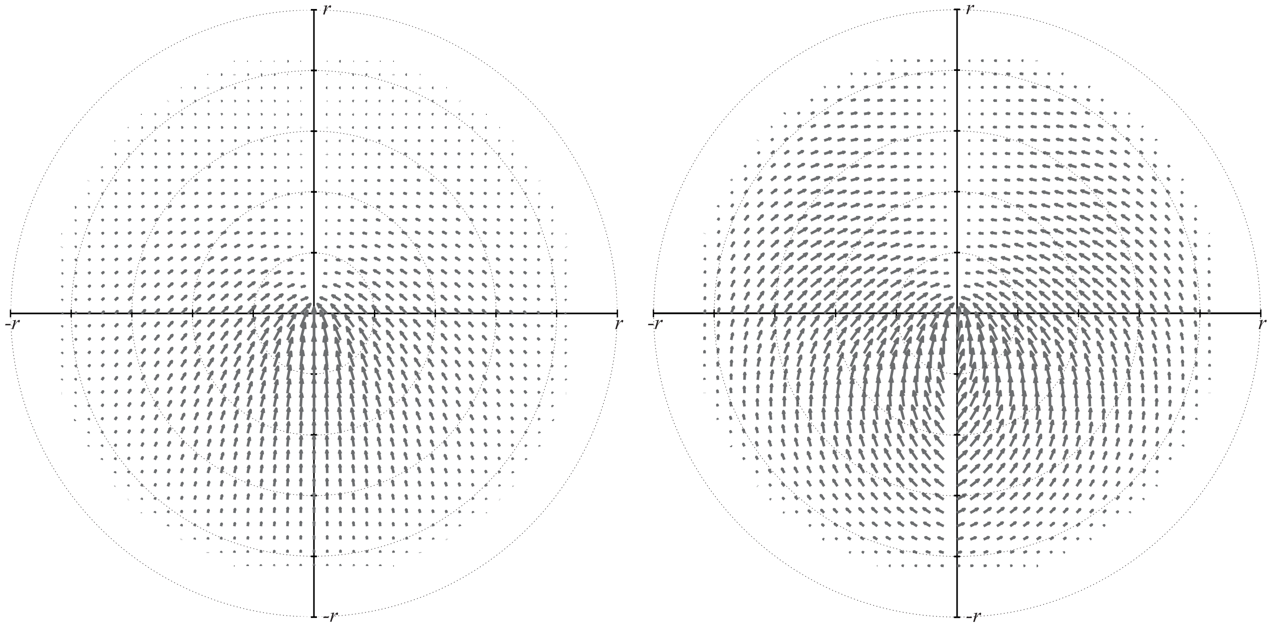


Fig. 4: Crisp (left) and fuzzy (right) alignment steering functions graphs.

The influence of the fuzzy implementation on the boids' flocking behavior shall be investigated with a simple experiment. Consider a set of fifty boids in an uninteresting environment, where with the term uninteresting we address an environment without obstacles. Every boid has a random initial position, heading and speed. All other parameters of the boid's internal state are fixed, time constant and equal for all boids. We shall run 2000 steps of the simulation, where at each frame we measure the cumulative number of collisions, the number of flocks, the average flock heading, the average flock speed, the average flock heading variation and the average flock speed variation. For reasons of brevity the formal definitions of these metrics shall be omitted. For a more detailed explanation it is advised to consult [9].

As we can see from the graph in Fig. 5 the fuzzy logic implementation is for this experiment faster at the generation of flocks. In the presented graph it can also be noticed that the use of fuzzy logic has no influence on flock stability. Due to the almost identical tendencies of both graphs we can conclude that the boids behave almost identically in both cases.

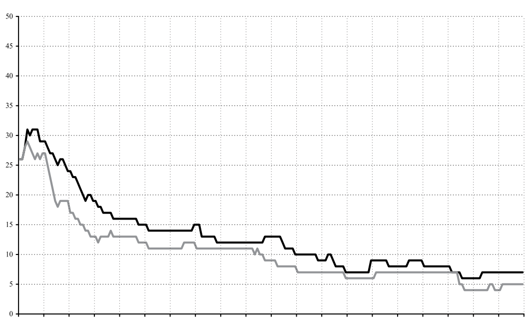


Fig. 5: Number of flocks graphs for the crisp (black) and fuzzy (gray) implementations of the alignment steering function.

The graphs in Fig. 6 present the average flock heading variation. Even in the case of flock heading variation it can be seen that the graphs present similar tendencies. Nevertheless it looks like the fuzzy implementation gives better results in some parts of the simulation (see steps 0-380 and 1250-1750) since it is more stable.

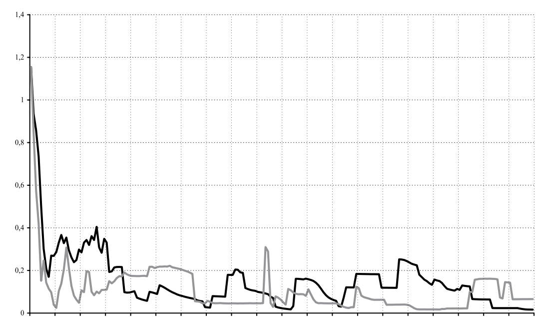


Fig. 6: Average heading variation for the crisp (black) and fuzzy (gray) implementations of the alignment steering function.

The higher stability of the fuzzy logic implementation is even more pronounced in the case of the average speed variation metric (see frames 1250-2000 in Fig. 7). Once again the two graphs show similar tendencies.

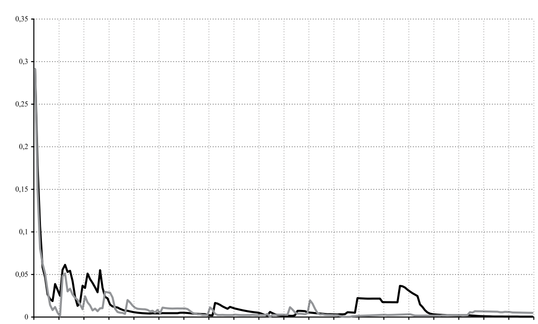


Fig. 7: Average speed variation for the crisp (black) and fuzzy (gray) implementations of the alignment steering function.

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## 5. Conclusion

In this study we suggest the use of fuzzy logic as a tool for the construction of artificial animals (animats), where we limit our research to the construction of a boid - a special type of animat. We suggest the use of fuzzy logic as the basis of the boid's decision about its next step. We introduce a set of simple fuzzy logic rules that describe the boids urge of alignment with its flockmates. This study investigates the influence of their use on the boid's flocking behavior. In our case, as in some other fields of modeling [11-13], the fuzzy logic approach results as more suitable and user friendlier than the traditional approaches. The behavior of a group of boids that use our set of fuzzy logic rules is comparable to the behavior of a group of boids that uses the original alignment steering function. This proves that a boid's decisions can be based purely on unclear evaluations of its environment and linguistic rules even without the knowledge of the Newton's laws of motion.

## 6. Acknowledgement

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