# Collective behaviour

Evolving collective behaviour

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## Evolution in a fuzzy artificial world

Demšar J & Lebar Bajec I, 2017
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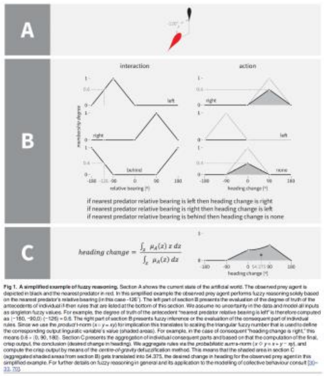

if nearest predator relative bearing is left then heading change is right
if nearest predator relative bearing is right then heading change is left
if nearest predator relative bearing is behind then heading change is none

$$heading\ change = \frac{\int_z \mu_A(z)\, z\, dz}{\int_z \mu_A(z)\, dz}$$

**Fig 1. A simplified example of fuzzy reasoning.** Section A shows the current state of the artificial world. The observed prey agent is depicted in black and the nearest predator in red. In this simplified example the observed prey agent performs fuzzy reasoning solely based on the nearest predator's relative bearing (in this case -126°). The left part of section B presents the evaluation of the degree of truth of the antecedents of individual if-then rules that are listed at the bottom of this section. We assume no uncertainty in the data and model all inputs as singleton fuzzy values. For example, the degree of truth of the antecedent "nearest predator relative bearing is left" is therefore computed as $(-180, -90, 0)(-126) = 0.6$. The right part of section B presents fuzzy inference or the evaluation of the consequent part of individual rules. Since we use the *product* t-norm $(x \odot y = xy)$ for implication this translates to scaling the triangular fuzzy number that is used to define the corresponding output linguistic variable's value (shaded areas). For example, in the case of consequent "heading change is right," this means $0.6 \odot (0, 90, 180)$. Section C presents the aggregation of individual consequent parts and based on that the computation of the final, crisp output, the conclusion (desired change in heading). We aggregate rules via the *probabilistic sum* s-norm $(x \oplus y = x + y - xy)$, and compute the crisp output by means of the *centre-of-gravity* defuzzification method. This means that the shaded area in section C (aggregated shaded areas from section B) gets translated into 54.375, the desired change in heading for the observed prey agent in this simplified example. For further details on fuzzy reasoning in general and its application to the modelling of collective behaviour consult [30–33, 70].

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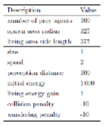
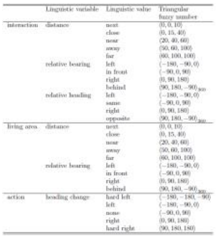
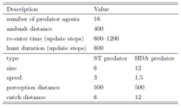


| Description | Value |
|---|---|
| number of prey agents | 100 |
| spawn area radius | 325 |
| living area side length | 375 |
| size | 1 |
| speed | 2 |
| perception distance | 100 |
| initial energy | 1000 |
| living energy gain | 1 |
| collision penalty | -10 |
| wandering penalty | -10 |



| | Linguistic variable | Linguistic value | Triangular fuzzy number |
|---|---|---|---|
| interaction | distance | next | $(0, 0, 10)$ |
| | | close | $(0, 15, 40)$ |
| | | near | $(20, 40, 60)$ |
| | | away | $(50, 60, 100)$ |
| | | far | $(60, 100, 100)$ |
| | relative bearing | left | $(-180, -90, 0)$ |
| | | in front | $(-90, 0, 90)$ |
| | | right | $(0, 90, 180)$ |
| | | behind | $(90, 180, -90)_{360}$ |
| | relative heading | left | $(-180, -90, 0)$ |
| | | same | $(-90, 0, 90)$ |
| | | right | $(0, 90, 180)$ |
| | | opposite | $(90, 180, -90)_{360}$ |
| living area | distance | next | $(0, 0, 10)$ |
| | | close | $(0, 15, 40)$ |
| | | near | $(20, 40, 60)$ |
| | | away | $(50, 60, 100)$ |
| | | far | $(60, 100, 100)$ |
| | relative bearing | left | $(-180, -90, 0)$ |
| | | in front | $(-90, 0, 90)$ |
| | | right | $(0, 90, 180)$ |
| | | behind | $(90, 180, -90)_{360}$ |
| action | heading change | hard left | $(-180, -180, -90)$ |
| | | left | $(-180, -90, 0)$ |
| | | none | $(-90, 0, 90)$ |
| | | right | $(0, 90, 180)$ |
| | | hard right | $(90, 180, 180)$ |



| Description | Value | |
|---|---|---|
| number of predator agents | 16 | |
| ambush distance | 400 | |
| re-enter time (update steps) | 600–1200 | |
| hunt duration (update steps) | 600 | |
| type | ST predator | HDA predator |
| size | 6 | 12 |
| speed | 3 | 1.5 |
| perception distance | 500 | 500 |
| catch distance | 6 | 12 |

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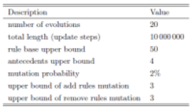
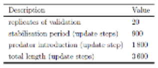
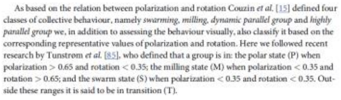


| Description | Value |
|---|---|
| number of evolutions | 20 |
| total length (update steps) | 10 000 000 |
| rule base upper bound | 50 |
| antecedents upper bound | 4 |
| mutation probability | 2% |
| upper bound of add rules mutation | 3 |
| upper bound of remove rules mutation | 3 |



| Description | Value |
|---|---|
| replicates of validation | 20 |
| stabilisation period (update steps) | 900 |
| predator introduction (update step) | 1 800 |
| total length (update steps) | 3 600 |



As based on the relation between polarization and rotation Couzin *et al.* [15] defined four classes of collective behaviour, namely *swarming*, *milling*, *dynamic parallel group* and *highly parallel group* we, in addition to assessing the behaviour visually, also classify it based on the corresponding representative values of polarization and rotation. Here we followed recent research by Tunstrøm *et al.* [85], who defined that a group is in: the polar state (P) when polarization > 0.65 and rotation < 0.35; the milling state (M) when polarization < 0.35 and rotation > 0.65; and the swarm state (S) when polarization < 0.35 and rotation < 0.35. Outside these ranges it is said to be in transition (T).

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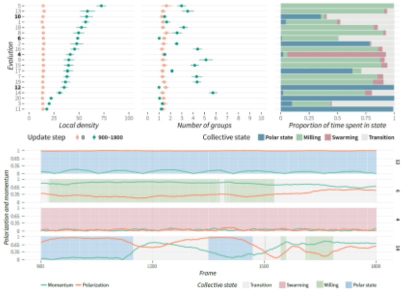

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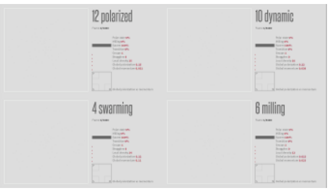

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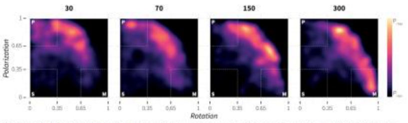

**Fig 5. Density plot of global polarization versus rotation for various group sizes in the case of evolution no. 10.** The density plots visualize the relationship between group size and behaviour stability. Increasing the number of agents leads global behaviour to change from predominantly polarized to predominantly milling.

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$$\rho^{a} = \frac{1}{n}\sum_{i=1}^{n}\frac{a_i^{a}}{a_i},$$

$$\varsigma = \frac{1}{n}\sum_{i=1}^{n}\frac{a_i - 1}{m - 1},$$

$$\beta = \frac{1}{2n}\sum_{i=1}^{n}1 + \frac{o_i}{180},$$

**Fig 6. Box plots of the distributions of the six parameters through which the evolved rule sets were summarized.** Grouping was based on the evolved behaviour class. Statistical significance of differences was obtained by means of a Benjamini-Yekutieli adjusted Dunn test. Symbols ns, * and ** indicate $p \geq 0.05$, $p < 0.05$, and $p < 0.01$, respectively. Unmarked cases denote significance at $p < 0.001$.

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*In this work we have presented an open-ended, artificial life-like evolutionary model where the drives of individual agents are encoded via linguistic fuzzy rule-based systems. We analysed the evolved behaviour and showed that based on biologically relevant observables (Vicsek & Zafeiris, 2012; Couzin, et al., 2002; Tunstrøm, et al., 2013) the system is capable of evolving a wide range of behaviours, some qualitatively similar to those reported in experimental research (Tunstrøm, et al., 2013). Through the analysis of the evolved rule bases we have also shown that when grouping the evolved rule bases by the type of evolved behaviour and observing the average proportion of rule antecedents that contain predator related linguistic variables there exists a statistically significant difference between the evolved rule bases.*