CONTINUOUS PREFERENCES FOR ACTION SELECTION

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Abstract: We have investigated the use of continuous alternatives for action selection by a behavior-oriented agent. Such an agent is made of concurrent "behaviors"; each of these behaviors reacts to specific stimuli and provides a response according to a low-level goal. Since the behaviors are specialized, they can provide concurrent responses and conflicts among them must be solved to perform a coherent global behavior of the agent. In this context, voting methods allow to select only one of the responses of the behaviors, while taking into account their preferences and respecting all of their constraints. Previous works are based on action spaces limited to few discrete values and have shown difficulties in determining the behaviors weights for the vote. Furthermore, these works generally not allow to express the indifference of a behavior on a alternative's component, i.e. the fact that a behavior has no preference on the value of one component of an alternative. We propose in this article a method to use continuous values for the alternatives and a fair vote based on one alternative proposition per behavior. Our framework also allows the expression of indifference between alternatives. This proposition has been tested and compared, and the results show that our approach is better than previous propositions to avoid locked situations.

1 INTRODUCTION

Autonomous situated agents like simulated robots or virtual characters have to adapt their behavior according to the changes occurring in their environment. One kind of behavior adaptation concerns the agent's short-term reaction to modifications of a dynamical environment. In this context, the agent decides what to do at the next step, in reaction to events or at regular time steps. The decision concerns which action to perform, i.e. a set of command values to control the actuators of a robot or the actions of a virtual character.

The problem of selecting the most appropriate action in the current situation, called the action selection (AS) problem (Maes, 1989), can be solved using different approaches. Our work belongs to the behavior-based approach (Brooks, 1986; Mataric, 1992; Arkin, 1998), common in robotics and applied in various domains such as underwater vehicle (Rosenblatt et al., 2002), virtual characters (Bryson and Thorisson, 2000) and services (Antonelli et al., 2008). According to the behavior-based approach, the agent is made of a set of concurrent behavior modules, called "behaviors"; each of them reacts to specific stimuli and provides a response according to a low-level goal. For example, one of a simulated mobile robot's behaviors can be dedicated to wall following, and reacts according to the distance to the wall.

Since the behaviors are specialized, they can provide concurrent responses. As a consequence, it is necessary to solve conflicts among the behaviors in the aim to perform a coherent global behavior of the agent. In a behavior-based agent, action selection is thus a collective decision process. The problem is to find a coordination process for the agent to make a decision based on multiple, concurrent and eventually conflictual tendencies, generally within time constraints (see Fig. 1).

Numerous methods have been proposed to select one of the actions proposed by the behaviors that compose a behavior-based agent. Some of them arbitrate among the propositions of the behaviors, while others make a fusion of these propositions. A third way exists, that arbitrates in taking into account the preferences of the behaviors: the voting-based meth-

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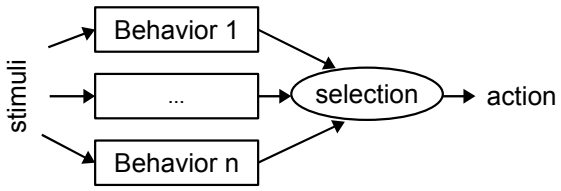


Figure 1: Behavior-based action selection.

ods (Rosenblatt, 1996; Hostetler and Karrney, 2002). The work presented in this paper is based on the action selection by a voting system to coordinate behaviors. We extend previous works by the study of two points: (a) how the behaviors can express their indifference towards some components of the action, and (b) how the expression of the action values by continuous values can contribute to avoid locked situations.

The rest of the paper is organized as follows. In Section 2, our work is situated in the context of relevant research. The action selection process is detailed in Section 3, and we present our solution. We explain how this proposition avoids some of the recurrent difficulties in using a voting system to coordinate the behaviors. The tests and results are described in Section 4, before discussion (Section 5) and conclusion.

2 RELATED WORKS

This study is based on previous works in the domain of behavior-based architectures and methods. We focus more specifically on the action selection problem, i.e. the problem of selecting the most appropriate action in the current situation (Maes, 1989). In the context of behavior-based agents, the action selection methods are usually classified in two main categories (Pirjanian, 1999): arbitration and fusion.

In the arbitration or competition category, the principle is to select one of the behaviors to which the control is delegated until the next step. The methods based on priorities (Brooks, 1986; Mataric, 1992), finite state machines (Bryson, 2002) and activation networks (Maes, 1989; Dorer, 1999) belong to the arbitration category.

In the fusion or cooperation category, the principle is to integrate all of the behaviors' responses into the resulting action. The methods based on linear combination (Reynolds, 1999), potential fields (Rosenblatt, 1996), schemas (Arkin, 1998), fuzzy behavior control (Tunstel, 1995; Pirjanian and Mataric, 1999) and GA (Flacher and Sigaud, 2003) belong to the fusion category.

The arbitration category is based on a dictatorial approach because the decision is made by one behavior. This may have two consequences: the violation of the other behaviors' constraints and an eventual oscillation of the system if different behaviors make alternatively the decision. The fusion category is based on a more democratic approach than the previous one, but it can produce results that are not satisfying for any of the behaviors.

These specific characteristics of each category can be solved in dynamically switching from a method to another like in the APOC system (Scheutz and Andronache, 2004). We have studied another solution, more democratic and fair: the use of a voting method (Rosenblatt, 1996; Hostetler and Karrney, 2002; Hanon et al., 2005). With this approach, one of the proposed responses is selected by a process which integrates the behaviors' preferences and constraints. This allows to respect these preferences and constraints while avoiding a fusion of the actions that are proposed. In this process, the behaviors propose a set of alternatives (propositions of values for the action) and they express their preferences among all the available alternatives. Then, the selected alternative is chosen, as the best alternative after aggregation of the behaviors' preferences.

However, in the existing AS voting systems, the set of alternatives is generally restricted to a very limited action space, due to complexity reasons or application dependent constraints. Another difficulty comes from the parameterization of the model due to the use of weights on the behaviors' vote. This is solved by learning mechanisms (Maes and Brooks, 1990) but the calculated weights are very specialized to a certain environment, and would not be adapted to other context. Concerning the expression of the indifference of the behaviors towards some components of the action, a first proposition has been made in (Hanon et al., 2005) to complete the alternatives before the vote, but the complexity of the treatment entails some difficulties to maintain the time constraint.

In this paper, we give a new solution to the problem of action selection. Objectives are both:

- use of a coordination function, which takes into account fairly all the behaviors (in a positive way for the wishes, in a negative way for the constraints) and contributes to avoid (dead- or live-) locked situations,
- diminution of the algorithm complexity, in order to keep the reactivity of the system.

3 ACTION SELECTION

The aim of the action selection process is to choose the next step action to perform. Action is a generic term that recovers distinct realities depending on the type of agent and its environment. For instance, concerning a robot, an action is the set of the actuators commands while for a software agent, an action is the set of its output values. In both cases, the action can be composed of several elementary actions: an action A is a n-uplet $A = (a_1, \ldots, a_n)$, where each action a_i has its value in a domain D_i. The set of the possible values for A is thus $D_1 \times \ldots \times D_n$. For example, in the autonomous navigation, $n = 2$ with $A = \{\text{velocity}, \text{orientation}\}$. According to the technical constraints specific to a certain application, we can have $D_1 = [-50, 50]$ (speed units) and $D_2 = [0; 360]$(degrees).

The elementary actions may not be independent: often, the value given to an elementary action a_i can influence the values given to other a_j. And this dependency may be different for the behaviors. In the precedent example, the behavior "obstacle avoiding" concerns the two elementary actions since the agent position depends both on its velocity and its orientation. As a consequence, the values of the elementary actions can generally not be selected separately: the decision is made at once on all the elementary actions, as a "whole" action and not on independent parts of it.

A behavior-based structure is composed of a set of distributed independent behaviors $B = (b_1, \ldots, b_p)$ and a centralized coordination system. Each behavior is concerned by a the subset of the stimuli, and reacts according to its specific (generally low-level) objectives, e.g. goal seeking, obstacle avoidance, wall-following, etc. Each behavior proposes action valuations to reach its goals. A proposition made by the behavior b_i is an alternative $A^{b_i} = (a_1^{b_i}, \ldots, a_n^{b_i}) \in D_1 \times \ldots \times D_n$. For example, the "goal seeking" behavior can propose the alternative $A = (2, 30)$ with its preferred values for the action: a value of 2 for the speed units and a heading of 30 degrees.

With a preference aggregation process like a voting system, the action selection by the behaviors is performed in four phases (see Algorithm 1):

1. proposition of the alternatives
2. constraints application
3. preferences elicitation
4. selection of one of the alternatives as the best choice.

The following subsections describe these four phases, their specific difficulties and the solutions we propose. More particularly, we will discuss the influence of two parameters on the result of the vote: the use of discrete or continuous alternatives and the number of alternatives.

Algorithm 1. Action selection by voting behaviors.

```
behavior set B = {b_1, ..., b_n}
alternative list l = ∅
// 1. proposition of the alternatives
for all behavior b_i ∈ B do
   add p alternatives to alternative list l
end for
// 2. constraints application
for all behavior b_i ∈ B do
   for all alternative A_j ∈ l do
      A'_j ← application of b_i constraints to A_j
   end for
   l ← (l \ {A_j}) ∪ {A'_j}
end for
// 3. preferences elicitation
for all behavior b_i ∈ B do
   b_i sorts alternatives ∈ l
end for
// 4. selection of one action
selected alternative ← winner of the preferences aggregation
return the selected action
```

3.1 Alternatives

The choices made in Algorithm 1 have a lot of consequences and have to be discussed. We have stressed three limitations: the obligation to choose exact discrete value for actions; the possibility for a behavior to give one, two, or any number of alternatives; and finally the difficulty of taking into account indifference.

3.1.1 Action Space

A difficulty comes from the size of the action space because the set of all combinations $D_1 \times \ldots \times D_n$ can be very large. The behaviors can not give their preferences in an extensive way. In our example, the action space of the orientation is a subset of $\mathbb{R}$.

This difficulty is avoided in most existing works by reducing the action space to few discrete values, even when the action space is initially a continuous domain. This allows to enumerate the values of the elementary action combination set, these values form the set of alternatives. This is reasonable when these values are strongly linked to actuators, like the seven motor commands , "hard left" "left", "soft left", "forward", ..., to "hard right" in (Kwong et al., 2002).

This is less understandable when these values are intended to command flexible actions, like the navigation of a virtual character in (Hostetler and Karrney, 2002). For example, a behavior which objective is to accelerate would be satisfied by any speed value greater than the current one. With s being the current value of the speed, the previous objective can be expressed by discrete values, e.g. the proposition of $(s+\Delta)$ or several values $\{(s+\Delta_1);(s+\Delta_2);(s+\Delta_3)\}$, or by the continuous set $]s;\infty[$.

Does the choice of using discrete or continuous values have any influence on the results of the action selection? Our hypothesis is that some locked situation could be avoided in using continuous values instead of discrete values. For example, even if a behavior can not accept the value a_1, nor the value a_2, it may accept some intermediate values in the interval $]a_1;a_2[$. We propose thus to express the alternatives as intervals $A^{b_i} = ([a_{11};a_{12}],\ldots,[a_{n1};a_{n2}])$ with $[a_{11};a_{12}] \subseteq D_1,\ldots,[a_{n1};a_{n2}] \subseteq D_n$.

3.1.2 Number of Alternatives per behavior

A behavior that proposes more than one alternative can influence the result of the vote in its favor. Let's take an example:

Three behaviors M_1, M_2 and M_3:

- M_1 proposes $A = (1.5,4,8)$
- M_2 proposes $B = (3,2,3)$
- M_3 proposes $C = (5,6,7)$

The votes are:

- M_1 votes $A > B > C$
- M_2 votes $B > A > C$
- M_3 votes $C > B > A$

The results are, using Inverse Borda Rule (1 points for the first alternative, 2 for the second and 3 for the third): 6 points for A, 5 for B and 7 for C. B is thus the winner.

If M_1 proposes more than one alternative, it can change the result:

- M_1 proposes $A = (1.5,4,8)$, $A_1 = (1,4,8)$ and $A_2 = (2,4,8)$
- M_2 proposes $B = (3,2,3)$
- M_3 proposes $C = (5,6,7)$

and the votes are:

- M_1 votes $A_2 > A_1 > A > B > C$
- M_2 votes $B > A_2 > A_1 > A > C$
- M_3 votes $C > B > A_2 > A_1 > A$

The results are: 12 points for A, 9 points for A_1, 6 points for A_2, 7 for B and 11 for C. A_2 is the winner. This example shows that the number of alternatives proposed by a behavior may change the result of the aggregating process (it is shown here with the Borda rule, but similar examples can be constructed with any other voting rule).

As a consequence, we propose to limit the alternatives to only one alternative per behavior ($p = 1$ in the Algorithm 1). This limitation ensures a fair treatment among all the concurrent behaviors. Furthermore, this can be combined with the use of continuous values. Following the example above, M_1 may propose $A = ([1;2],4,8)$ if this alternative matches its goals.

3.1.3 Indifference Handling

Behaviors can be indifferent to some of the elementary actions. For example, a behavior which objective is only to reach a certain speed would be indifferent to the value of the orientation. Expressing the indifference towards the value of a_i can be made in using a specific value (like the "Joker" value in (Hanon et al., 2005)). This proposition is interesting and simple but a difficulty is then to sort vectors of actions when one or two values are lacking. Replacing value by a joker symbol induces a problem of incomparability between vectors of actions. An other solution to express indifference consists in replacing the missing value by the set of all the possible values, i.e. the D_i domain. But in this case, one vector is transformed in d_i vectors, where d_i is the cardinality of the domain D_i. This transformation is not compatible with the limitation to one alternative for each behavior.

During the proposition phase, each behavior proposes at most one alternative and this alternative can include intervals of values. The result of this first phase is thus a list of p alternatives $l = \bigcup_i A^{b_i}$, with $A^{b_i} = ([a_{11};a_{12}],\ldots,[a_{n1};a_{n2}])$. To express its indifference towards the elementary action a_i, a behavior proposes the interval of all possible values, i.e. the whole domain D_i of a_i. This value is then used as any other component of the alternative.

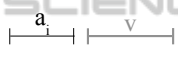
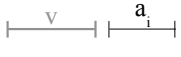
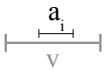
3.2 Constraints Application

The knowledge of the constraints due to the environment or the context, e.g. the presence of an obstacle, are distributed among the behaviors, just like the elementary objectives of the agent are distributed. As a consequence, each behavior can restrict the space of the possible actions. In (Hostetler and Karrney, 2002)), a restriction is called a "veto" because each

of the behaviors can eliminate any of the alternatives in the agenda.

When an action is composed of independent parts, constraints can easily be expressed as restrictions on the elementary actions domains. But in most cases, the values of the elementary actions depend from each other and the restrictions are functions that link these values. For example, a constraint on heading and velocity should express that "heading h and speed s must be chosen such as $s * tan(h) < 10$ units". For this reason, and since each behavior has its own objective, we propose that each behavior applies its own constraints to the alternatives list (see application of interval constraints on values in Table 1). The new agenda is the smallest common resulting set of the constraint application phase.

Table 1: Application of the restriction ($v = [v1; v2]$) to the alternative component ($a_i = [a_{i1}; a_{i2}]$).

Respective positions of restriction and action values	Resulting action Value
	$a_{i'} = a_i$
	
	$a_{i'} = [a_{i1}; v1]$
	$a_{i'} = [v2; a_{i2}]$
	$a_{i'} = \emptyset$
	$a_{i'} = [a_{i1}; v1] \cup [v2; a_{i2}]$

As the alternatives are expressed by continuous values in our proposition, a restriction can produce a "splitting" of the intervals (Cf. 4th case in Table 1). For example, consider the alternative $x = ([x_{11}, x_{12}], x_2)$ and the restriction $v = [v_1, v_2]$ with $[v_1, v_2] \subset [x_{11}, x_{12}]$. The application of v to x leads to replace x by the two alternatives $([x_{11}, v_1], x_2)$ and $([v_2, x_{12}], x_2)$.

At the end of this phase, the resulting *agenda* respects all of the behaviors' constraints.

3.3 Preference Elicitation

The agenda is proposed to the behaviors, and each behavior produces a classification among the available alternatives according to its preferences. Each behavior has its own utility function. The comparison between the alternatives can be based on different criteria according to the behavior, since the behavior's goals are distinct. The comparison can be made on the values of all or only parts of the decision components in case of indifference toward some of them.

The use of continuous alternatives may cause some difficulties in the expression of their preferences by the behaviors, which is more difficult with continuous data than with discrete data.

In the preference elicitation phase, the difficulty is, for each behavior, to classify the interval alternatives. With the assumption that a behavior has defined its preferred action values as intervals, how can it compare these values to the alternatives?

One first solution is to approximate an interval by its median value. This strongly reduces the problem to a comparison of discrete values. But we lose the richness brought by the use of continuous values. Another solution is to find similarity metrics that can be used to compare the alternatives. The Hausdorff distance and dissemblance index are two functions of primary distances that are used to build compatibility measures (Cross and Sudkamp, 2002).

The Hausdorff distance q measures the distance between two compact subsets of the real numbers X et Y:

$$q(X,Y) = max(\sigma(X,Y), \sigma(Y,X))$$

with

$$\sigma(X,Y) = sup_{x \in X} inf_{y \in Y} d_2(x,y)$$

where d_2 is the euclidian distance between real numbers. Informally, the value of $q(X,Y)$ represents the maximal distance between any element of the set X to the set Y.

The distance between two intervals of reals $V = [v_1, v_2]$ and $W = [w_1, w_2]$ with this measure is given by:

$$q(V,W) = max(\mid v_1 - w_1 \mid, \mid v_2 - w_2 \mid)$$

The measure of dissimilarity between two intervals of real numbers V and W is calculated by:

$$D(V,W) = \frac{\mid v_1 - w_1 \mid + \mid v_2 - w_2 \mid}{2(\beta_2 - \beta_1)}$$

where the interval $[\beta_1, \beta_2]$ includes V and W. Dividing by $2(\beta_2 - \beta_1)$ results in a normalized measure $0 \leq D(V,W) \leq 1$. For example, if $V = [6,7]$ and $W = [9,11]$, one possibility for $[\beta_1, \beta_2]$ is to select $[6,11]$. With this choice, the dissimilarity between V and W is equal to $(9-6) + (11-7)/2.5 = 7/10$.

The measure of dissimilarity is maximal and equal to 1 if $V = [\beta_1, \beta_1]$ and $W = [\beta_2, \beta_2]$. This maximal value can be obtained in very different cases, for example when we have $([10,10],[20,20])$ and

$([10,10],[1000,1000])$. To differentiate these cases, we can add another measure, e.g. the interval length.

3.4 Preference Aggregation

From the set of all the propositions of values by the behaviors, the decision process must provide one value for each action A.

Many voting systems can be used in this phase. In our context, the chosen voting system must be well-adapted to un-weighted vote and determine a winner as fast as possible. We choose a scoring voting method because this method satisfies reinforcement and participation (see (Moulin, 1988)). More precisely, we use Inverse Borda Rule: 1 point is given to the best alternative, 2 points to the second, and so on. Then, a sum is made and the winner is the alternative with the least score (in case of ex-aequo, the winner is chosen randomly). This rule is "effectiveness" for Weber (Weber, 1978), the expected satisfaction of behaviors if the utilities associated with the alternatives are independently and uniformly distributed is optimal with this rule.

Once an alternative is chosen, we obtain intervals for the action values. A difficulty is then to determine the value to affect to the action at the next step: a transformation has to be realized because the action command must be a discrete value. Different solutions are possible to replace the winner interval by one of its values: the median, or a randomly chosen value, or chosen using an heuristic, etc. This transformation may also take into account the actual value of the system, depending on wether the actual value belongs to the winner interval or not.

While explaining the four phases of the action selection by voting behaviors, we have made the hypothesis that the use of continuous values in the alternatives enables to avoid some locked situations and to express the indifference toward some action values. To confirm this, we made experiments on a virtual autonomous agent.

4 EXPERIMENTS

The aim of the experiments is to compare different methods of action selection based on voting. Our hypothesis is that the use of continuous alternatives can prevent locked situations in which the agent does not find any solution.

The application context is a simulated environment with obstacles and moving agents. Important simplifications have been made in comparison to a real robotic navigation context: for example, no limitation is made on the velocity or the rotation of the agent.

In this context, the action includes $n = 2$ components, with the speed $x_1 \in D_1 = [0;3]$ and the heading $x_2 \in D_2 = [0;360]$.

4.1 Behaviors

The agent includes three permanent behaviors – GoFast, TowardGoal, Inertia– and one behavior – AvoidObstacles– that is activated according to the perceived environment:

- the behavior "GoFast" tends to reach a wished speed; it is indifferent to the heading. It proposes one alternative that expresses the will to go faster whatever the heading is.
- the behavior "TowardGoal" tends to orientates toward the goal on the base of the current speed.
- the behavior "Inertia" is used to regulates the moving in avoiding unuseful changes from one step to the next one.
- the behavior "avoidObstacle" is dynamically activated according to the perceived environment: one "avoidObstacle" behavior is created for each perceived obstacle. Each behavior of this type proposes an alternative on the base of the current speed as the maximal wished speed and a heading that avoids the obstacle.

4.2 Methods

The action selection phases are those described in Algorithm 1. We have tested 6 methods that use behavior- and voting-based action selection. These methods have common features:

- the behaviors propose alternatives;
- the behaviors can express their constraints in partially or completely eliminating some of the alternatives;
- the behaviors express their preferences in ordering the alternatives; the order is non-strict (there can be ex-aequo) and complete (all is ordered);
- the preferences are aggregated using an Inverse Borda politics.

We have tested different methods based on the following choices:

- discrete or continuous values
- indifference for an action component can be expressed or not

- for the continuous values, the alternatives can be changed into discrete values before the vote or not

Numerous techniques can be used to change the continuous values of the action into discrete ones: mean, median, randomization, heuristics,... We have chosen to study the use of median and randomization techniques.

The methods we have tested are summed up in Table 2):

- The three first methods use alternatives with *discrete* values. Two methods do not allow to express the indifference toward one of the action component value, which is thus replaced by its current value: in Method **no indiff. 1**, each behavior proposes one and only one alternative; in Method **no indiff. 2**, the "avoidObstacle" behavior proposes two alternatives, i.e. one for each bound of the obstacle. In the third method, Method **product**, the behaviors can express indifference toward one of the action in using a "Joker" value. The alternatives that include Joker values are completed by the values proposed in the other alternatives.
- The three last methods use alternatives with *continuous* values, i.e. the values can be express as intervals. In Method **median before vote**, the intervals are changed into their median values before the vote. In the two other methods, the vote is made on the intervals. The behaviors must be able to express their preferences in sorting intervals. We use the dissemblance function for the comparison of the intervals. The result is an interval that must be changed into a discrete value for the action to be performed: in Method **median after vote**, the winner interval is changed into its median value; in Method **one of result**, one of the values is randomly chosen in the winner interval. In this last method, we have chosen to favour the current value in the aim to have a globally "smoother" behavior: random is a normal distribution that is centered on the current value when this one belongs to the winner interval. When the alternatives are made of intervals, the application of the restrictions consists in "crossing" the alternative intervals and the restriction intervals (see Table 1). This operation can divide the alternatives into subsets as mentioned in Part 3.2.

4.3 Environment

For the experiments, we used the NetLogo (Wilensky, 1999) environment, that offers the possibility to use continuous spaces for the agent's position (continuous x and y coordinates). The state of the model is set up at each simulated time step. Independently of the simulated time count, the real duration of the run can be measured. This measure is not meaningful regarding its absolute value (depending on parameters like the processor frequency), but we use it to compare the methods.

In the following experiments, the agent must reach a target within a given number of simulation steps while avoiding obstacles. At each simulation step, the agent perceives its environment in a 2 units radius circle, and then selects a speed and a heading to move. When it does not find any solution or when its solution is wrong because the action would make it occupy a non idle place, the agent is stopped during one step or more; we call it a "locking situation". The environment changes dynamically, according to a parameter that determines the rate of obstacles that change between two simulation steps. In fact, the environment changes, then there is a stable step during which the agent moves, and then the environment changes again.

The environment is simulated by a 21x21 patches grid, with 20 pixels per patch. The obstacles occupy the environment at the constant rate of 25% of the grid cells, but their places vary according to the change rate: from 5% to 25% of the obstacles places that change at each step (see the example given in Fig. 2). The results are the average values given by 200 runs on each configuration, i.e. one method with one change rate.

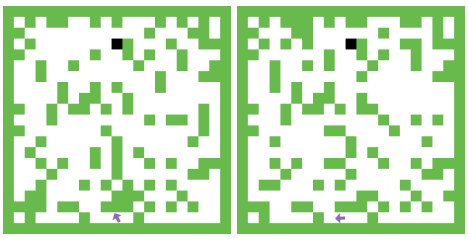


Figure 2: Example of two successive environmental situations with a change of 25% of the obstacles. In green: the obstacles, in white: free spaces, in black: the target.

4.4 Results

We have evaluated the selection methods with an increasing change rate in the environment. In each environment, we have measured:

- the time taken by the agent to make its decision about the action selection;
- the success rate in reaching the target within a limited amount of steps;
- the number of steps in which the agent is stopped (called "locked steps").

Table 2: The experimented methods (method name in bold text).

Alternative type	Indifference	Before vote	After vote
Discrete values	no	1 alternative / behavior **(no indiff. 1)**	discrete results
		n alternatives / behavior **(no indiff. 2)**	
	specific discrete value (Joker)	Joker replaced using cartesian product with the other alternatives **(product)**	
Continuous values	Value domains	interval replaced by their median **(median before vote)**	
		interval alternatives	winner interval replaced by its median **(median after vote)**
			winner interval replace by one of its value **(one of result)**

The average time required by the decision making does not vary a lot according to the change rate (cf. Fig. 3). Methods using discrete values are faster than methods using continuous values, the method **Median before vote** that converts the continuous values into discrete values before the vote being situated in the middle between the two types of methods. These results are easy to understand as the voting process requires to compare alternatives, and this task is more complex with continuous values than with discrete values.

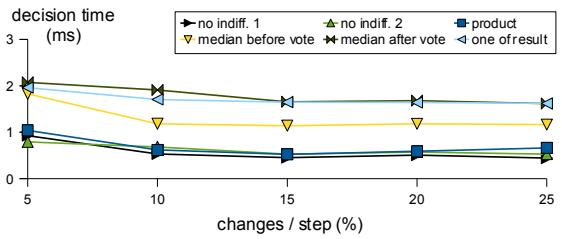


Figure 3: Mean decision time.

The total number of steps remains almost constant even with the increase of the number of changes per step (cf. Fig. 4). In our tests, all of the methods except one require between 30 and 40 steps to reach the target. One method needs more steps than the others: the **Median after vote** method. From our analysis of the results, it seems that choosing the median of the resulting interval causes to strengthen the avoiding behaviors, as if the agent turns back to avoid collision, and thus, requires a higher amount of steps before reaching the target.

About the locked steps (cf. Fig. 5), the results show that methods using continuous values cause less locking situations than the methods using discrete values. The disadvantage is even worst for the method **No indiff. 1** that proposes only one alternative per

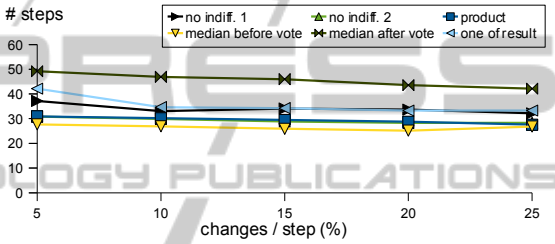


Figure 4: Mean number of steps required to reach the target.

behavior, eliminating thus potential solutions. The general tendency of all curves to decrease is due to unlocking when an obstacle disappears with a change in the environment.

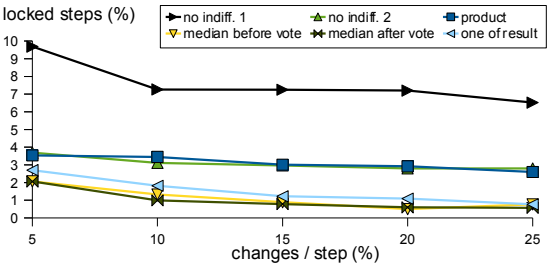


Figure 5: Mean number of locked steps (% of the number of steps required to reach the target.)

5 DISCUSSION

In this article, we have made a proposition using intervals like in fuzzy control systems (Tunstel, 1995; Selekwa et al., 2008). The difference is that the result is not produced by a combination of the fuzzy functions, but by an arbitration among the sets proposed by the behaviors, i.e. the selected action is not issued from a fusion operation: the selected action is not a

mixed solution that would risk to satisfy none of the behaviors (Pirjanian and Mataric, 1999), but one of the preferred alternatives.

Compared to the other methods based on the vote, our objective has been to propose solutions to the limitation of the action space and to the weighting problem (Hostetler and Karrney, 2002; Rosenblatt et al., 2002). Compared to (Hanon et al., 2005), the continuous values constitute another solution to the indifference expression; they allow to decrease the number of locked steps, but the time taken to make a decision remains high.

Indeed, continuous values comparison, what is realized with the Hausdorff distance in our proposition, is time consuming. This is certainly the main limitation of the method proposed here. However, in these first tests, the decision time remains stable according to the amount of changes in the environment. The method should thus be chosen conditioned to stay under the threshold value determined by the application context, e.g. 50 MHz for screen refreshment in a video game. More generally, the use of continuous values seems to be relevant when the application context presents three characteristics: the environment is dynamical, the agent can perform actions that really belong to continuous domains and the supplement of time taken to manage the continuous values is acceptable considering the application constraints.

These results have to be confirmed by complementary experiments in more complex environments and situations, and with a higher number of action components. Additional tests must be done too, in the aim to compare the proposed method with other different (non voting based) AS methods.

6 CONCLUSIONS

We have proposed an action selection method for behavior-based agents that uses continuous values for the alternatives, allows a fair vote based on one alternative proposition per behavior and the expression of the indifference.

Different versions of the method have been tested on a small dynamical environment. The results show that the use of continuous values enables to avoid some locking situations. Such methods are more time-consuming than methods processing discrete values, but the difference remains stable even with an increasing change rate in the environment. These characteristics must be confirmed by new experiments in larger and various environments, and with several agents.

The methods discussed here can be integrated in a lot of different contexts. For example, they could be used at the reactive low level of a multi-level agent, composed of other, more cognitive and higher level competences, such as in (Bryson and Thorisson, 2000). Another idea is to use this action selection process to coordinate inter-agent actions, at the macro-level of a multi-agent system, instead of the internal behaviors of an agent, at a micro-level. Another interesting perspective is to study these methods associated with learning mechanisms.

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