Enhancing Appropriateness of Executive Decisions Using AIS

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Abstract

This paper presents an enhanced version of the AED (Appropriate Executive Decisions) algorithm, which is based on biological immune system (BIS) and whose purpose is the generation of appropriate executive decisions aimed at business environments. A new metric has been incorporated to the algorithm and a larger and more representative database was used to train and validate results. Moreover, this paper offers better directions on how to apply AED in executive decisions, affording the learning process quality improvement through immunoinformatics concepts, namely decision cells, thereby producing more appropriate executive decisions. Experiments were carried out with executive officers experienced in executive decisions in order to suitably validate the appropriateness of responses generated by the enhanced AED algorithm.

1. Introduction

Over the past two decades, research and development of techniques for supporting decision-making received increasingly attention. This may be motivated by the considerable complexity associated with current decision-making that constantly demands for tools capable of automating and speeding it up [1].

Currently, to manage competitively an enterprise demands more and more fast decisions, regardless of whether they are programmed or non-programmed decisions (*i.e.* decisions that may be taken in the presence of novel situations). Impacts of those decisions are especially critical when they are taken at a strategic level, because they can dramatically alter the future of a company. Many companies pay a high price because they prepare for the future with a limited vision of the present [2].

Strategic decisions involve a great variety of internal and external information. As for symbolism, quantitative information is easy to handle, whereas the qualitative information needs further pre-processing. Depending on the economic sector, strategic decisions involve great uncertainty due to the large number of decision variables that have to be taken into consideration and to some likely novelty [3]. Occasionally, the nonexistence of deterministic assessments of relevance of decision variables is an extra problem. Decision and Control theories, when combined, can generate methods that lead to more rational decisions in choosing alternatives that produce satisfactory results [4].

Since the majority of executive decisions are unique (or rarely repeatable), the need for effective means of preserving the essence of decisions, as opposed to simple memorization, is very clear. This would be very useful for the generation of future increasingly appropriate executive decisions [2]. The biological immune system (BIS) has a strong similarity to this kind of thought mechanism, especially with regards to its capability of reacting appropriately (*i.e.* effectively and efficiently) to exposure to unknown pathogens when a class-representative prototype has been previously "introduced" in the system [5].

This paper presents an enhanced version of the AED (Appropriate Executive Decisions) algorithm [6], an immunoinformatics algorithm inspired by the functioning of BIS for obtaining appropriate executive decisions. Section 2 explains some concepts on executive decisions and presents the AED algorithm. Section 3 presents the improvements made to the algorithm. Section 4 presents some results of experiments carried out to validate the enhanced version of AED. Finally, conclusions are drawn and future work listed and commented upon.

2. Background

2.1. Executive Decisions

Business executive decisions are destined to perpetuate the business mission [7]. They are the transformation of complex information context, uncertainty and company ethos into actions that result in suitable business results. These actions are characterized as non-programmed, involving imprecision, and suffers from dealing with inadequate data and lack of structure of the problems [8]. The complexity of actions for generating an efficient response (*i.e.* executive decision) inside a company is thought to be very similar to the generation of a homeostatic response in BIS [9], thereby inspiring and motivating the development of the AED algorithm as a tool for supporting business executive decisions.

2.2. Appropriate Executive Decisions

Caldas *et al.* [6] originally proposed a computational architecture based on immunologic engineering [10], aiming at representing executive decisions components, assessing interactions of these components with regard to appropriateness of the decision and implementing the AED algorithm. AED preserves the principles of the BIS mechanisms (*e.g.* negative selection) in generating "immunedecisions" [11].

Figure 1 presents an overview of the original AED learning and operation phases. In the learning phase decision-makers supply specific decision cells of determined types (*e.g.* buying, selling, transforming, etc). Each cell consists of appropriate "decision receptors" (*i.e.* decision components [12]) that are arranged in a given order; together, these cells comprise the pool of candidate decision cells. The learning process is completed when the decision cells are stored permanently (*i.e.* become memory decision cells). In the operation phase, specific memory cells are activated as if the decisions they encode are considered appropriate and, therefore, will be used to generate clones.

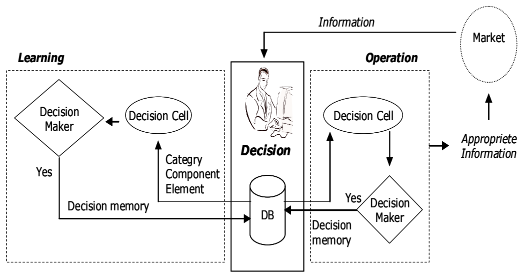

Figure 1. Overview of the original AED algorithm.

Decision cells are computational data structures made of receptors that represent elements of a specific type of executive decision, based on a model for managerial decision-making [12]. In the operational phase, Hamming distance is used to measure affinity between stored decision cells (*i.e.* "mother cells") and the supplied ones. The generated clones are evaluated by two kinds of affinity: (*i*) minimum affinity, ε – distance between clone and its "mother" cell; and (*ii*) cross affinity, ε_c – distance between clones and all decision cells of the same type (*e.g.* "buying" in a business company). Next, elected clones are those which satisfy minimum and cross affinities, while all others are discarded. Figure 2 shows a pictorial representation of this evaluation.

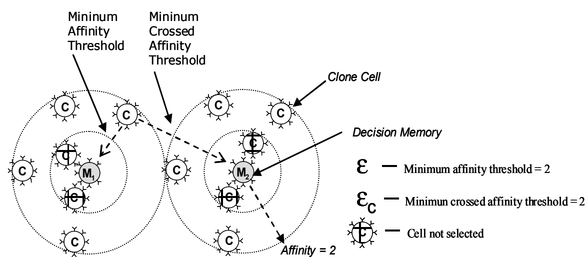

Figure 2. Pictorial representation of clone cell evaluation. Note that clone cells may lie within or without affinity thresholds, *i.e.* they can be considered or not as acceptable decisions.

After that, a set of generalist clones – as they attend to many appropriate memory cells – are presented to the decision-maker to whom is guaranteed that there is at least one cell for which ε is satisfied [6].

The AED algorithm is different of the ASN negative selection [13], because the "self" (or appropriate) information is not defined by the ε and ε_c parameters, but by the decision-maker judgment. The AED algorithm is not also directly guided by "antigens", like the CLONALG algorithm [14], because executive decisions are inherently unstructured. Therefore, in the AED algorithm the matching with the antigen occurs only when this is appropriate based on the company's decisions history for a particular decision-maker.

The AED algorithm follows the administrator man's simplified model of reality [15].According to this model, inherent uncertainty involved in executive problems are avoided, while possible good and creative solutions are pursued in the neighborhood of current decision options (*i.e.* in the AED, the memory cells).

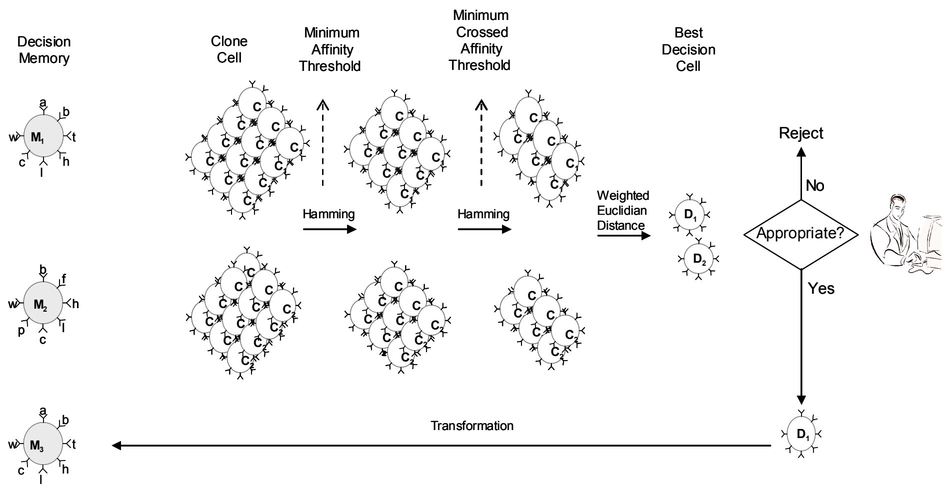

Figure 3. Weighted Euclidian distance introduced in this new AED algorithm as a mean to better provide a more appropriate set of decision cells to decision-maker.

3. New Features

After initial results of the AED [6], further analyses and experiments reveled that some shortcoming should be addressed by:

- Obtaining a more representative database for the purchasing executive decision (our test case);
- Conception of a new metric – weighted Euclidian distance – to provide a more consistent set of decision factors to the decision-maker.

In the original AED algorithm, only Hamming distance was used to select clones. Each memory cell generates a set of clones whose receptors are permutations of the original ones and the generated clones are submitted to affinity (ε threshold) and crossed affinity (ε_c threshold) filters, of which a set of selected clones are obtained and presented to decision-maker. Indirectly, ε and ε_c thresholds have a strong influence over the number of decision cells finally presented to decision-maker. For the purchasing problem explored in previous work [6] with cells of size ten receptors, we have analyzed the influence of ε and ε_c thresholds over the number of cells generated.

This work adds a new filter – the weighted Euclidian distance – to this selection stream in order to provide a more consistent set of cells to decision-maker. The new filter is more sensitive to positional variations of receptors; Figure 3 shows the pipeline.

After decision cells and their clones are evaluated, in order to be accepted they need to pass through the minimum and cross affinities filters. These affinities are the minimum acceptable distance from clones or decision cells to memory cells. The *minimum affinity*, ε, relates clones or decision cells to the "mother" memory cell which generated them, so one might see this sort of clonal selection as an *exploitation* in the decisions search space. The *cross affinity*, ε_c, relates clones or decision cells to all "mother" memory cells of the same type, that is, all generated clones that have passed by the minimum affinity threshold, representing an *exploration* in the decisions search space. To avoid problems of scale, values of ε and ε_c shall be in the range [2…*n*]. The lower limit is the minimum Hamming distance possible and the upper limit is the number of receptors.

In both minimum and crossed affinities, regular Hamming distance was used. Next, the winner clone to be presented to the decision-maker is selected by evaluating its weighted Euclidian distance in relation to its mother memory cell. The clone with the lowest weighted Euclidian distance to its mother is then selected. The weighted Euclidian distance between a clone and its mother is shown by Equation 1. Partial distance between equivalent receptors is weighted (*i.e.* decision elements incorporate decision-maker preferences) and are relative to their position, not to their values.

$$d = \sqrt{\left(\sum_{i=1}^{n} w_i \left(m_i - c_i \right)^2 \right)} \qquad \textbf{(1)}$$

where n is the number of receptors, w is the receptor weight, m is the position of a receptor of the memory cell and c is the position of the equivalent receptor of the clone cell. Receptors weights are determined by the number of occurrences of each receptor, representing the percentage of them in the whole set of memory cells.

4. Experiments and Results

This section presents some experiments and results used to validate the enhanced AED algorithm. A more representative database of executive decisions related to purchasing problems was utilized.

4.1. Data Characterization

The experiments carried out henceforth utilized qualitative data obtained during a survey in which executive officers of 20 private mid-size business companies in the IT (Information Technology) sector in Brazil were interviewed. Nevertheless, as we intended this experiment to simply validate the concept of AIS as a tool for providing appropriate executive decisions, the origin and specificity of the data utilized could be abstracted.

Even so, for the sake of information reliability, a number of criteria were established prior to the interviews. The most important ones were: (i) companies had to have been in regular operation for more than ten years; (ii) people interviewed had to be partners in the business with active participation in the executive decision process; (iii) all interviewed personnel had to have more than five years of experience with executive decisions; (iv) all interviewed had to have some experience with purchasing; (v) all interviews were carried out in private; and (vi) all the people interviewed were informed of the purpose of the exercise. On average all interviews lasted for no less than 20 minutes.

In short, the questionnaire applied required that all executive officers state: (a) the decision factors they regularly use for purchasing and (b) the receptor order deemed to be most appropriate for supporting their strategic purchase decision. Figure 4 shows the ten factors (*i.e.* candidate receptors) found most appropriate for strategic purchase decisions within all the companies in question, according to their interviewed executive officers. The histogram generates the following set of weights for each receptor: ***W*** = {0.75, 0.70, 0.60, 0.60, 0.55, 0.55, 0.50, 0.45, 0.40, 0.40}.

4.2. Results for the Enhanced AED

In order to validate the new AED functionalities we used the data gathered in the interviews mentioned in section 2.1. The aim of the experiment was to check the appropriateness of executive decisions generated by the enhanced AED system, as it learns from the appropriate decision cells supplied by all executive officers.

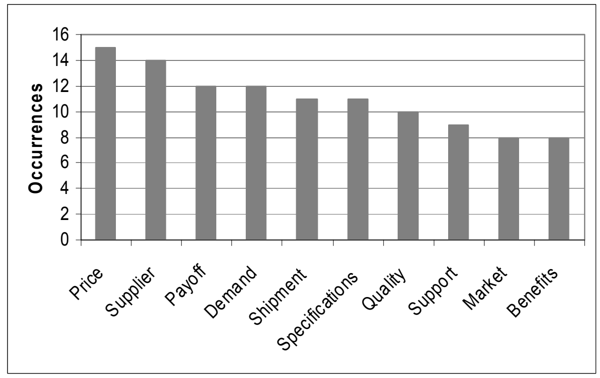

Figure 4. Ten most appropriate factors in purchasing decisions for the interviewed executive officers.

After the learning phase, which consisted of memorizing all appropriate decision cells, the AED system generated several clones associated with the same decision. Table 1 presents an example of a decision cell supplied by the decision-maker – later saved as memory cells (M) during "training" and a possible clone cell (C) generated by the enhanced AED algorithm, respectively.

Table 1. Example of decision cell obtained during the operation phase.

Decision Cells	Order of purchase factors (receptors)				
	R_1	R_2	R_3	R_4	R_5
M	Specif.	Serv.	Qual.	Price	Payoff
C	Qual.	Price	Specif.	Payoff	Serv.

For validation, five executive officers from the interviewed set were asked to assess the appropriateness of AED generated decisions. Five different parameter configurations were selected. The results of this evaluation are presented in the five tables below. One may see that across decision makers, parameters and generated decisions, the AED algorithm seems to produce results that are deemed to be appropriate. Parameters ε and ε_c were varied to reveal changes in appropriateness of decisions. In all tables the decision makers were asked to say (Y)es or (N)o regarding to the appropriateness of every candidate decision. Table 2 shows seven cells generated by the AED algorithm evaluated by five executive officers with parameters $\varepsilon = 5$ and $\varepsilon_c = 5$. Decision D_1 in Table 2 obtained 40% acceptance because randomness factors in the algorithm became more prominent. The high level of acceptance for the others cells show the generalization capability of the enhanced system.

Table 2. Assessments of AED-generated decisions as deemed 88.6% appropriate by the five executive officers; parameters used were $\varepsilon = 5.0$ and $\varepsilon_c = 5.0$.

Decision	Decision-Makers (DM) {Opinions: (**Y**)es or (**N**)o}					Totals *DM*
	DM_1	DM_2	DM_3	DM_4	DM_5	
D_1	Y	N	N	Y	N	40%
D_2	Y	Y	Y	Y	Y	100%
D_3	Y	Y	Y	Y	Y	100%
D_4	Y	Y	Y	Y	Y	100%
D_5	N	Y	Y	Y	Y	80%
D_6	Y	Y	Y	Y	Y	100%
D_7	Y	Y	Y	Y	Y	100%
Totals *D*	86%	86%	86%	100%	86%	Avg. **88.6%**

Table 3 shows the evaluation results when cross affinity $\varepsilon_c = 7$ and $\varepsilon = 5$. This means that the AED algorithm generated more "aggressive" (i.e. generated cells that are more distant of the memorized ones). Notice that this parameter setting generated decisions that were viewed as less appropriate than the ones showed in Table 2. Results presented in Table 5 and Table 6 confirmed the previous observations. This time two decision cells were evaluated as the system has only produced two of them. Experiments of Table 5 show results for $\varepsilon = 5$ and $\varepsilon_c = 3$ (conservative), while the experiments of Table 6 show results for $\varepsilon = 3$ and $\varepsilon_c = 5$ (aggressive).

Table 4 shows the evaluation results when $\varepsilon = 7$ and $\varepsilon_c = 5$. This means that the AED algorithm generated more "conservative" decisions. Notice that a more conservative parameter set also generated decisions that were deemed to be less appropriate than the ones showed in Table 2, even tough they are better than the one showed in Table 3.

Table 3. Assessments of AED-generated decisions as deemed 65.7% appropriate by the five executive officers, parameters used were $\varepsilon = 5$ and $\varepsilon_c = 7$ (*i.e.* a more aggressive decision).

Decision	Decision-Makers (DM) {Opinions: (**Y**)es or (**N**)o}					Totals *DM*
	DM_1	DM_2	DM_3	DM_4	DM_5	
D_1	Y	N	Y	Y	N	60%
D_2	Y	Y	Y	Y	Y	100%
D_3	N	Y	Y	Y	Y	80%
D_4	N	Y	Y	N	Y	60%
D_5	N	Y	N	N	N	20%
D_6	Y	Y	Y	Y	Y	100%
D_7	Y	Y	N	N	N	40%
Totals *D*	57%	85%	71%	57%	57%	Avg. **65.7%**

Results presented in Table 5 and Table 6 confirmed the previous observations. This time two decision cells were evaluated as the system has only produced two of them. Experiments of Table 5 show results for $\varepsilon = 5$ and $\varepsilon_c = 3$ (conservative), while the experiments of Table 6 show results for $\varepsilon = 3$ and $\varepsilon_c = 5$ (aggressive).

Table 4. Assessments of AED-generated decisions as deemed 74.3% appropriate by the five executive officers, parameters used were $\varepsilon = 7$ and $\varepsilon_c = 5$ (*i.e.* a more conservative decision).

Decision	Decision-Makers (DM) {Opinions: (**Y**)es or (**N**)o}					Totals *DM*
	DM_1	DM_2	DM_3	DM_4	DM_5	
D_1	N	N	Y	N	Y	40%
D_2	Y	Y	Y	Y	Y	100%
D_3	Y	Y	N	Y	Y	80%
D_4	Y	Y	N	Y	Y	80%
D_5	Y	Y	Y	N	N	60%
D_6	Y	Y	Y	Y	Y	100%
D_7	Y	Y	Y	N	N	60%
Totals *D*	85%	85%	71%	57%	71%	Avg. **74,3%**

Table 5. Assessments of AED-generated decisions as deemed 70.0% appropriate by the five executive officers, parameters used were $\varepsilon = 5$ and $\varepsilon_c = 3$ (*i.e.* a more conservative decision).

Decision	Decision-Makers (DM) {Opinions: (**Y**)es or (**N**)o}					Totals *DM*
	DM_1	DM_2	DM_3	DM_4	DM_5	
D_1	Y	Y	N	N	Y	60%
D_2	Y	Y	Y	Y	N	80%
Totals *D*	100%	100%	50%	50%	50%	Avg. **70%**

Table 6. Assessments of AED-generated decisions as deemed 50.0% appropriate by the five executive officers, parameters used were $\varepsilon = 3$ and $\varepsilon_c = 5$ (*i.e.* a more aggressive decision).

Decision	Decision-Makers (DM) {Opinions: (**Y**)es or (**N**)o}					Totals *DM*
	DM_1	DM_2	DM_3	DM_4	DM_5	
D_1	N	N	Y	N	Y	40%
D_2	Y	Y	N	Y	N	60%
Totals *D*	50%	50%	50%	50%	50%	Avg. **50%**

5. Conclusions

The improvements made to the original AED algorithm resulted in producing decisions perceived as more appropriate by the executive officers. The basic principles of immune system were preserved and correlated closely with executive decisions.

Calculation of the final affinity with weighted Euclidian distance enhanced the representation of variations among solutions generated in a better way than with Hamming distance. This constitutes a more reliable way of evaluating decisions.

Clones deemed to be that are more appropriate and stored in the database of memory cells increase the appropriateness of decision suggestions, in a similar way to the process of clonal selection.

The use of a more representative real database for the algorithm validation afforded a better assessment of real executive decision-making in business companies.

Parameters selection impacts greatly on the system behaviour, referred here as of “aggressive” or “conservative” kinds of decision generation. We notices that higher values of ε and lower values of ε_c generate less variety (*i.e.* it is more conservative, because generated cells are closer of the memorized ones) and lower values of ε and higher values of ε_c generate more variety (*i.e.*, it is more aggressive, because generated cells keep more distance to the memorized ones).

The possibility of tuning the algorithm to different strategies of exploration and exploitation allows the realization of good temporal performance simulations, while it generates good solutions in extremely dynamical environments (*i.e.* when new situations arise in the decision-making process).

The great advantage in using AIS in the AED algorithm in relation to others computational intelligence techniques is the little number of prototypes needed in the training phase to enable the AED tool in executive decision-making support.

Based on the experiments carried out here it seems that the executive officers interviewed do prefer more equilibrated decisions with regards of exploration and exploitation (*i.e.* similar values of ε and ε_c) rather than aggressive or conservative parameterizations. This can be concluded by analyzing the results shown from Table 2 to Table 6; Table 2 exhibits the best results.

In summary, the results of the experiments explicit the benefits afforded by using the AED algorithm and ratified the initial assumptions that the algorithm is now more robust in generating appropriate executive decisions.

As future work, we envision: (*i*) using data from various other decision areas, (*ii*) devising a means to extrapolate knowledge across different decision-makers and maybe, market sectors, (*iii*) incorporating more effective mechanisms for increasing diversity without loss of affinity, (*iv*) finding out the balance between exploration and exploitation – a kind of decision profile or preference of a decision-maker.

6. References

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