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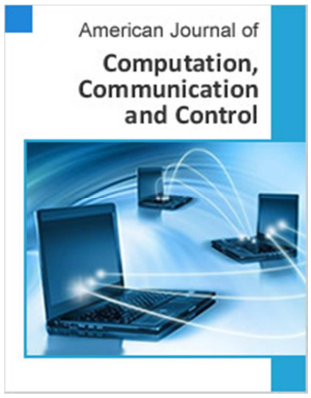

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The Application of Multiple Criterion Analysis Approach for Disambiguation in Arabic Natural Language Processing

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Abstract
The aim of this paper is to present a combination of natural language processing and multi-criterion analysis in order to reach an effective analysis when dealing with linguistic data from various sources. The coexistence of these two concepts has allowed us, based on a set of actions and criteria, to develop a coherent system that integrates the entire process of textual data analysis (no-vowelezed Arabic texts) into decision making in case of ambiguity. Our solution is based on decision theory and a MCA approach with a TOPSIS method. It allows the multi-solution classification of morpho-syntactical ambiguity cases in order to come out with the best performance and reduce the number of candidate solutions.

1. Introduction

In the Arabic language, the duality between the word and vowels implies a large increase in tidal volume of the tongue, knowing that a word can sometimes take more than twenty forms depending on the configuration that accompanies it. In fact, it leads to the most complex problems in understanding humans and machines [4]. The phenomenon that arises from this multiplicity is called ambiguity. The determination of a unique morpho-syntactic category for each word in the text of a treaty, for instance, is necessary for vowels in the text, and resolves most issues related to automatic processing of Arabic. The specific context of Arabic emphasizes the presence of a multitude of criteria that reflect the function of several constraints (e.g., grammar, semantics, logic and statistics). Therefore, a proper parsing system is required to be robust, fast, and most importantly less ambiguous.

This paper is organized as follows. First, an overall presentation of our morphological analyzer is given with a brief and comprehensive description of the phenomenon of ambiguity. The second part, we deal with the approach for ambiguity removal or disambiguation. Next, the proposed model is presented a long with the complete aggregation method known as TOPSIS[1] and the weighting method called Entropy. Then, we show the implementation of our model. Finally, we summarize our findings in the conclusion.

1 TOPSIS: Technique for Order Preference by Similarity to Ideal Solutions

Contrary to probabilistic and constraint based rules models, the proposed model of morpho-syntactical disambiguation of Arabic implements an original method base on decision theory as an approach to categorize multi solutions disambiguation in order to bring out the best. This approach has the advantage of reducing dominated solutions and ranking the rest by different criteria evaluation.

2. Morpho-syntactical Analysis

The morphological processing of the morpheme is based on two key concepts: the synthesis step that generates words or phrases based on a set of derivation rules, and in flectional adaptations, and the analysis step that associates a word graph to a set of information that describe the morphological and grammatical units of their composition (proclitic, prefix, basic, suffix, enclitic). This information allows the morphological analysis phase to determine the morphological properties of a word, such as: category (or part of speech: verb, noun or article), gender (male or female), number (singular or plural), voice (active or passive), time of action (accomplished or fulfilled), mode of the verb (indicative, subjunctive), and person (first, second or third person).

At this stage, the morphological ambiguity occurs when the analysis assigns a word more than one set of information (or the vice versa), which generates a combinatorial notion. Thus, prior to parsing, we must remove the ambiguity of many morphological labels that are associated to one word (W).

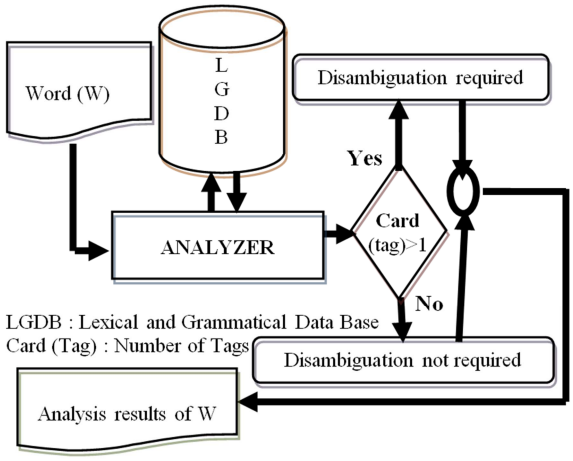

Figure 1. *General architecture of the morpho-syntactical analyzer.*

3. Disambiguation

Disambiguation is a crucial step in the process of morphological analysis. The morphological ambiguity in Arabic is mainly caused by the absence of vowels [2]. According to [4], 43.03% of words are ambiguous in the Arabic vocalized text. This proportion increases to 72.03% when the text is not vocalized. To sum up, the absence of these signs generates more cases of morphological ambiguity for instance; the word with no vowelsكتب (writing) may have 16 possible vowels, which leads to 9 different grammatical categories [1].

However the phase of disambiguation is not always required in the analysis process. The disambiguation module intervenes if the word receives more than one tag, which generates a situation of confusion or ambiguity (see Figure 1).

3.1. Existing Approaches to Disambiguation

Current analyzers are classified according to their mode of disambiguation. Yet, they all fall into two model classes; the probabilistic models that are meant grammatical labeling, and the constraint models [4]. A summary of the different disambiguation techniques are given in Figure 2.

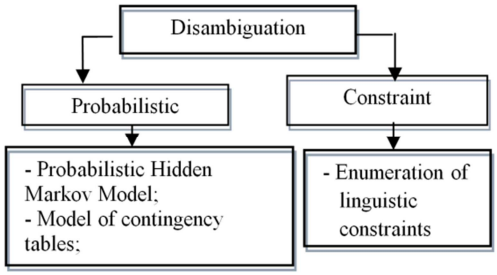

Figure 2. *Different disambiguation techniques.*

3.1.1. The Constraint Approach

This approach is based on a model that involves a linguist, which will allow the establishment of list of rules per class or category in order to be able to disambiguate. These categories can be: grammatical, structural, semantic, logical, etc. The grammatical constraints are mainly used for removing the ambiguity due to the simultaneous member ship of the semantic unit to more than one grammatical model. The use of grammatical constraints may be sufficient by itself, but sometimes other semantic constraints are imposed.

3.1.2. The Probabilistic Approach

In this approach, the probabilistic and statistical factor classifies constraints based on their redundancy. This is done on the basis of the highest rate of presence of a language constraint which can be lexical, morphological, syntactic, morpho-syntactic or semantic. The statistical and probabilistic constraints are determined by searching in the language (corpus) to assess the rate of occurrence of each constraint in relation to other constraints. This rate is estimated using complex arithmetic. The removal of ambiguity is performed using two types of information: the words label and the contextual syntax.

Then one proceeds to a combination of both information and learning[3]on their corpus annotated on hand. The Markov

2Consider a set of codes that provide a number of functions have diacritical marks placed above or below the letters appear in some texts as: the Quraan, Hadith, poetry and textbooks in particular.

3The technique of learning and classification: A set of examples is stored in memory; each set contains a word or its lexical representation, its context

technique is a probabilistic model commonly used due to its efficiency [10].

3.2. Comparison Between Approaches

Many researchers have found that constraint analyzers are faster and easier to implement than the stochastic parsers. In addition, they are more reliable and efficient in terms of analysis [10]. A third class of analyzers that combines the two previous approaches is added to increase performance and analysis suitability.

4. Proposed Approach: Multiple Criterion Analysis Model

The NLP[4]has frequent decision-making practices that meet a series of choices. Knowing the context of a specific language such as Arabic emphasizes the presence of criteria that reflect the function of several constraints (e.g., grammatical inflectional, structural, semantic, logical and statistics). So, the use of decision tools that support multi-criteria is very effective [8].

Our goal is to propose a new model of disambiguation based on a mathematical approach called MCA[5]. The basis of this method is to involve the collection of many criteria from various sources to form a mega rule that guides a parsing process. The advantage of this approach is to reduce the number of disambiguation solutions discarding the dominated solutions (i.e., solutions with no better assessment and dominated by all used criteria) and classifying the effective solutions (i.e., the ones that are not dominated) by a calculated overall score. All this is based on a clear definition of assessment criteria.

4.1. Main phases of Proposed Model

The establishment of a morpho-syntactic disambiguation process based on multiple criteria decision requires us to follow a number of steps shown in Figure 3.

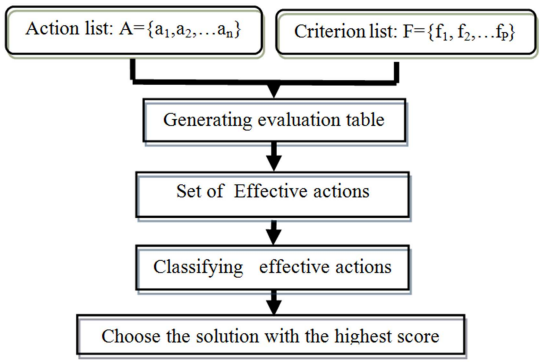

Figure 3. *Representation of the main phases of the MCA approach.*

(anterior and posterior) and its grammatical category that is related to the context. The analysis is done as follows: for each word in the sentence, the Tager will look for a stored similar example (in memory) and deduce its grammatical category.

4 NLP: Natural Language Processing

5 MCA: Multiple Criterion Analysis /or Multiple Criterion Decision-Aid

4.2. Description of the Approach

Our approach is summarized in the following steps [6]:

Step 1: *Compilation of a list of potential actions*.

The establishment of a set of all possible solutions or actions. In our case, these solutions are the ambiguous tags.

So, let A is the set (a_1, a_2,..., a_n), where a_i is considered like a candidate label, then a set of morpho-syntactic information is generated.

Step 2: *Constructing of a coherent family of criteria F={f1, f2,..., fp}*.

Proper application of a multi-criteria approach requires a good choice for the applied criteria. These criteria are defined on the base of different concepts such as consistency, indifference, strict preference and comparability.

However, developing a test that influences the choice of solution i compared to another solution is not an easy task.

But most importantly in defining a criterion is its power of discrimination between solutions. In fact, discrimination becomes easier when the appropriate solution is selected. However, a test that is discriminatory in some situations may not be so in other cases. Therefore, we need to construct a set of criteria that must meet three conditions namely: comprehensiveness, coherence and no-redundancy.

Step 3: *Defining an evaluation function and an array of performance*

For each criterion we must generate an evaluation function that must be maximized or minimized depending on the type of the test used. The result of this function is a scorecard called the evaluation matrix. This later contains all the evaluation results of each potential action when criteria are applied. Evaluation matrix rows correspond to the potential actions and the columns correspond to criteria. The matrix elements are the calculated estimates.

Step 4: *Aggregation and criteria weighting*

a. Aggregation: it reduces the number of labels, and classifies them according to their overall scores. Choosing a method of aggregation will help standardize the evaluation table for better reading. To aggregate the different evaluations of a solution calculated by the criteria, we propose to apply the TOPSIS aggregation method.
b. Weighting: it determines the weight of each criterion according to its importance[6]. So, weighting generates a vector of weights π, where each coordinate corresponds to a criterion. In our model, and to weigh the different criteria we adopt the Entropy weighting method.

Step 5: *Selecting the label with the highest score*

In order to obtain the solution with the highest score, a classification of labels is performed decreasingly.

4.3. Aggregation Method: TOPSIS

4.3.1. Principle

The basis of the method is to choose a solution that is closest to the ideal solution, based on the relationship of

6The important criteria are able to discriminate between the solutions; and these criteria will have significant weights.

dominance resulting from the distance to the ideal (the best on all criteria) and to leave the most of the worst possible solution (which degrades all criteria). TOPSIS allow reduce the number of disambiguation solutions discarding the dominated ones, and ranking them according to their effective over all scores. In case of a tie, the closest solution to the ideal, based on segregation measurements, is chosen.

4.3.2. Algorithm [5]

Step 1: Standardizing the performance (i.e., calculation of the normalized decision matrix); The normalized values "e_{ij}" are calculated as follows:

$$e'_{ij} = \frac{f_j(a_i)}{\sqrt{\sum_{i=1\ldots m}[f_j(a_i)]^2}} \quad (1)$$

With i=1,..., m, j=1,..., n. where $f_j(a_i)$ are the deterministic values of share(s) i for criterion j.

Step 2: Calculation of the normalized and weighted decision matrix (i.e., calculating the product performance standard by the coefficients of relative importance of attributes). The matrix elements are calculated as follows:

$$e''_{ij} = \pi_j \cdot e'_{ij} \quad (2)$$

With i=1,..., m, j=1,..., n, πj is the weight of j^{th} criterion.

Step 3: Determination of ideal solutions (a+) and anti-ideal solutions (a-):

$a^+ = \{Max_i$ e"ij, i=1,…, m; and j=1,…, n};

$a^+ = \{e^*_j, j=1,\ldots, n\} = \{e^*_1, e^*_2, \ldots, e^*_n\}$;

$a_- = \{Min_i e''ij\}$, i=1,…, m; and j=1,…, n};

$a_- = \{e_{j*}, j=1,\ldots, n\} = \{e_{1*}, e_{2*}, \ldots, e_{n*}\}$;

$$e^*_j = Max_i\{\text{ e"ij}\}\ e_{j*} = Min_i\{\ e''ij\ \} \quad (3)$$

Step 4: Calculation of removal (i.e., calculate the Euclidean distance compared to the profiles a^+ and a-). The distance between the alternatives is measured by Euclidean distance of dimension n. The remoteness of the alternative I with respect to the ideal (a^+) can be assimilated to the extent of exposure to risk and is given by:

$$D^*_i = \sqrt{\sum_{j=1\ldots n}(e''_{ij} - e^*_j)^2} \quad (4)$$

$$D_{i*} = \sqrt{\sum_{j=1\ldots n}(e''_{ij} - e_{j*})^2} \quad (5)$$

Step 5: Calculating a coefficient that measures closeness to the ideal profile:

$$C^*_i = \frac{D_i}{D^*_i + D_{i*}} \quad (6)$$

Step 6: Storage of shares following their order of preferences (i.e., according to decreasing values of C_i^*; *i is better than j if* $C^*_i > C^*_j$).

4.4. Weighting Method: Entropy

4.4.1. Principle

The Entropy method is an objective technique for the weighting of criteria. The idea is that a criterion j is more important than the dispersion of stock valuations. Thus the most important criteria are those that discriminate most between actions (in our case actions are labels).

4.4.2. Algorithm

The entropy of a criterion j is calculated by the next formula [9]:

$$E_j = -\mathrm{K} \times \sum_{i=1\ldots m} X_{ij} \times Log(X_{ij}) \quad (7)$$

Where K is a constant chosen so that for all j, such as $0 \leq E_j \leq 1$, and K=1/(n*logn) (n is the number of solutions disambiguation). The entropy "Ej" is much larger than the values of ej which are close. Thus, the weights are calculated according to the D_j (opposite of entropy):

$$D_j = 1 - E_j \quad (8)$$

The weights are then normalized:

$$W_j = \frac{D_j}{\sum_{j=1\ldots n} D_j} \quad (9)$$

5. Proposed Solution

To better understand the proposed solution, we will keep the same approach mentioned above.

Let P = الوطنِ إلَى المغترِب رجع, presented to our analyzer.

After segmenting the sentence into words, the analysis is done without any problem for units 2, 3 and 4. However, unit 1 "رجع" presents a typical morphological ambiguity. To remove this ambiguity we will apply our approach called multi-criteria disambiguation as follows:

Step 1: Building a list of Analysis Solutions

The list (the set A) is obtained directly after the process of morphological analysis.

Table 1. *Example of ambiguity generated when analyzing the verb "*رجع*".*

Verb	Solution	Root
رجـــع	فَـعَـلَ	رجـــع
	فَـعِـلَ	رجـــع
	فَـعُـلَ	رجـــع
	فُـعِـلَ	رجـــع

Step 2: Application of Criteria

To build a coherent family of criteria F, we propose two basic criteria to discriminate between the solutions of the analysis: the test of *vowel consistency*, and the *occurrence frequency* test.

a) *Criterion 1: Concordance of Vowels*

This test will verify the correlation between the vowels of the lexical unit and the vowels of each candidate solution. This test maximizes the function of assessment that goes with it is the addition (+).

b) *Criterion 2: The Frequency of Occurrence.*

This criterion is based on a statistical calculation on the basis of an annotated corpus so that the solution that occurs most frequently will always score the highest. (Each appearance is one (1), so this is a test and to maximize the evaluation function that goes with it is the addition (+)). The results of applying this criterion are made on the basis of an annotated corpus is composed of 300 units spread over 10 arbitrarily selected paragraphs that are selected from (the books school) an Algerian school text book.

Step 3: Application of the Evaluation Function

For both criteria (Concordance of vowels and frequency of appearance) the evaluation function is addition (+).

Step 4: Generating a Score Table (or score matrix)

Table 2. *Evaluation Table (matrix).*

Solutions / Criteria	S1 فَـعَـلَ	S2 فَـعِـلَ	S3 فَـعُـلَ	S4 فُـعِـلَ
Vowel Concordance	3	2	2	1
Appearance Frequency	16	5	2	1

Step 5: Aggregation and Weighting of Performance Criteria

Normalization of the scorecard is made by applying the formula (1) of the TOPSIS method.

Table 3. *Normalization of the Score Table.*

Solutions / Criteria	S1 فَـعَـلَ	S2 فَـعِـلَ	S3 فَـعُـلَ	S4 فُـعِـلَ
Vowel Concordance	0.71	0.47	0.47	0.24
Appearance Frequency	0.95	0.30	0.12	0.06

a) Weighting of Criteria

In order to weight the criteria we use the entropy method, with respect of the initial condition mentioned in TOPSIS, i.e., the sum of the weights must be equal to 1. The following table shows the calculation Entropy values (Ej), the opposite of Entropy (Dj) and normalization of weight (Wj) of the two criteria.

Table 4. *Weighting the criteria.*

E_j	D_j	W_j
0,24	0,76	0,47
0,15	0,85	0,53

Note: Checking the Status of weighting:

$\sum_{j=1...n} W_j = W_1 + W_2 = 0.47 + 0.53 = 1$ (Condition tested)

b) Weighting of Evaluation Table (standard):

This weighting is done using the formula (2) of TOPSIS method.

Table 5. *Weighting of Score Table.*

Solutions / Criteria	S1 فَـعَـلَ	S2 فَـعِـلَ	S3 فَـعُـلَ	S4 فُـعِـلَ
Vowel Concordance	0.33	0.22	0.22	0.11
Frequency of appearance	0.50	0.16	0.06	0.03

c) Calculation of Removal Measures

After applying formulas (3), (4) and (5), TOPSIS method reacts with different measures of distance for each solution as illustrated in the following table:

Table 6. *Removal Measures*

	S1 فَـعَـلَ	S2 فَـعِـلَ	S3 فَـعُـلَ	S4 فُـعِـلَ
D^*	0.33	0.22	0.22	0.11
D_*	0.50	0.16	0.06	0.03

d) Calculation of the Measure of Closeness to Ideal Profile

To calculate coefficients C^*_i, we use the formula (6) of the TOPSIS method, and then establish a decreasing ranking of the factors. The solution with the highest score I selected. So, these are the values obtained:

$$C^*_1=1>C^*_2=0.32>C^*_3=0.24>C^*_4=0.$$

In our method the solution 1فَـعَـلَ will be selected by the system, so the following morphological information will be generated.

Table 7. *Information generated by tagging the verb* رجـع

	Information
Root	رجـــع
Pattern	فَـعَـلَ
Tag	AVA3PMSIA
Designation in English	Accomplished Verb Active 3rd Pers. Masc. Sing. Invar. Accusativ.
Designation in Arabic	الغائب، المذكر للمفرد للمعلوم مبني ماضي فعل الفتح. على مبني
Verb vowelzed	رَجَـعَ

6. Conclusion

Using multiple criteria decision is a methodology that provides decision makers with tools to solve a decision making problem, taking into account several points of view. This paper attempts to present a new mathematical approach based on MCA in order to categorize multi-solutions of disambiguation and extract the best. This method has the advantage of reducing dominated solutions and ranking the rest by different evaluation criteria. Even though this technique is not widely used, it shows that the path of a multi-criteria analysis in NLP (based on recurrent common phenomena and to texts in all languages combined) is very interesting. This technique offers an alternative and crucial complement method compared to systems that are based on a probabilistic approach and can be an indispensable complement to the model by contextual constraint.

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