A NOVEL APPROACH FOR RECOGNIZING TEXT IN ARABIC ANCIENT MANUSCRIPTS

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ABSTRACT

In this paper a system for recognizing Arabic ancient manuscripts is presented. The system has been divided into four parts. The first part is the image pre-processing where the text in the Arabic ancient manuscript will be recognized as a collection of Arabic characters through three phases of processing. The second part is the Arabic text analysis which consists of lexical analyzer; syntax analyzer; and semantic analyzer. The output of this subsystem is an XML file format that represents the ancient manuscript text. The third part is the intermediate text generation, in this part an intermediate presentation of the Arabic text is generated from the XML text file. The fourth part of the system is the Arabic text generation, which converts the generated text to a modern standard Arabic (MSA) language (this part has four phases: text organizer; pre-optimizer; semantics generator; and post-optimizer).

KEYWORDS

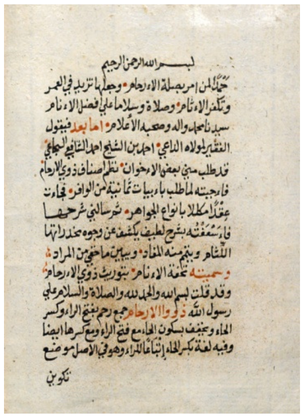
Ancient Manuscripts, Arabic Text Recognition System, Arabic Text Analysis, Arabic Text Generation.

1. INTRODUCTION

Libraries over the world have a huge amount of ancient Arabic manuscripts that have been kept in safe places. Those manuscripts are subject to many aging artifacts; natural disasters; theft or damage. Many of those manuscripts have not been recently published or even have an electronic copy. For those reasons and in order to benefit from the Arabic ancient library, it becomes a necessity to create a system that not only converts those manuscripts into an electronic version that researchers and concerned people can read, but also converts the text included in these manuscripts into modern, readable, and understandable forms.

Arabic ancient manuscripts carry the civilization and the religions of the Arabic area from the different historical ages. The Arabic ancient manuscripts hold all the different writing styles of the Arabic language. After the appearance of Islam in the Arabic area, many copies of the holy Koran were written and sent to different cities of the Middle East and North Africa. Different Arabic writing styles appeared in the newly converting to Islam cities. Figure 1 shows a sample of an Arabic ancient manuscript [1].

The required work for developing a system like this includes two primary factors: text recognition, and text analysis. The text recognition, manipulates the ancient manuscript as an image that must be converted to a set of characters and sentences. Due to the reason that these manuscripts had been written in different periods of time through the Islamic history, also, these manuscripts had been written by people belonged to different countries and therefore, different cultures which make it even more diverse and more complex to understand. The importance of the second factor has been represented in translating the generated characters and sentences into another easier and understandable form to the current researchers and readers.



بسم الله الرحمن الرحيم
حمدًا لمن امر بصلة الارحام وجعلها تزيد في العمر
وتكفر الاثام وصلاة وسلاما على افضل الانام
سيدنا محمد واله وصحبه الاعلام اما بعد فيقول
الفقير لمولاه الداعي احمد بن الشيخ احمد الشافعي البجائي
قد طلب مني بعض الاخوان نظم اصناف ذوي الارحام
فاجبته لما طلب بابيات ثمانية من الوافر فجاءت
عقدًا مكللا بانواع الجواهر ثم سالني شرحها
فاسعفته بشرح لطيف يكشف عن وجوه مخدراتها
اللثام ويتم منه المفاد ويبين ما خفي من المراد
وسميته تحفة الانام بتوريث ذوي الارحام
وقد قلت بسم الله والحمد لله والصلاة والسلام على
رسول الله ذووا الارحام جمع رحم بفتح الراء وكسر
الحاء ويخفف بسكون الحاء مع فتح الراء ومع كسرها ايضا
وفيه لغة بكسر الحاء اتباعا للراء وهو في الاصل موضع
تكوين

Figure 1. Arabic ancient manuscript.

Al–Khalil is a project for building an Arabic infrastructure ontology system [2]. The project aimed to build an ontology centred infrastructure for Arabic resources and applications.

Arabic WordNet (AWN) is an expending project for Arabic words, their properties and relations. AWN is an extension to the WordNet (WN) project [3]. WN is a machine-readable lexical database that groups words into clusters of synonyms called synsets. Every synset can be thought of as a representation of a unique word sense meaning or concept. Currently AWN consists of 11,270 synsets, and contains 23,496 Arabic expression words and multiword [4].

In[5]authors present an Arabic Computational Morphology system. Their approach is a computational approach to Arabic morphology description that is drawn from lexeme-based morphology. The priority is given to stems and granting a subordinate status to inflectional prefixes and suffixes. In [6] authors present a Memory-based Morphological Analysis, and Part-of-speech Tagging of Arabic system. The system was based on data from the Arabic Treebank. Morphological analysis is performed as a letter-by-letter classification task. Classification is performed by the k-nearest neighbour algorithm. Part-of-speech tagging is carried out separately from the morphological analyzer. A memory-based modular tagger is developed with a sub-tagger for known words and one for unknown words.

The remainder of this paper is organized as follows; the next section is a presentation of our Arabic text recognition system and its four parts. Then our conclusion and future work.

2. ARABIC TEXT RECOGNITION SYSTEM

The Arabic ancient manuscripts recognition system is composed of three main sub-systems: manuscripts recognition; Arabic text analysis; and Modern Standard Arabic (MSA) text generation. Figure 2 shows those three sub-systems and the different steps of each subsystem.

2.1. Manuscript Recognition

The manuscript recognition sub-system deals with the manuscript as an input image and produces a series of Arabic character shapes that represent the handwritten Arabic text inside the manuscript; also it extracts the formats of the original manuscript such as the number of paragraphs, margins, and text size. Those formats are to be used in presenting the final output of the system. The manuscript recognition subsystem consists of four steps as indicated in Figure 3.

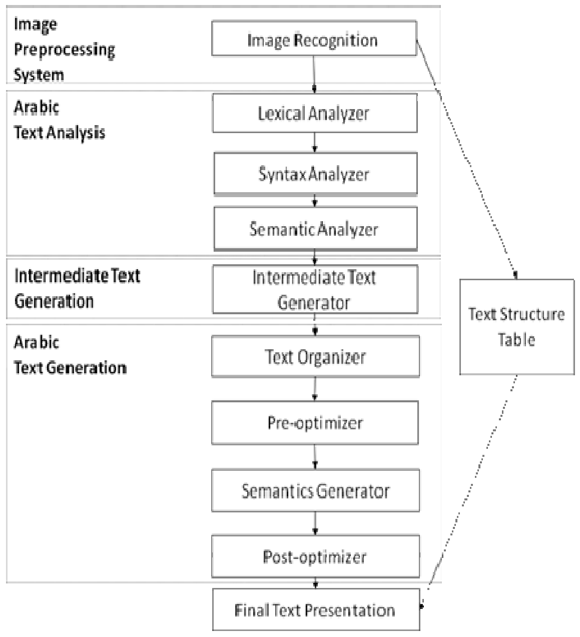


Figure 2. Arabic ancient manuscripts text recognition system main parts and subsystems.

2.1.1 Manuscript Binarization

The binarization step converts the manuscript image into black text pixels representing the text and a white background, a special binarization algorithm was designed to deal with different aging, storage and weather effects of the ancient manuscripts in general [7].

2.1.2 Manuscript Segmentation

The Arabic handwritten segmentation is considered as a difficult problem because of the high variability of the Arabic semi-cursive script language. An algorithm for performing manuscript segmentation was developed so that it does not look for words but instead it deals with the segmentation problem as a collection of Parts-of-Arabic Words (PAWs) [8]. This method gives a good result for segmentation of the handwritten Arabic text and avoids most of the segmentation known problems [8]. Figure 4 shows the different steps of the segmentation process.

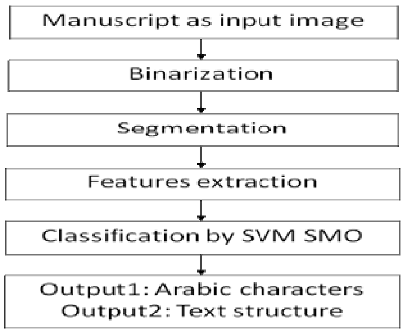

Manuscript as input image
Binarization
Segmentation
Features extraction
Classification by SVM SMO
Output1: Arabic characters
Output2: Text structure

Figure 3. Image recognition subsystems.

In the pre-processing step, the white margins of the manuscript were removed using vertical and horizontal histograms of the manuscript image. Figure 5 shows the results of removing the margins of a manuscript. After that, skew detection was applied to detect any slant in the handwritten text. A slant correction method was applied to each text area inside the manuscript to fix the skew. Projection profiles were used to find the slant angle. The angle with the maximum variance of the black pixels is chosen to be the slant angle [9].

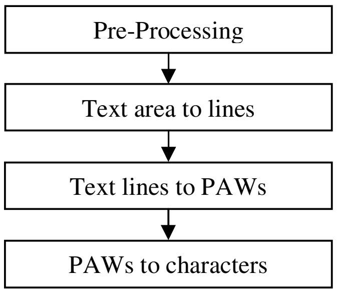


Figure 4. Segmentation algorithm four steps.

The coordinate rotation transformation method was used to correct the angle of the text. At the end of this pre-processing step a salt and pepper noise remove is applied to remove any artifact caused by the previous pre-processing methods. Figure 6 shows the results of the skew correction of an Arabic text.

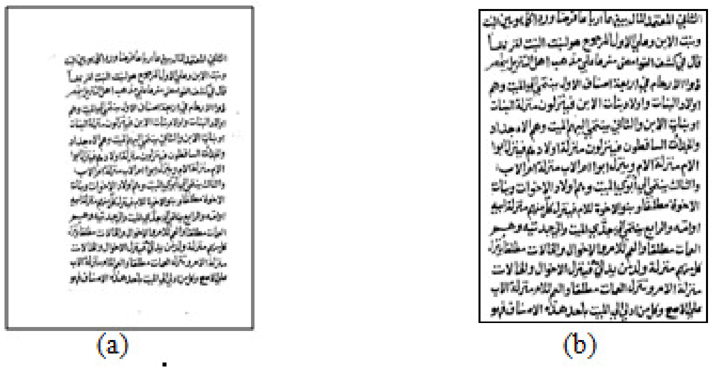


Figure 5. (a) Binarized manuscript page with white boarders. (b) Binarized image of (a) after removing boarders

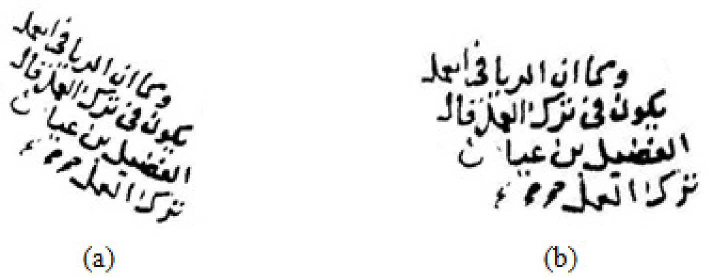


Figure 6. (a) Binary text area with skewing problem. (b) skew corrected text area of (a).

The second step is the segmentation of lines using projection profiles (PP). PPs are used to find the maximum variances of black pixels inside the text area as it passes between text lines [3], [4], [5]. Figure 7 shows the result of segmenting two Arabic lines.

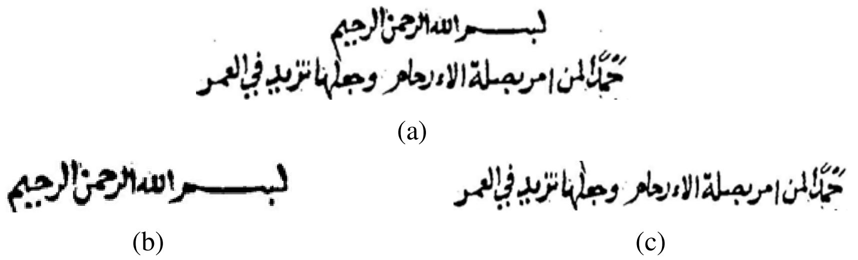


Figure 7. (a) Binary Arabic text area. (b) and (c) segmented text lines of (a).

In the third step, the generated text lines are divided into part of Arabic words (PAWs). The vertical histogram of each line was used to identify between PAW areas [3]. Figure 8 presents an example of the segmentation results of a handwritten line into PAWs.

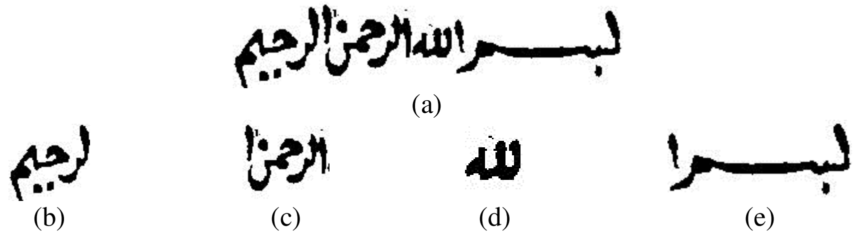


Figure 8. (a) Part of text line, (b), (c), (d), (e) segmented PAWs of (a)

In the last step of the segmentation process the generated PAWs was segmented into simple-to-process characters. The Connected Components (CC) method was applied to identify the different parts of the PAW. The largest CC is considered the main object of the PAW. After that, the base-line detection method of main object was applied to detect the base line of the PAW. Figure 9 shows the output of the CC method. Relatively small CCs above and below the detected base-line of the PAW are considered as points, diacritics or Hamza (refers to Arabic alphabet character (ء)). More details about base-line detection method are available in [2] [3] [5] [6].

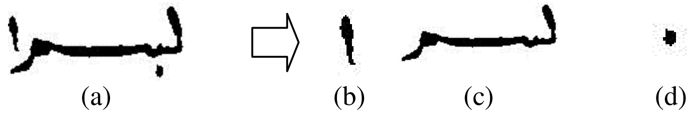


Figure 9. (a) PAW, (b), (c) and (d) are the results of the CC method.

The segmentation of words to individual characters method in [10] was used to divide the PAWs into a collection of characters according to the calculated width and the vertical projection histogram of the middle zone for each PAW. The input and the output of this method were shown in fig. 10.

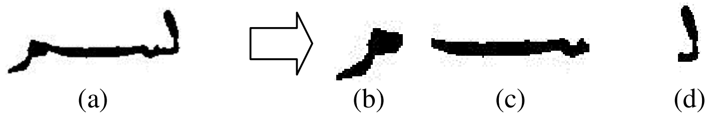


Figure 10. (a) CC of a PAW, (b), (c) and (d) segmentation results of (a)

2.1.3 Features Extraction

A new enhanced edge detection method based on cooperation between edge algorithms was developed to improve the results of the SIFT and holes features extraction of our system [11].

Nine types of features were used in our system to extract all the varieties of the ancient handwritten characters. Figure 11 shows the main steps of the features extraction process, and Figure 12 shows the different steps of the feature extraction process.

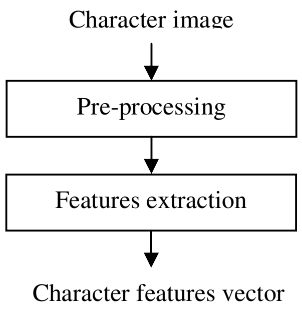


Figure 11. Features extraction process

Each entry undergoes a pre-processing before the features extraction. Thinning is one of the main pre-processing used in our system. This process simplifies the features extraction process and makes it faster. Following, we will describe each of those features in details.

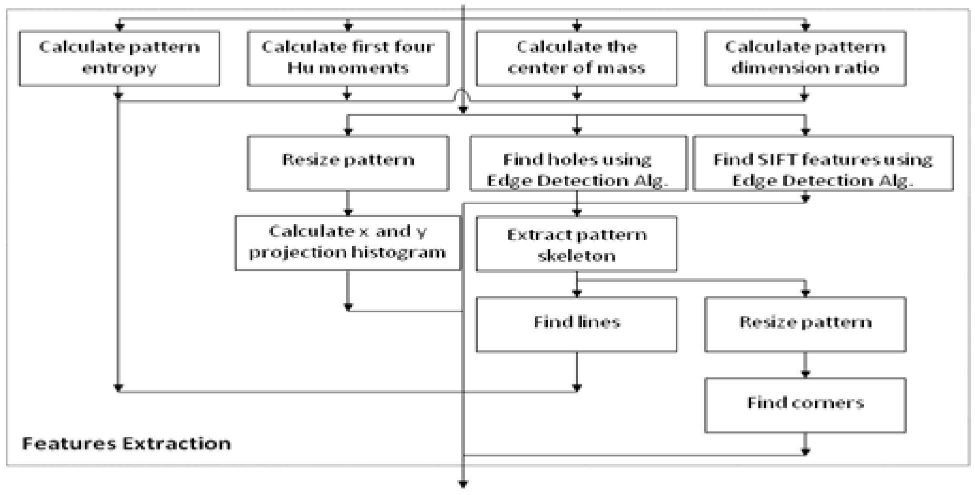

Calculate pattern entropy
Calculate first four Hu moments
Calculate the center of mass
Calculate pattern dimension ratio
Resize pattern
Find holes using Edge Detection Alg.
Find SIFT features using Edge Detection Alg.
Calculate x and y projection histogram
Extract pattern skeleton
Find lines
Resize pattern
Find corners
Features Extraction

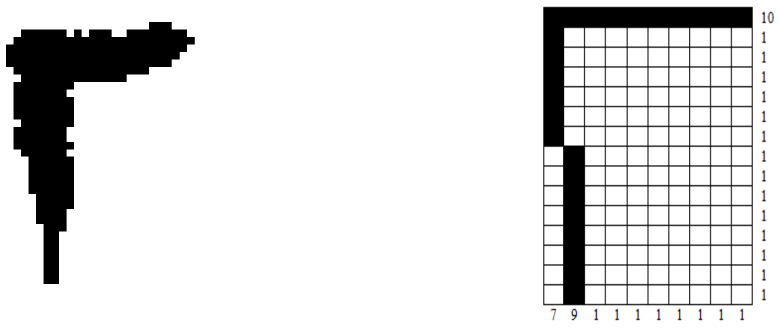
Figure 12. Features used in the features extraction phase

a. Central Hu-Moments: the first four central Hu-moments of the character are parts of the features. Those moments are invariant to scaling; orientation; and position changing [11].
b. SIFT: is a feature vector of four numbers that represents the location coordinates (x , y), scale, and orientation of the feature inside the character image. A maximum of 10 SIFT features for each character image are used in our system [12][13] [14].
c. Shannon Entropy: measures its average information content [11].
d. Center of Mass: is a geometric feature of the character [14]. The computation of center of mass was done on the character before applying the thinning process. The distribution of black pixels of the character is balanced around this point.
e. Pattern Dimension Ratio: the value of the character image (CI) width divided by the height of the black pixels boundary box [14].
f. Holes: used to record location and dimension of all the founded holes in the CI [8]. This can be done by dividing the CI into four by four numbered boxes and record the box number that have the center of the hole as a feature. Also, the relative diameter of the hole is computed and recorded as a feature. Figure 13 shows the extraction of a hole from a PAW "Fi".

(a) (b)

Figure 13. (a) CC result of PAW, (b) extracted hole from (a)

g. Black Ink Histogram: each CI has two black ink histograms vertical and horizontal [14] by normalizing the CI to a fixed size of 15X10 pixels (see Figure 14). The twenty five histogram values of both the vertical and the horizontal directions are added to the features vector of the CI.



(a) (b)

Figure 14. (b) The vertical and horizontal histogram values of the Arabic number two "Ethnan" in (a).

h. Lines: Hough transform is used to process the skeleton of CI so that the line parameters are added to the features vectors if the length of the line exceeds a relative threshold [9].
i. Corners: four different 4X4 templates are used to extract corners of characters [15] [16][17]. Then the CI is divided into three vertical areas (top) and three horizontal areas (right). These templates and the result of the corner feature extraction are presented in fig. 15.

2.1.4 Classification

Classification is the final step of the proposed system, and it includes two steps: learning and running operations. In the learning operation, the system is fed by a collection of CI's features vectors along with their belonging classes. The system is trained to identify those different characters and connect each with its relative class using features. The learning operation is usually done once until a satisfied result is reached. The testing of this operation is done on another collection – other than those used in the leaning part – of CI's features vectors. This process is continued until satisfactory results have been reached.

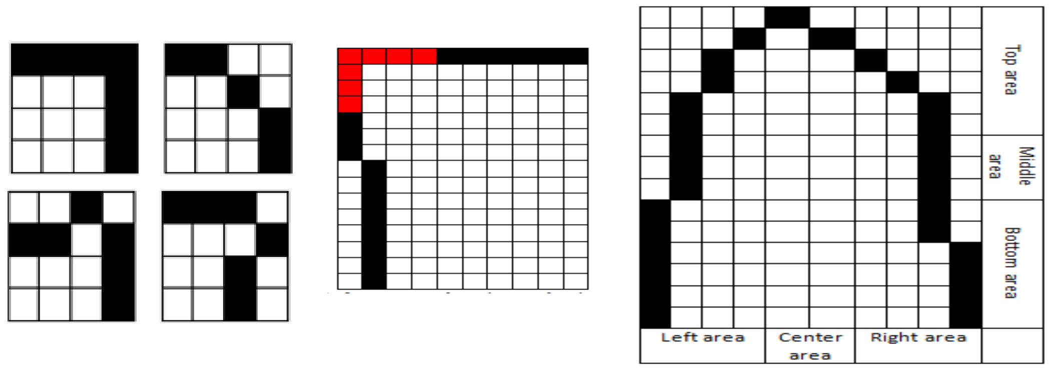


Figure 15. (a) Four different templates (b) result (c) horizontal and vertical areas.

In the running operation, the system can recognise the class to which the entered CI's belongs to, according to the training operation. The system efficiency depends largely on the training operation.

Two well known classifiers have been used during our experiments, artificial neural network (ANN) [9] and support vector machine (SVM) [9][18][19]. Although ANN is considered one of the oldest and successful classifiers, it has a remarkable low speed performance than SVM [9][18][19]. SVM is more efficient due to the use of sequential minimal optimization (SMO) training techniques.

A comparison was conducted between ANN and SVM using a sample of 20 Arabic handwritten numbers categorized from 0 to 9. The results of this comparison were showed in Table 1. These results indicate that SVM is more efficient and takes less run time than ANN classifier.

Table 1. Comparison Between NN and SVM-SMO Classifiers Results

Classifier	**Model Run time (seconds)**	**% of correctly classified instances**
Neural Network (NN)	6.02	95
Support Vector Machine (SVM) – SMO	1.6	100

Table 2 indicates the run time and the accuracy for training set of 3800 characters and testing of other 380 characters.

Table 2. SVM-SMO Classifiers Results for the Test Set

Classifier	**Model Run time (seconds)**	**% of correctly classified instances**
Support Vector Machine (SVM) - SMO	32.6	71

The ancient Arabic manuscripts recognition system gave promising results. The unavailability of a database of Arabic ancient manuscripts or Arabic ancient words made the comparison of any available recognition system impossible. Furthermore, all the research done so far on Arabic ancient handwritten scripts focused on one of the important phases mentioned before such as segmentation or binarization.

2.2 Arabic Text Analysis

The Arabic text analysis is the second part of the ancient Arabic text recognition system. This part takes the output of the image recognition part in a form of a text document. It consists of three phases: the lexical analyzer, the syntax analyzer, and the semantics analyzer.

2.2.1 Lexical Analyzer

The lexical analyzer phase has two components: Arabic text segmentation (cuts the input text document into different Arabic POS), and the POS checking (spelling check and suggestions for incorrect spelled POS are presented to choose from).

Arabic Text Segmentation: The input to this component consists of a set of paragraphs each paragraph consists of a set of sentences. These paragraphs will be divided into individual sentences as described in Fig.16.

Input: Text document
Output: a set of sentences and paragraphs that constitute the input text document.
Process:
Step 1: Search for spaces between characters and mark the group of characters between any two spaces as POS.
Step 2: Mark the start of each paragraph as a start of new sentence.
Step 3: Search for the symbols (., ;, ?, !) and mark its position as end of sentence.
Step 4: Mark the next position to the end of sentence as a start a new sentence.
Step 5: If the starts of a paragraph or a sentence mark the characters between the first paragraph or sentence and the space as POS.

Figure 16. Arabic Text Segmentation Algorithm.

Arabic POS Checking: The individual POS results of the previous phase are checked for completeness. Missing parts would be identified and completed by referring to the Arabic dictionary[20]. Different suggestions may be provided for a single POS. Each of those is then tagged according to its type [21][22]. Figure 17 presents the Arabic POS missing characters deduction algorithm.

```
Input: set of POS
Output: corrected set of POS.
Process:
Step 1: For every POS:
Look for the symbol (◆) as part of the POS.
Replace the symbol (◆) by an arbitrary Arabic character.
Check the correctness of the new POS. Replace the old POS with this new one if it is correct. If
not correct, find the POS close to the newly produced POS and choose the first one that replaces
the symbol (◆) by one character.
Step 2: If the previous step ends without a solution, replace the symbol (◆) by another character
and repeat the previous step again until a solution is found.
```

Figure 17. Arabic POS missing characters deduction algorithm.

An advances hash table was used to provide fast and reliable access to most of the Arabic dictionary words [23]. Figure 18 shows the Arabic text spell-checking algorithm using hash table. After that, we use the minimum edit distance technique in fig. 19 to find the suggestions of a given string. The minimum edit distance is the minimum number of operations like insertions, deletions and substitutions that is required to transform one text string into another. After the comparison processes, the words having minimum edit distance are chosen as suggestions for the incorrect string. Different algorithms for calculating distances can be used [24] [25]. The Levenshtein algorithm is the algorithm used for the weighting process. The algorithm assigns a cost of 1 for every edit operation like insertion, deletion and substitution. Those assignments are added to represent the distance between the incorrect string and the POS inside the dictionary.

```
Input: set of POS
Output: corrected set of POS.
Process:
Step 1: Look inside the dictionary using the hash table for matching. If matched, tag it as
correct. If not provide a list of suggestions.
Step 2: Sort the list of suggestions and put the POS having minimal changes in the top of
the list.
Step 3: If the top of the list is a one part-of-speech choose, replace it with the incorrect
part-of-speech.
Step 4: If not, move to the next item inside the list and repeat the previous step.
Step 5: If reached the end of the list with no solution, use the first item in the list as the
suggested correct replacement.
```

Figure 18. Arabic text spell checker algorithm.

```
Minimum Edit Distance technique
Input: set of POS
Output: ordered list of suggestions
Process:
Search every part-of-speech inside the Arabic text document:
Step 1: If Arabic string was tagged as incorrect. Then, compute the minimum edit distance
between the string and the dictionary POS using Levenshtein algorithm*.
Step 2: Find the minimal distance(s) between the string and the Arabic POS.
Step 3: List the suggestions in order.
* Levenshtein algorithm: for a given two strings with equal length, move one character on
each string. Add 1 for every change between the two characters and 0 for a match. Add the
results after reaching the end of the strings.
```

Figure 19. Arabic text spilling error detection and correction algorithm.

Figure 20 shows sample results of the Arabic POS checking algorithm.

```
<NN text="ز♦قاء" spelling="incorrect">
<Suggestions>
<Suggestion>زرقاء</Suggestion>
</Suggestions>
</NN>
<NN text="جا♦عة" spelling="incorrect">
<Suggestions>
<Suggestion>جامعة</Suggestion>
<Suggestion>جائعة</Suggestion>
<Suggestion>جعة</Suggestion>
</Suggestions>
</NN>
<DTNN text="الاءرحام" spelling="incorrect">
<Suggestions>
<Suggestion>إلا أرحام</Suggestion>
<Suggestion>ألا أرحام</Suggestion>
<Suggestion>آلا أرحام</Suggestion>
<Suggestion>الأرحام</Suggestion>
</Suggestions>
</DTNN>
</NNP>
```

Figure 20. Arabic POS checking results.

2.2.2 Syntax Analyzer

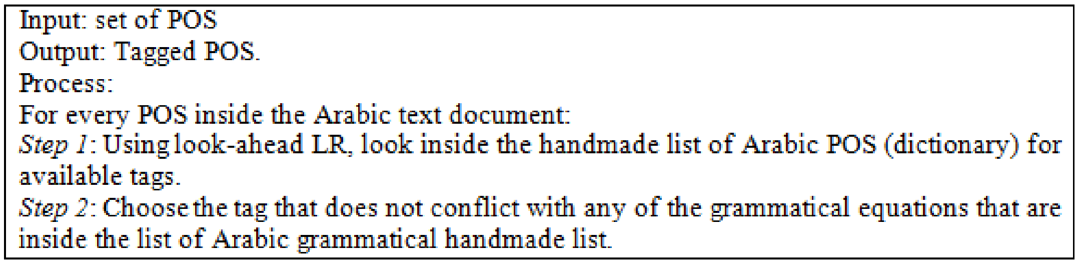
The syntax analyzer is the second phase in the Arabic text analysis part. It has two components, Arabic POS tagging and Arabic text linking and transition. We have used a look-ahead LR (LALR) parser algorithm to build the syntax tree during the syntax analyzer phase[26][27] [28]. This LALR parser was used to handle all the grammatical and morphological “sarf” rules of the Arabic language.

Arabic POS Tagging:

Table 3 presents a sample of the different tagging codes for the individual POS. The result of this phase is an ordered list of POS along with different suggestions for incomplete ones. Beside each POS a tag that describes its type. Figure 21 presents the Arabic POS tagging algorithm.

Table 3. Sample of Arabic POS Tagging Codes

Tag	POS	Tag	POS
VB	Verb, base form	IN	Preposition
VBN	Verb, past participle	JJ	Adjective
NN	Noun, singular	WP	Pronoun
NNP	Proper noun, singular	PRP	Personal pronoun

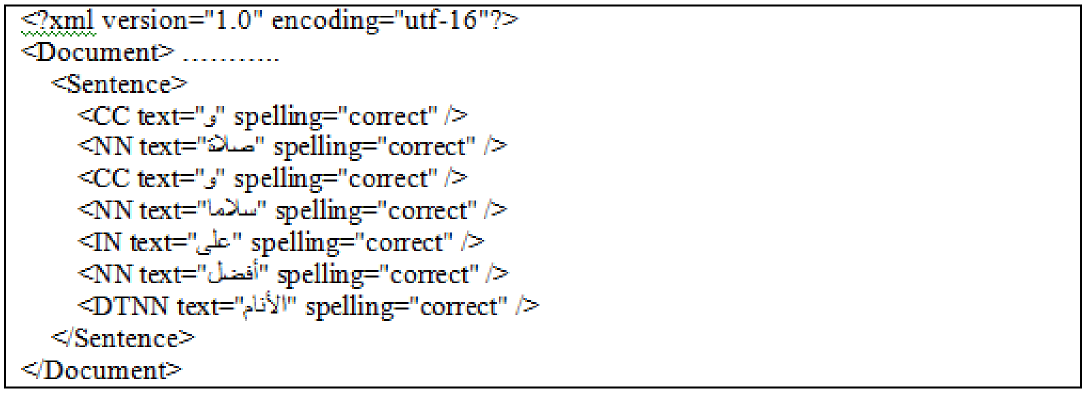


Input: set of POS
Output: Tagged POS.
Process:
For every POS inside the Arabic text document:
Step 1: Using look-ahead LR, look inside the handmade list of Arabic POS (dictionary) for available tags.
Step 2: Choose the tag that does not conflict with any of the grammatical equations that are inside the list of Arabic grammatical handmade list.

Figure 21. Arabic POS tagging algorithm.

POS Tagging Results:

Figure 22 presents the Arabic POS checking and tagging results of the algorithm in fig. 20.



```
<?xml version="1.0" encoding="utf-16"?>
<Document> ...........
  <Sentence>
    <CC text="و" spelling="correct" />
    <NN text="صلاة" spelling="correct" />
    <CC text="و" spelling="correct" />
    <NN text="سلاما" spelling="correct" />
    <IN text="على" spelling="correct" />
    <NN text="أفضل" spelling="correct" />
    <DTNN text="الأنام" spelling="correct" />
  </Sentence>
</Document>
```

Figure 22. Arabic POS checking and tagging results.

Arabic Text Linking and Transition:

After finishing the sentences tagging, the system starts to look for linking connectivity POS inside the paragraph and whole text. There are many kinds of connectivity POS in the Arabic language. Some of those connect different sentences, other connect paragraphs, and some can do both.

Arabic Text Transition Words and Phrases:

Transition or linking words and phrases connect separate sentences and paragraphs in the same document together. All prepositions, pronouns, reference names, connected names, and enumeration words, are all considered linking tools. Furthermore, there is a couple of connectivity phrases in Arabic that also connects sentences and paragraphs. Table 4 presents some of those connectivity words and phrases.

Table 4. Some of the Arabic Connectivity Words and Phrases Between Sentences, Paragraphs and Text.

Arabic transition word/ Phrase	Meaning	Arabic transition word/ Phrase	Meaning
نتيجة لذلك	as a result	وبالمقابل	in contrast
بالاضافة الى	in addition to	خلاصة القول	in summary
ومن ثم	and then	لاشك	no doubt
بسبب	Because	أخيرا	finally

Input: text document
Output: text document with linking and transition words and phrases marked.
Process: For every POS inside the Arabic text document:
Step 1: Look for Arabic transition word or phrases inside the handmade list of transition word and phrases.
Step 2: Mark each transition word or phrase with a special mark.
Step 3 Look for the proper linking noun or phrase inside the previous sentence or sentences.
Step 4: Link the transition word or phrase with that noun.

Figure 23. Arabic text linking and transition algorithm.

Each of those identifies connections are linked to one or more POS inside the paragraph or text. More than one link may be presented for a given connectivity POS. Figure 23 presents the Arabic text linking and transition algorithm. Arabic text linking and transition results are shown in fig. 24.

بسم الله الرحمن الرحيم
حمدا لمن أمر بصله الأرحام. و جعلها تزيد في العمر و تكفر الآثام . و صلاة و سلاما على أفضل الأنام سيدنا
محمد و آله و صحبه الأعلام. أما بعد فيقول الفقير لمولاه الداعي. أحمد بن الشيخ أحمد الشافعي السجاعي. قد
طلب مني بعض الأخوان. نظم أصناف ذوي الأرحام. فأجبته لما طلب بأبيات ثمانية من الوافر. فجاءت عقدا
مكللا بأنواع الجواهر. ثم سألني شرحها فأسعفته بشرح لطيف يكشف عن وجوه مخدراتها اللثام و يتمم منه
المفاد

Figure 24. Arabic linking and transition words and phrases (Marked in red and blue).

2.2.2 Semantic Analyzer

The semantic analyzer is the third phase in the Arabic text analysis part. It has one component: the Arabic sentences checking.

Arabic Sentences Checking:

Sentences tagging starts after finishing all the POS tagging during the previews syntax analysed part. The system receives all the POS of a given sentence along with their types and characteristics. The whole sentence is analysed at this phase. The role of each POS inside the sentence is identified and the type of sentience is found[29][30][31]. We used top-bottom parsing to check and tag the sentences[32]. Figure 25 shows the Arabic sentences and phrases tagging algorithm.

Sentences Tags:

The different tags of this stage are presented in Table 5. The sentences type tagging is also presented in Table 6. **Error! Reference source not found.** presents the Arabic sentences and phrases tagging algorithm.

Table 5. POS (Sarf) Ontology Tagging

Tag	Sarf Tag	Tag	Sarf Tag
OBJ	Object	PRD1	First predicate
SUB	Subject	PRD2	Second predicate
CANN	"Can" noun	ENN	"Ena" noun
CANK	"Kabar Can"	ENK	"Kabar Ena"

Table 6. Phrase/Sentence Tagging

Tag	Phrase/Sentence	Tag	Phrase/Sentence
SQ	Question	S	Simple clause
VP	Verb Phrase	ADJP	Adjective Phrase
NP	Noun Phrase	ADVP	Adverb Phrase
PP	Prepositional Phrase	X	Uncertain

Input: XML file
Output: XML file with phrases and sentences tagged. Process: For every POS inside the Arabic text document:
Step 1: For each POS that has no morphology "sarf" tag: According to the handmade Arabic grammatical equations for "sarf" extraction tag each with the proper tag.
Step 2: According to the handmade Arabic grammatical equations group each sentence or phrase with the proper tag.

Figure 25. Arabic sentences and phrases tagging algorithm.

Figure 26 presents a sample result of the sentences tagging results.

```
<?xml version="1.0" encoding="utf-16"?>
<Document> ………………………………
  <S>
    <CC text="و" />
    <VP>
      <VBD text="جعلها" />
      <S>
        <S>
          <VP>
            <VBP text="تزيد" />
            <PP>
              <IN text="في" />
              <DTNN text="العمر" />
            </PP>
          </VP>
        </S>
        <CC text="و" />
        <S>
          <VP>
            <VBP text="تكفر" />
            <DTNN text="الآثام" />
          </VP>
        </S>
      </S>
    </VP>
  </S>
…………………………… </Document>
```

Figure 26. Arabic sentences tagging sample results.

2.3 Intermediate Text Generator

After finishing the last phase of the text analysis part, the Arabic text is now in a tree XML format. The current subsystem is to translate the produced code of text into an intermediate text format that would be applicable for the coming subsystems to investigate and modify. The new intermediate representation is essential for the optimizer subsystem. We used the three-address code algorithm for building the rules and generating the intermediate representation. Some of the Arabic grammar rules did not obey the three-address code restriction, so we had to extend the rules to have a four-address code for some special ones. Figure 27 presents the algorithm for this intermediate text generation subsystem.

```
Input: XML file
Output: text document with intermediate presentation Process: For every sentences or phrase inside the Arabic tree XML:
Step 1: Look for keywords: convert the tree structure into an intermediate text specifying the rule of each string.
Step 2: List the intermediate representation in order.
Step 3: Group each paragraph intermediate representation in separate places.
```

Figure 27. Intermediate text generation algorithm.

Figure 28 presents a sample result of the intermediate text generation subsystem.

(a)	<S>
	<VP>
	<VBD text="أكل" />
	<NP role="SUBJECT">
	<NNP text="احمد" />
	<CC text="و" />
	<NNP text="سمير" />
	</NP>
	<DTNN text="التفاحة" role="OBJECT" />
	</VP>
	<PUNC text="." />
	</S>
(b)	Obj :التفاحة (SUB:احمد و سمير) ← VBD :أكل

Figure 28. Intermediate text generation sample results, (a) tree XML text format, (b) intermediate code for (a).

2.4 Modern Arabic Text Generation

2.4.1 Text Organizer

Different sentences with different POS order, and, different sentences with different synonymous for the POS are available to choose between[33][34]. Rhetorical structure theory (RST)[35] [36] was used to organize the available Arabic text. RST was used to produce different forms of text using the relations between its different parts[37].

Text Organization Results:

Figure 29 presents the algorithm for the Arabic verbal sentences organizer.

Input: intermediate text representation
Output: text document with reorganized verbal sentences
Process: For every sentences or phrase inside the Arabic text document:
Step 1: Look for verb sentences. If the subject of the verbal sentence is found switch places between the verb and the subject. Ignore any transition words or phrases at the begging of the test sentence.
Step 2: If the subject is not available, look for the predicate if found switch places between the verb and the predicate. Ignore any transition words or phrases at the beginning of the test sentence.

Figure 29. Arabic verbal sentences organizer algorithm.

Figure 30 presents a sample results for the Arabic sentences organization phase.

Sentence after organization	Original Arabic sentence
عائشة شربت كوب الماء.	شربت عائشة كوب الماء.
المسافر اصبح نشيطا.	اصبح المسافر نشيطا.
احمد أكل.	أكل احمد.
العامل نقل الأدوات.	نقل العامل الأدوات.
الجامعة رحبت بطلابها.	رحبت الجامعة بطلابها.

Figure 30. Arabic text organization sample results.

2.4.2 Pre-optimizer

Text summarization is one of the optimization techniques frequently used in natural language generation system [38][39]. We have used an extractive text summarization method based on Arabic conjunctive tools to summarize the ancient Arabic text. Figure 31 presents the input of the algorithm shown in fig. 32. The result of the algorithm is shown in fig. 33.

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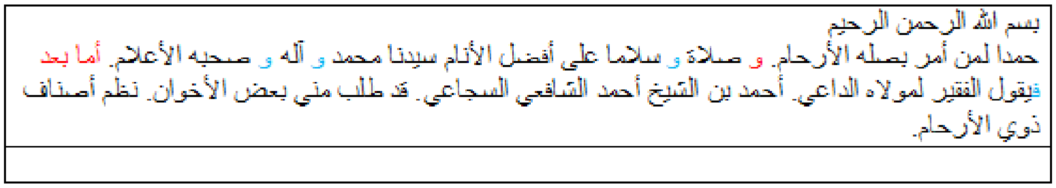
Figure 31. Sentences deduction algorithm.

Input: text document
Output: summarized text document
Process:
For every sentence inside the Arabic text document:
Step 1: Look for Arabic conjunction letters and words.
Step 2: If the sentence begins with conjunction and has one string and up to double the size of the previous sentence, and,
Step 3: If this sentence does not include any primary word**, remove this sentence.
** Primary words: words that are repeated 3 percent or more of the total words count of the whole document.

Figure 32. Arabic text summarization, sentences deduction algorithm.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ذوي الأرحام.

Figure 33. Sentences summarization results.

Table 7 presents the results of the sentences summarization component.

Table 7. Sentences Pre-optimization Results

Document	Original document (words)	New optimized document (words)	Sentences optimization	Sentences optimization (%)
Number of words	126	108	18	14 %

Figure 35 presents the input of the Arabic text summarization, words and phrases optimization algorithm shown in fig. 34. The result of the algorithm is shown in fig. 36.

Input: text document
Output: summarized text document
Process:
For every sentence inside the Arabic text document:
Step 1: Look for Arabic conjunction letters and words.
Step 2: If the word or phrase begins with conjunction and it consists of exactly one or two words, and,
Step 3: If it does not include any primary word**, remove this conjunction phrase.
** Primary words: words that are repeated 3 percent or more of the total words count of the whole document.

Figure 34. Arabic text summarization, words and phrases optimization algorithm.

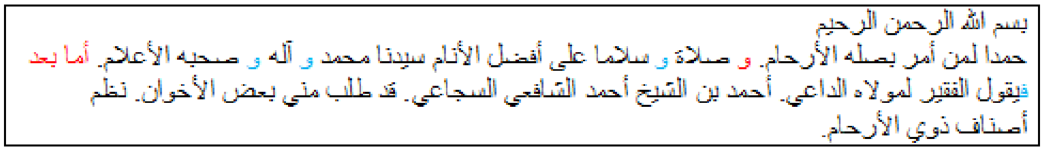
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Figure 35. Words and phrases text summarization.

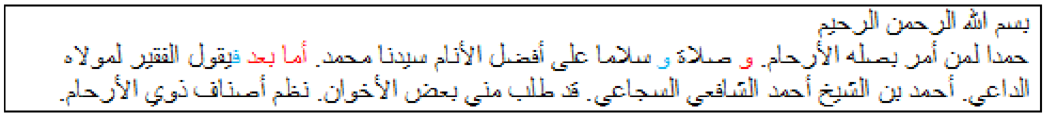
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Figure 36. Words and phrases text pre-optimization results.

Table 8 presents the results of the words and phrases summarization part. Whereas, Table 9 presents the overall results of the pre-optimization phase.

Table 8. Primary Words and Phrases Summarization Results.

Document	Sentences Optimized document (words)	New optimized document (words)	Words and phrases optimization	Words and phrases optimization (%)
Number of words	108	91	17	16 %

Table 9. Overall Primary Summarization Results.

Document	Original document (words)	New optimized document (words)	Words and phrases optimization	Words and phrases optimization (%)
Number of words	126	91	35	28 %

2.4.3 Semantics Generator

Arabic POS Synonymous Generator:

Synonymy is one of the lexical semantic relations (LSRs). It represents the relation between the meanings of the different words. [40]. Using the dictionary of Arabic to Arabic words "Ma'jam", the synonymous of all the words inside the ancient text document are obtained. A special manually built "Ma'jam" was prepared for this purpose. Arabic words with their different synonymous were added to this list along with other features. An important feature is the subject of the synonym. This filed represents the domain of usage. Each feature in the dictionary has a code representing its different values. The available synonymous and their features together provide the most suitable alterative for the given word[41]. Synonymous for a given word inside a sentence are placed in the original word place provided that both have the same POS type. Sentences that do not have synonymous for any of its POS would be left without any modifications. Figure 37 shows the Arabic synonymous generator algorithm, and fig. 38 shows a sample results of the algorithm. Figure 39 shows the algorithms sample results after removing confusions.

```
Input: text document
Output: text document with words replaced by their synonymous
Process:
For every word or phrase inside the Arabic text document:
Step 1: Look inside the handmade list of Arabic synonymous (Ma'jam), if found a synonymous, replace the original word or phrase with the proper synonym.
Step 2: After reaching the end of document go to the next step:
Step 3: Starting from the beginning of the document remove any confusions on sentence like the existence of two matching words inside the same sentence, or unneeded conjunction.
```

Figure37. Arabic synonymous generator algorithm.

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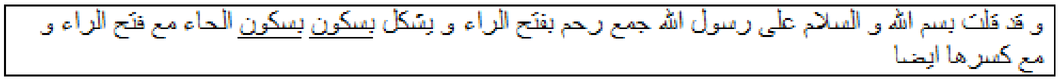
Figure 38. Arabic synonymous generator sample results (underline words).



و قد قلت بسم الله و السلام على رسول الله جمع رحم بفتح الراء و بشكل بسكون بسكون الحاء مع فتح الراء و مع كسرها ايضا

Figure 39. Arabic synonymous generator sample results after removing confusions (underline words).

Table 10 presents the results of the synonymous generator component.

Table 10. Arabic Synonymous Generator Results

Document	Original Document	Synonymous found	Synonymous found (%)
Number of words	91	22	24 %

2.4.4 Post-optimizer

The post optimizer phase uses the same optimization algorithms used in the pre-optimizer phase shown in fig. 32 and fig. 34. The two algorithms are applied to the output text generated after the semantics generator phase. Figure 40 presents the input text for this phase. Potential sentences to be removed by the first algorithm are underlined. Figure 41 shows the results after applying the Arabic text summarization and sentences deduction algorithm.

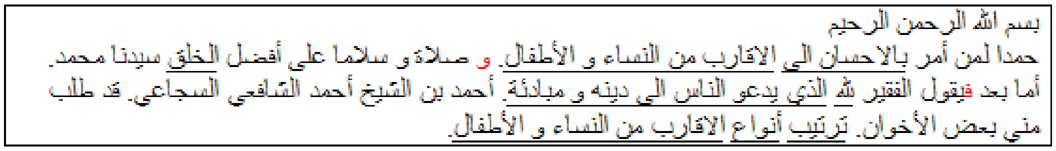


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Figure 40. Sentences post-optimization.

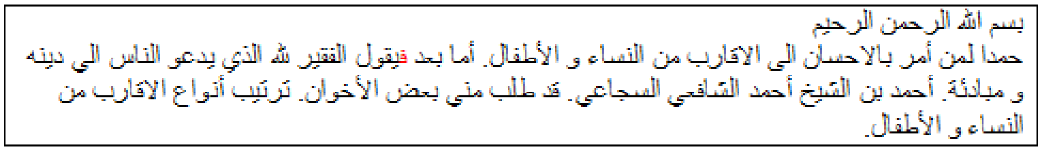

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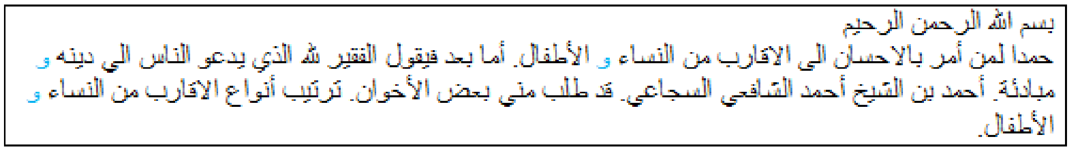
Figure 41. Sentences post-optimization results.

Table 11 presents the results of the sentences summarization component.

Document	Original document (words)	New optimized document (words)	Sentences optimization	Sentences optimization (%)
Number of words	115	107	8	7 %

Table 11. Sentences Summarization Results

Figure 42 shows the results after applying the Arabic text summarization and words and phrases deduction algorithm.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الأطفال.

Figure 42. Words and phrases post-optimization results.

Table 12 presents the results of the words and phrases post-optimization component. Whereas, Table 13 presents the overall results of the optimization phase.

Table 12. Words and Phrases Summarization Results.

Document	Sentences Optimized document (words)	New optimized document (words)	Words and phrases optimization	Words and phrases optimization (%)
Number of words	107	105	2	2 %

Document	Original document (words)	New optimized document (words)	Words and phrases optimization	Words and phrases optimization (%)
Number of words	126	105	21	17 %

Table 13. Overall Summarization Results.

3. CONCLUSIONS

A novel approach to recognizing text in Arabic ancient manuscripts was fully implemented and tested using different ancient Arabic manuscripts. The first phase of the image recognition part, the binarization phase, produced better results using the new hybrid binarization algorithm than two of the well-known binarization algorithms. As expected, the training process of the system took a huge amount of processing time especially when the training set was large. After that, the recognition process was considerably fast and the recognition rate reached 71 percent.

The text organizer phase produced accurate results for the available sentences organization algorithms. The output of this subsystem dependents on the added rules; more rules generate more different forms of a sentence but on the expense of the system speed. The pre-optimizer phase is performing the optimization with 28 percent. The semantics generator found synonymous for 24 percent of the text in the test manuscript. This phase was fast and greatly depends on the size of the synonymous list. The post-optimizer phase is done on the text produced by the semantics generator phase. The overall optimization of the ancient text after the post-optimizer phase reached 17 percent of the total word count.

Our future work will focus on the following points:

- Improve the current system by improving the existing segmentation techniques for PAWs using individual parts-of-lines with similar features. And, add new features to the classifier to improve recognition rate.
- Expand the system to deal with the ancient Arabic manuscripts with handwritten styles that had no dots or diacritics by adding a new smart part to the system to add those dots and diacritics.
- Build a database or set for ancient Arabic manuscripts to improve the research on binarization and recognition.
- Build an Arabic dictionary system along with a tagging system for the grammatical and morphology “sarf” rules.

REFERENCES

[1] A. Al Shaf'ei, تحفـــة الأنـــام بتوريـــث ذوي الأرحـــام, Cairo, Egypt, 1206.

[2] H. Aliane, Z. Alimazighi and M. A. Cherif, "Al–Khalil: The Arabic Linguistic Ontology Project," Seventh International Conference on Language Resources and Evaluation, pp. 3826-3829, 2010.

[3] A. Weisscher, "Arabic WordNet: The Global WordNet Association," The Global WordNet Association, 10 February 2014. [Online]. Available: http://globalwordnet.org/arabic-wordnet/. [Accessed 5 11 2015].

[4] M. Alkhalifa and H. Rodríguez, "Automatically Extending Named Entities Coverage of Arabic WordNet using Wikipedia," International Journal on Information and Communication Technologies, vol. 3, no. 3, June 2010..

[5] A. Soudi and V. Cavalli-Sforza, "Arabic Computational Morphology: A Trade-off Between Multiple Operations and Multiple Stems," in Text, Speech and Language Technology, Netherlands, Springer Netherlands, 2007, pp. 89-114.

[6] A. v. d. Bosch, E. Marsi and A. Soudi, "Memory-based Morphological Analysis and Part-of-speech Tagging of Arabic," in Text, Speech and Language Technology, Netherlands, Springer Netherlands, 2007, pp. 201-217.

[7] A. Nijim, M. AboKresha, A. El Shenawy and R. Abo Alez, "A New Hybrid Binarization Algorithm for Manuscripts," International Journal of Advanced Research in Computer and Communication Engineering, vol. 4, no. 4, 2015.

[8] A. Kacem, N. Aouiti and A. Belaid, "Structural Features Extraction for Handwritten Arabic Personal Names Recognition," 2012 International Conference on Frontiers in Handwriting Recognition (ICFHR), p. 268 – 273, 2012.

[9] M. Cheriet, N. Kharma, C.-L. Liu and C. Suen, Character Recognition Systems: A Guide for Students and Practitioners, Canada: John Wiley & Sons Inc., 2007.

[10] M. Sarfraz, S. N. Nawaz and A. Al-Khuraidly, "Offline Arabic Text Recognition System," 2003 International Conference on Geometric Modeling and Graphics, p. 30–35, 2003.

[11] A. A. Nijim, M. T. Abo Kresha and R. Abo Alez, "New Edge Detection Enhancement Method based on Cooperation between Edge Algorithms," International Journal of Computer Applications (IJCA), vol. 91, no. 7, pp. 41-47, April 2014.

[12] D. G. Lowe, "Object recognition from local scale-invariant features," Proc. 7th International Conference on Computer Vision (ICCV'99) (Corfu, Greece), pp. 1150-1157, 1999.

[13] D. G. Lowe, "Local Feature View Clustering for 3D Object Recognition," Conference on Computer Vision and Pattern Recognition (CVPR), vol. 1, pp. 682-688, 2001.

[14] A. Rosenberg, "Using SIFT Descriptors for OCR of Printed Arabic," Telaviv university, Feb 2012.

[15] M. A. Qatran, "Template Matching Method for Recognition MUSNAD Characters Based on Correlation Analysis," The 12th International Arab Conference on Information Technology, 2011.

[16] T. P. Patel and S. R. Panchal, "Corner Detection Techniques: An Introductory Survey," International Journal of Engineering Development and Research IJEDR, vol. 2, no. 4, pp. 3680-3686, 2014.

[17] Z. Luo, "Survey of Corner Detection Techniques in Image Processing," International Journal of Recent Technology and Engineering (IJRTE), vol. 2, no. 2, pp. 184-185, May 2013.

[18] J. McCullock, "Kohonen Self-Organizing Maps," [Online]. Available: http://mnemstudio.org/neural-networks-kohonen-self-organizing-maps.htm. [Accessed 20 August 2015].

[19] D. Fradkin and I. Muchnik, "Support Vector Machines for Classification," DIMACS Series in Discrete Mathematics and Theoretical Computer Science, vol. 70, pp. 13-20, 2006.

[20] H. Rodríguez, D. Farwell, J. Farreres, M. Bertran, M. Alkhalifa and M. A. Martí, "Arabic WordNet: Semi-automatic Extensions using Bayesian Inference," International Conference on Language Resources and Evaluation Main Conference, 2008.

[21] Z. Abu Khalil, الإمـــلاء الميســـر, Amman, Jordan: Dar Osama for Publishing, 1998.

[22] S. B. S. Al Athemean, قواعـد فـي الإمـلاء, Egypt: Ebad ElRahman Library, 2009.

[23] L. Salifou and H. Naroua, "Design of A Spell Corrector For Hausa Language," International Journal of Computational Linguistics (IJCL), vol. 5, no. 2, pp. 14-26, 2014.

[24] R. Mishra and N. Kaur, "A Survey of Spelling Error Detection and Correction Techniques," International Journal of Computer Trends and Technology, vol. 4, no. 3, pp. 372-374, 2013.

[25] S. Shivani and S. DharamVeer, "State of the Art of Spell Checker Design for Indian Languages: A Survey," Advances in Computer Science and Information Technology (ACSIT), vol. 2, no. 3, pp. 191-195, January-March, 2015.

[26] M. Tomita, "LR Parsers For Natural Languages," 10th International Conference on Computational Linguistics, pp. 354-357, 1984.

[27] A. Moubaiddin, A. Tuffaha, B. Hammo and N. Obeid, "Investigating the Syntactic Structure of Arabic Sentences," Communications, Signal Processing, and their Applications (ICCSPA), 2013 1st International Conference on, pp. 1-6, 2013.

[28] F. BEN FRAJ, C. BEN OTHMANE ZRIBI and M. BEN AHMED, "Patterns of Syntactic Trees for Parsing Arabic Texts," Natural Language Processing and Knowledge Engineering (NLP-KE), International conference on, pp. 1-8, 2010.

[29] S. AlAfagani, فـي اصـول النحـو, Damascus, Syria: The Syrian University, 1957.

[30] R. Al Asmar, المعجـم المفصـل فـي علـم الصـرف, Beiruit, Lebanon : Dar al-Kotob al-Ilmiyah, 1997.

[31] A. H. Al Fadly, مختصـر الصـرف, Beiruit, Lebanon: Dar Al-Kalam.

[32] P. Pradhan, "A Code Generator to translate Three-Address intermediate code to MIPS assembly cod," International Journal of Innovations in Engineering and Technology (IJIET), vol. 5, no. 3, pp. 138-144, June 2015.

[33] A. Siddharthan, "A survay of research on text simplification," International Journal of Applied Linguistics, vol. 165, no. 2, pp. 259-298, 2014.

[34] R. ALGULIEV and R. ALIGULIYEV, "Evolutionary Algorithm for Extractive Text Summarization," Intelligent Information Management, pp. 128-138, November 2009.

[35] W. C. Mann, Thompson and S. A., "Rhetorical Structure Theory: Toward a Functional Theory of Text Organization," Text - Interdisciplinary Journal for the Study of Discourse, vol. 8, no. 3, pp. 243-281, November 2009.

[36] K. Staykova, "Natural Language Generation and Semantic Technologies," CYBERNETICS AND INFORMATION TECHNOLOGIES, vol. 14, no. 2, pp. 3-23, 2014.

[37] M. H. Al Aqad, "Syntactic analysis of Arabic adverb's between Arabic and English: X bar theory," International Journal of Language and Linguistics, vol. 1, no. 3, pp. 70-74, 2013.

[38] M. D. Nikoo, A. Faraahi, S. M. Hashemi and S. H. Erfani, "A Method for Text Summarization by Bacterial Foraging Optimization Algorithm," IJCSI International Journal of Computer Science Issues, vol. 9, no. 4, pp. 36-40, July 2012.

[39] M. Shardlow, "A Survey of Automated Text Simplification," International Journal of Advanced Computer Science and Applications (IJACSA), Special Issue on Natural Language Processing 2014 , 2014.

[40] T. Wang and G. Hirst, "Exploring patterns in dictionary definitions for synonym extraction," Natural Language Engineering, vol. 18, no. 3, pp. 1-30, July 2012.

[41] A. Henriksson, H. Moen, M. Skeppstedt, A.-M. Eklund, V. Daudaravicius and M. Hassel, "Synonym Extraction of Medical Terms from Clinical Text Using Combinations of Word Space Models," In Proceedings of Semantic Mining in Biomedicine (SMBM), Zurich, Switzerland, 2012.