Auto-Encoder-BoF/HMM System for Arabic Text Recognition

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Abstract

The recognition of Arabic text, in both handwritten and printed forms, represents a fertile provenance of technical difficulties for Optical Character Recognition (OCR). Indeed, the printed is commonly governed by well-established calligraphy rules and the characters are well aligned. However, there is not always a system capable of reading Arabic printed text in an unconstrained environments such as unlimited vocabulary, multi styles, mixed-font and their great morphological variability. This diversity complicates the choice of features to extract and segmentation algorithm. In this context, we adopt a new solution for unlimited- vocabulary and mixed-font Arabic printed text recognition. The proposed system is based on the adoption of Bag of Features (BoF) model using Sparse Auto-Encoder (SAE) for features representation and Hidden Markov Models (HMM) for recognition. As a result, the obtained average accuracies of recognition vary between 99.65% and 99.96% for the mono-font and exceed 99% for mixed-font.

Keywords: OCR, Feature Learning, Bag of Features, Sparse Auto-Encoder, Hidden Markov Models, Unlimited-Vocabulary, Mixed-font

1. Introduction

With the technological evolution, digitizing documents into an electronic form is widespread because of its improved efficiency of space and its increasing access speed. Actually, digitization covers different applications. Each application attempts to provide a digital solution to the challenges issued by the volume of information available in paper form. Nevertheless, the main objective is always to purvey the user
with a degree of interaction with the document at least equivalent to that which it would have had with the paper, while at the same time raising the challenge of the mass of data. Beyond, digitization facilitates the implementation of techniques for document classification and retrieval [1, 2], document understanding [3, 4] and information extraction [5, 6, 7, 8]. These techniques require a text recognition system for converting printed documents to digital form. A robust system of document analysis relies on an efficient segmentation and text recognition phase. Several systems were proposed in the literature to segment a line into words and a word into symbols. After that, the recognition step concerns the segmented symbols [9, 10, 11, 12, 13, 14].

Nevertheless, the recognition in these systems depends on its correct segmentation. Note that an accurate segmentation to character, word or line level is dificult to achieve which lead to failures in the recognition. Hence, many recognition errors are mainly due to the segmentation phase. Moreover, it is a time-consuming task. Since the Arabic script is inherently cursive, it is difficult to determine the end of a character and the beginning of its next. Indeed, it is possible for one character to end after the start of the next character which generates an overlapping between adjacent characters. For this reason, model based techniques have emerged, especially HMM. They are among the most successful statistical models. Their powerful tool in speech recognition [15] proved its utility and robustness to Arabic and Latin text recognition.

The main benefit of HMM is to avoid the explicit segmentation before recognition. During the last years, several text recognition approaches based on HMM have been developed for Arabic printed text recognition. The difference between them resides mainly in the feature extraction phase. This phase is crucial, it is hard to decide appropriate features and needs considerable efforts. The basic shortcoming of the proposed systems is that their features are font-dependent and so are not adaptable to many fonts with the same parameters. Then, they suffer from lack of robustness.

In the present work, we propose a new system for printed Arabic text recognition using SAE-BoF-HMM. We use BoF based on SAE in order to extract robust features. BoF framework utilizes unsupervised algorithm to learn features for codebook
generation. Despite the application of this framework in several Arabic text recognition applications [16, 17, 18], their codebook was learned by k-means application which limits their performance, mainly, for learning generative models of data. In our work, we consider SAE instead of k-means for codebook generation. Our motivation in using SAE-BoF-HMM relies on the combination of a statistical local features and a sequence model. Our experiments have been carried out on printed Arabic and handwritten digits text images. The first work using BoF-HMM was in [19, 20]. The novelty of our work is the adoption of SAE and the use of unlimited vocabulary text recognition. The reason for using SAE is its representation learning method that can encode data in an unsupervised way into a new representation while exploiting its spatial relations. Also, it has the aptness to learn complicated nonlinear relationships and the robustness according to the data provided, and produces better results [21].

Our recognition system is realized at text line, word and character levels. It comprises unlimited vocabulary recognition wherein no Language Model is utilized during the recognition. This system has demonstrated to be more powerful than the employed methods for recognition text associating with the font identification step before text recognition for mixed-font.

The remainder of this paper is organized as follows: Section 2 provides a literature review covering HMM works for printed Arabic text recognition. The architecture of our proposed system is described in Section 3. Section 4 illustrates our experiments and results.

2. Literature Review

While the great number of proposed approaches for printed Arabic characters recognition, ago yet requires the improvement of accuracies in Arabic text recognition systems. This part provides a literature review covering HMM works for text recognition.

Jiang et al. [22] proposed a system for discovering boundary model of small-size Arabic printed text recognition. This system is founded on state HMM number
optimization and bootstrap modification to enhance accuracy by selection HMM with the more better performance. This approach achieved as results 14% for character error recognition and 13.3% for word error recognition.

Khorsheed [23] introduced a method for printed Arabic text recognition in line level. The main contribution is related to the use of discrete HMM. The pixel density features are extracted from cells falling into overlapped vertical windows. The proposed method was tested on a corpus containing 15,000 text line images written in 6 fonts in 600 format A4 pages. The obtained recognition rate is 95%. None peculiar handling for mixed-font recognition was presented.

Slimane et al. [24] presented an open vocabulary printed Arabic text recognition from APTI database containing words in low resolution. They proposed specific features to handle complicated fonts: Thuluth, Naskh and Diwani Letters. Several features were extracted from images, but a few of them are shared between all fonts, and others are peculiar to each font. The system reached 98.1% for character recognition and 90.5% for word recognition. The APTI database which is generated synthetically, was used for the evaluation of the developed system. But, the behaviour of the system was not studied in a more challenging task, i.e. the recognition on a real word images.

Prasad et al. [25] described an Arabic printed glyph recognition system based on HMM and Language Modeling. The glyphs are a conversion of the basis shape character transcriptions founded on the character form. The present work uses Position Dependent Tied Mixture (PDTM) HMM to model the different glyph representation models. The tree based state tying is used the position dependent training. For 176 characters, 339K Gaussians are trained. Although the previous work is considered as an efficient method, it presents few drawbacks. While the recognition of text in word level is acceptable, it is more suitable to recognize entire text lines rather than character or word levels. The recognition of entire text lines is beneficial since it allows to encompass every complication of segmentation and analysis of spaces between established words.

Natarajan et al. [26] presented a system recognition for Arabic, English, and Chinese scripts. Their contribution lies in the adoption of pixel percentile features which are
robust to noise. Features are extracted from accumulated overlapped window cells. Also, angle and correlation from window cells are computed. The values at equal 20 divided pixel percentile (from 0 to 100) are attached to form a feature vector. Also, horizontal and vertical derivatives of intensity are also appended. They prove the efficiency of their features to recognize text from different scripts.

Al-Muhtaseb et al. [27] described an unlimited-vocabulary printed Arabic text recognition technique for 8 fonts; Akhbar, Andalus, Arial, Naskh, Simplified Arabic, Tahoma, Traditional Arabic, and Thuluth. The novelty in this system is the adoption of sliding window in a hierarchical structure. 16 features are extracted from vertical and horizontal overlapping and non-overlapping windows. The obtained average accuracies of recognition vary between 98.08% and 99.89% for the eight fonts.

Dreuw et al. [28] presented a novel HMM based RWTH OCR system. It represents a large vocabulary OCR. Many features are computed which are Appearance-based slice features, horizontal and vertical Sobel features, nine geometric features and Local features (SIFT, SURF). Maximum Mutual Information (MMI) and Minimum Phone Error (MPE) criteria are utilized for training. An unsupervised confidence-based discriminative concatenated with two-pass decoding are proposed during decoding. To retrain the Gaussian HMM, other features are extracted using Multi Layer Perceptron (MLP).

Irfan et al. [29] presented mono-font and mixed-font Arabic printed text recognition based HMM. In this work, the features are extracted from adaptive sliding windows. The text is recognized at line level from 8 fonts: Akhbaar, Andalus, DecoType Thuluth, Naskh, Tahoma, Traditional Arabic, Simplified Arabic and Times New Roman. The proposed approach includes two phases. In the first phase, the font of the input text line is identified. In the second phase, the HMM is trained on the associated font for recognition. The obtained results show the efficiency of the proposed method for mono-font. The achieved recognition rates are between 98.96% and 92.45% CRR. By cons, this method suffers from limited results with mixed-font, about 87.83%.

The previously detailed methods presented a successful application of HMM to provide segmentation free in mixed-font printed text recognition. As HMM are used
in different contexts, the difference is highlighted in the enhancement of features representation resulting in a high recognition rate. In last years, approaches based on feature learning have acquired substantive encouragement. They are utilized with success to hard problems in visual object classification and retrieval, facial recognition, and newly in Arabic text recognition.

The novel tendency in machine learning and computer vision is to conceive techniques that may learn robust features automatically wanting the need for specific domain knowledge [30]. Several feature learning paradigms have been utilized in handwriting recognition, e.g. Convolutional Neural Networks (CNN) [31, 32], Recurrent Neural Networks (RNN) [33, 34], Artificial Neural Networks (ANN) [28], and Deep Believe Networks (DNN) [35, 36]. Note that the effectiveness of RNN was proved in the works of [37, 38]. Despite their successes in learning robust features for handwritten text of several scripts, the aforementioned approaches rely on deep neural networks, which are computationally expensive and require large datasets for training. SAE, however, is an alternative paradigm which is computationally efficient and can be trained with a reasonable number of samples [39]. It has been successfully applied for image scene classification [40, 41, 42] and recently in Handwritten Arabic Digits Recognition [43].

In this context and after a review of systems recently developed, we designed a new mixed-font text recognition. The proposed system overlaps the segmentation and the recognition processes. It adopts BoF framework using SAE to encode DSIFT descriptors for feature extraction and HMM for recognition. The learned feature representations, considered here, are the BoF powered with SAE of DSIFT descriptors [44]. As the latter are scale-invariant features, our system is robust against scale, variation of size and rotation. In [45], it was shown that BoF representations can be computed without needing any preceding segmentation. So, the integration of BoF model coupled with a codebook creation using SAE in feature extraction, and HMM in recognition tends to be very robust mixed-font text recognition.

BoF are of interest for multiple areas such as texture classification [46], object classification and retrieval [39, 47, 48, 49, 50], face recognition [51, 52, 53], action
recognition [54, 55, 56, 57], writer identification and verification [58], and scene character recognition [59, 60]. Their application is new in recent trends of Arabic text recognition [19, 20, 16, 17, 61, 18].

Usually, k-means is utilized to generate a codebook. It is used to quantize the input data by computing histograms of visual words. However, the codebook generation with k-means has multiple inconveniences. Although low-level code book has been proven to be effective for scene classification, it is not semantically meaningful and thus has difficulty to deal with unconstrained environment of Arabic recognition tasks. Then, k-means based clustering provides linear representation which performs bad for bad distributed data.

To overcome these problems, the use of Auto-encoder for codebook learning has been successfully applied for image scene classification [62, 63]. Its robustness and its ability to capture the high level content of an image encourage us to use it. This shows its power against image clutters and occlusions.

Applied to our recognition system, the experiments, detailed in Section 5, show the strength of SAE that resides in its robustness to the mono font and mixed font recognition. It fits well with the elusive notion of similarity that includes the diversity between instances of the same character and the similitude between instances of different character categories. Our choice of SAE for codebook generation has a great impact on the performance of recognition.

Hereby in the present work, we propose a new system to generate a codebook by converting the k-means based BoF into SAE, seen that the codebook generation and features coding still confine the performance of classification or recognition task.

To our best knowledge, the BoF based SAE integration with HMM has not been published before.
3. SAE-BoF-HMM for Unlimited-Vocabulary and Mixed Font Text Recognition

The use of Auto-encoder for codebook learning has shown its robustness and its ability to capture the high level content of an image. This demonstrates its power against image clutters and occlusions. The codebook generated by SAE has proven its effectiveness for classification and recognition in unconstrained environment. Applied to text recognition, the experiments show the strength of SAE that resides on its robustness to the mono font and mixed font recognition. It fits well with the elusive notion of similarity that includes: the diversity between instances of the same character and the similitude between instances of different character categories. Our chosen of SAE for codebook generation has a huge impact on the recognition performance.

The reason for using SAE is also its representation learning method that can unsupervisedly encode data into a new representation while exploiting its spatial relations. Also, it has the aptness to learn complicated nonlinear relationships and the robustness according to the data provided, and produces better results. Hereby in the present part, we detail the proposed system for text recognition based on SAE-BoF-HMM. As shown in Figure 1, the system consists of four principal steps: preprocessing, SAE based BoF extraction, training and recognition with HMM. The preprocessing is a fundamental step for text recognition. Generally, it serves to remove noise and reduce variations between images. In our system, Gaussian smoothing and image re-scaling are applied. For features extraction, we sample patches from a set of text images and then we apply DSFIT to extract descriptors from these images. After that, the codebook is constructed through the application of the SAE. Then, a sliding window is shifted vertically beyond the image. At every window positioning, a BoF histogram is extracted by considering only the interest indexes within the window. In this step, an adopted BoFs model using SAE to encode DSIFT descriptors is applied. The extracted features are used with the transcription files of text images for HMM training which involves two steps. Firstly, the number of
Gaussians is increased by application of a binary fragmentation process. Secondly, to estimate the parameters of these Gaussians, the Baum-Welch re-estimation process [64] is started off. For text recognition, a HMM with ergodic topology is built by all HMM character models. This topology allows the transition from a character model to all the other character models. The recognition is handled with research of the best sequence of states that models a character using a Viterbi algorithm [64].

3.1. Preprocessing

Before feature extraction step, several image preprocessing techniques are applied. They aim at pretreat the text images for simplifying the following task. To do so, Gaussian smoothing (Figure 2 (B)) and image re-scaling (Figure 2(C)) are applied. An outstanding effective application of the Gaussian smoothing is motivated by the properties in SIFT descriptors [65]. Applying Gaussian smoothing reduces the noise associated with Arabic text image due to the writing font. Re-scaling image is the easiest technique to obtain a normalized height for all images. After normalization, each text image is shown as a suite of BoF histograms computed in a vertical windows.

3.2. SAE based BoF Extraction

The entire unlimited vocabulary text recognition is built upon BoF representation. BoF model the sequences that are generated locally in text line images. First, overlapping DSIFT descriptors are extracted. Next, a codebook is required in order to compute BoF histograms. The codebook is obtained by clustering DSIFT descriptors from a text lines dataset with SAE.

3.2.1. DSIFT descriptors

DSIFT is similar to SIFT feature generation, except for the key points detection using Difference of Gaussian Filtering (DoG) [66]. Herein, plenty of time is consumed during DoG calculation. In contrast, DSIFT does not identify interest points, it simply divides the image into overlapping patches (Dense grid).
Figure 1: SAE-BoF-HMM for Unlimited Vocabulary Text recognition System
The histograms are computed over 4 x 4 patch grid, so, the gradient directions are quantized into 8 bins. The final DSIFT descriptor of a patch has dimensions of 128 (4 x 4 x 8).

3.2.2. SAE based Codebook Learning and BoF extraction

Let $Z$ be a set of $L$-dimentional local descriptors ($L = 128$), with $S$ number, extracted from an image, $Z = [z_1, z_2, ..., z_S] \in \mathbb{R}^{L \times S}$. Given a codebook $D$ with $M$ visual words, $D = [d_1, d_2, ..., d_M] \in \mathbb{R}^{L \times M}$. The objective is to quantize each descriptor $z$ into a $M$-dimentional codebook to generate a histogram representing the image. This section reviews the existing coding scheme K-means and introduces our proposed SAE technique.

3.2.2.1. Encoding descriptors with K-means

In K-means approach, a set $Z$ of $S$ feature vectors is quantized into a histogram of $M$ visual words:

$$\arg\min_{\gamma} \sum_{i=1}^{S} \|z_i - D_{\gamma_i}\|^2$$

\text{st. } \text{card}(\gamma_i) = 1, |\gamma_i| = 1, \gamma_i \geq 0, \forall i$$

where $\gamma = [\gamma_1, \gamma_2, ..., \gamma_S]$ is the set of clusters for $Z$. $\|\cdot\|$ denotes the $L_2$-norm of vectors. The cardinality constraint $\text{card}(\gamma_i) = 1$ means that there is one only nonzero factor in every code $\gamma_i$, correspondent to the quantification of $z_i$. The non-negative imposition $\|\gamma_i\|_{\ell^1} = 1, \gamma_i \geq 0$ means that the coding weight for $z$ is 1.
3.2.2.2. Encoding Descriptors with SAE

A new encoding SAE algorithm is presented to learn a mid-level codebook dictionary. We choose SAE to generate image representation because of its attractive properties. In comparison with the k-means encoding, SAE encoding is more discriminative and can achieve a less reconstruction error. Moreover, the inputs of SAE codebook dictionary possess more significances than the k-means codebook built in a merely downward mode. Surprisingly, SAE based clustering provides non-linear representation, in contrast, k-means based clustering provides linear representation which does not perform well for bad distributed data. Thus, sparsity allows the learned representation to capture salient properties of local descriptors.

Suppose that we have an input local descriptor \( z \in \mathbb{R}^S \) in a high dimensional space. While learning, for a given \( S \) data samples in \( \mathbb{R}^L \) represented by a matrix \( Z = [z_1, z_2, ..., z_S] \in \mathbb{R}^{L \times S} \), we learn a codebook \( D = [d_1, d_2, ..., d_M] \in \mathbb{R}^{L \times M} \) with \( M \) denotes the \( d \)th neurons in the hidden layer. The SAE algorithm consists of two phases. First one is a feed forward encoder module that maps the input \( z_i \in \mathbb{R}^L \) to a hidden representation \( c_i \in \mathbb{R}^M \), by a non-linear activation function:

\[
c_i = f(Wz_i + b_1)
\]

where \( W = [w_1, w_2, ..., w_M] \in \mathbb{R}^{M \times L} \) and \( b_1 \) is an adaptive bias. A logistic activation function is the sigmoid function \( f(v) = \frac{1}{1 + \exp(-v)}^{-1} \). We note that the visual words of the codebook \( D \) represent the encoder weights of \( W \). The second one is a decoder module in which the hidden features representation are mapped by a non-linear activation function to a reconstruction by:

\[
\hat{z}_i = f(\hat{W}c_i + b_2)
\]

where \( \hat{W} = [\hat{w}_1, \hat{w}_2, ..., \hat{w}_L] \in \mathbb{R}^{L \times M} \) and \( b_2 \) is the bias of the output layer.

The SAE parameters \( \theta_{AE} = \{W, \hat{W}, b_1, b_2\} \) are learned through the following cost function minimizing:

\[
F(\theta_{AE}) = \frac{1}{2S} \sum_{i=1}^{S} \|z_i - \hat{z}_i\|_2^2 + \frac{\beta}{2} (\|W\|_2^2 + \|\hat{W}\|_2^2) + \lambda \sum_{j=1}^{M} KL(q||\tilde{q}_j) \tag{4}
\]

\[
KL(q||\tilde{q}_j) = p \log \frac{q}{\tilde{q}_j} + (1 - q) \log \frac{1 - q}{1 - \tilde{q}_j} \tag{5}
\]
where the initial idiom in (4) is the rebuilding of the term error over the $S$ examples. The second idiom is a weight regularizer with weight-loss $\beta$ that is taken on to support tiny weights. It improves the generalization ability and reduce over-fitting. In the third idiom, the parameter $\lambda$ of sparsity penalty control, based on Kullback Leiber divergence ($KL$) [67], is used to promote sparse relationships among layers in autoencoder. The KL is computed among the average activation $\hat{q}_j$ of the $j$th hidden node beyond the training data and the average of the target activation $q$ and is determined by (5). Let (6) be the average activation function of the $j$th hidden unit beyond the training set, where $[c_j]_i$ is the activation of the $j$th hidden unit for the $i$th sample. The objective is to force the imposition $\hat{q}_j = q$, where $q$ is the sparsity parameter, typically a tiny value near to 0. To gratify this imposition, the hidden node activations shall be mainly passive and near to 0, thereby, most of the neurons are passive. To attain this, the SAE learning minimizes the rebuilding error with a sparsity imposition.

An example of text image encoded with the SAE codebook is illustrated in Figure 3(C). SAE based BoF representations are extracted from a sliding windows (Figure 3(D)) for using a HMM models for training and recognition. At every window positioning, we obtain a BoF histogram, as illustrated in Figure 3(E). During training process, Baum-Welch algorithm is utilized to impart weights, means and variances of the Gaussian Mixtures (GM) [64].

### 3.3. Training

For training, each character is modeled with HMM model. We employed Linear HMM topology, in which only self and next state probabilities are taken with fixed number of states per model, as illustrated in Figure 4. A model of text image is composed by a succession of character models.

#### 3.3.1. Gaussian Mixtures

The transition probabilities correspond to the initial values of the training phase, and
are recomputed at training time. In each state, the output emission probabilities are a GM models. The latters are computed by:

\[ p(f_n|C_i) \cong \sum_{j=1}^{M} W_j S(f_n, \mu_j, \Sigma_j) \]  

where \( M \) is the number of Gaussians and \( W_j \) is the weight of Gaussian \( j \).

The probability function \( p(f_n|C_i) \), also called \textit{likelihood}, given a character model \( C_i \), of a feature vector \( f_n \), is estimated. A Gaussian mixtures \( S \) are parameterized by the means \( \mu_j \) and covariances \( \Sigma_j \). The \textit{log-likelihood} of a model \( C_i \) is calculated by the following equation:

\[ G_i = p(F|C_i) = \prod_{n=1}^{N} p(f_n|C_i) \]  

3.3.2. Baum-Welch Re-estimation

A binary split serves to rise the Gaussians number. Firstly, 2 GM through state are used and the number is increased every 10 training iterations. The Baum-Welch serves to align iteratively the SAE histograms with the HMM characters so as to get the HMM maximum likelihood appreciations.

The initialisation of the models is performed with a flat start procedure setting the mean vectors and covariance matrices of all states similar to the mean vectors and covariance matrices of the full training set. Then, the statistics of all the character models are simultaneously updated in the maximisation step of the iterative EM procedure. The training is realized using a BoF histograms extracted from sliding windows of each text image and corresponding ground truth transcriptions. The latters represent the characters in ASCII format. The main benefit of the Baum-Welch algorithm is no need of character segmentation and the algorithm performs automatically the alignment between the characters in the ground truth transcriptions and the sequence of feature vectors.

3.4. Recognition

Over recognition phase, preprocessing and feature extraction steps are applied to each text image, as described in 3.1 and 3.2 subsections. The Viterbi algorithm looks for the most likely Viterbi path that owns the best observed sequence of feature vectors. The trained BoF-HMM models are used as input to the Viterbi algorithm.
For complete text image recognition, an ergodic HMM is used to concatenate the models. In ergodic HMM topology, each character model may be achieved from any other character model in a finite number of transitions. Thanks to this topology, it allows the recognition in unlimited vocabulary. An example of ergodic HMM with 4 character models is presented in Figure 5.

4. Experiments and Results

In order to assess the performance and generality of our system, three datasets are used to show results across multiple data types, as detailed in subsection 4.1. In order to be able to evaluate our experiments leded in mixed-font text line level, we use P-KHATT dataset to compare our results to [29]. To demonstrate the efficiency of our system in several databases, we present a comparative study with other systems tested using the Arabic Printed Text Image (APTI) database [68]. Then, in subsection 4.2, we describe our experiments. Finally, we present, in subsection 4.3, a detailed evaluation of our system.

4.1. Datasets

4.1.1. P-KHATT Dataset

P-KHATT [29] contains text lines from eight fonts: Akhbaar, Andalus, Naskh, Simplified Arabic, Tahoma, DecoType Thuluth, Times New Roman and Traditional Arabic. The text is scanned at resolution 300 dots/inch. It includes the staple 28 Arabic letters with their different shapes and combinations, Space, 10 digits and punctuations (’.’, ‘,’ ‘:’, ‘;’, ‘!’, ‘(’, ‘)’, ‘?’, ‘-’, ‘/’, ‘%’, etc).
Figure 4: 9 states right to left HMM for modeling characters. The starting state S and ending state E are non-emitting states.

It contains 6472 text line images for training, 1414 text line images for development and 1424 text line images for testing. For another information about the total number of text lines, words and characters in P-KHATT, we assign [29]. A few samples of this dataset are shown in Figure 6.

4.1.2. APTI Dataset
APTI [68] consists of a word images generated in 10 fonts (Arabic Transparent, Tahoma, Andalus, AdvertisingBold, Simplified Arabic, Traditional Arabic, Diwani Letter, M Unicode Sara, Naskh, and DecoType Thuluth), 10 font sizes (6, 8, 10, 12, 14, 16, 18 and 24 points), and 4 font styles (plain, bold, italic, and combination of italic bold). It contains 113,284 words synthetically generated in low resolution with 72dpi. The ground truth is supplied in XML files. APTI is elected for the evaluation of OCR systems. Some images are shown in Figure 7.

4.2. Configurations of Text Recognition System
4.2.1. Parameters for Preprocessing and Features Extraction
Our system involves four processing steps: i) preprocessing, ii) feature extraction with SAE-BoF, iii) training and iii) recognition. Table 1 summarizes the key configuration of our system for preprocessing and feature extraction steps. In the preprocessing step, Gaussian smoothing is applied to reduce the noise associated with Arabic text image due to the writing font. The normalization height of 55 pixels, while observing the width aspect ratio, allows to reduce the side effect of the variety in font size. As shown in Table 2, 55 pixels height is likely to give best recognition. For feature extraction with DSIFT, the image spatial area is divided into a grid of overlapping fixed-sized where the descriptors are extracted from each patch.
For feature extraction with DSIFT, the descriptors are extracted from each patch. The SAE architecture used in this work is formed by one Auto Encoder (AE). Feeding the latent representation \(c\) of the AE, where the input of the AE is the original data features.

### 4.2.2. Training and Recognition with HTK

For training and recognition, we exploited the toolbox Hidden Markov Model Toolkit (HTK) [69]. In the first step, the BoF representation are taken from each text image and the transcription file is prepared.
In the training step, firstly, the HMM model of each character is initialised using the HTK tool \textit{HCompV}. Secondly, the Baum-Welch re-estimation is done in several iterations using the HTK tool \textit{HERest}. This phase involves an extra step applied to increase the Gaussian mixtures number. Then, the recognition is done by looking for the maximum probability of each character model using the Viterbi algorithm executed with the tool \textit{HVite}. Finally, an ergodic HMM is used to concatenate character models. The HTK tool \textit{HResult} reported the performance of our system in terms of Line Recognition Rate (LRR) and Character Recognition Rate (CRR) rates, which take into consideration the errors due to substitution, insertion and deletion.

Guided by [70], the number of character models has a strong effect on the performance of recognition. They proposed 10 systems with different set of character models: Set35, Set36, Set38, Set42, Set62, Set64, Set120, Set124, Set68. In the present work, we apply Set62 which leads to the best results. All parameters, previously detailed, are set based on the recognition results for the Tahoma font of P-KHATT database.

### 4.3. Experiments

Various experiments are applied to evaluate the statistical features extracted by the proposed SAE-BoF framework. Also, we concentrate on the evaluation of parameters for HMM characters modeling.
Table 1: Configuration of our Text Recognition

| Parameter         | Value                                      |
|-------------------|--------------------------------------------|
| Preprocessing     | Smoothing=2                                 |
|                   | Height Normalization =55                   |
| Descriptor        | DSIFT                                      |
| AE                | Hidden Size : 500                          |
|                   | L2WeightRegularization : 0.1               |
|                   | SparsityRegularization : 1                 |
|                   | SparsityProportion : 0.95                  |
|                   | Loss Function : msesparse                  |

Table 2: Impact of Varying Height Size

| Height Size | Accuracy  |
|-------------|-----------|
|             | CRR       | SRR       |
| 45          | 99.91%    | 98.25%    |
| 55          | 99.95%    | 99.40%    |
| 60          | 99.92%    | 98.00%    |

The experiments are conducted on mono-font and mixed-font text recognition. Like in [29], for Tahoma font recognition, 2000 text lines were used for the training and 1424 text lines for the testing. For mixed-font recognizer, the set of training and the testing text lines from the eight fonts were employed.

4.3.1. Impact of Varying Patch and Stride Size

In the implementation of proposed text recognition system, there are a few significant parameters combined with text recognition performance, notably, the variation of the number of patch and stride size for the BoF. We draw samples of three patches: 3 x 3 with 1 stride, 5 x 5 with 2 strides and 8 x 8 with 4 strides. The best values for the patch size and stride were generated based on the recognition results for the Tahoma font of P-KHATT database.

Table 3 reports the results of our strategy for the P-KHATT database. We observe that our system provides the best accuracy recognition rate of 99.95% at character level and 99.40% at text line level for a patch size P=5 and stride D=2. Herein, it is interesting to notice that more we increase the patch size, more the recognition rate decreases.
Considering that the best performance was obtained with histogram features parameterized with \( P=5 \) and \( D=2 \), we keep these configurations for the following described experiments.

### 4.3.2. Impact of Varying Window and Shift Size and States Number

In Table 4, we studied different sliding window widths (\( W \)) and Shifts (\( S \)) with several number of states to find the best values of character models. The optimal accuracies are obtained with parameters \( W=4, S=3 \) and Number of States=10.

### 4.3.3. Effect of Hidden Neurons Number of SAE

The feature learning layer represents the hidden layer of SAE. The neurons number in the hidden layer represents the size of the SAE codebook. Different hidden neurons number (50, 250 and 500) are adopted to test its impact on the SAE learning.

#### Table 3: Impact of Patch and Stride Size

| Patchs/Strides | Accuracy | CRR | SRR |
|----------------|----------|-----|-----|
| 3/1            | 99.88%   | 98.20% |
| 5/2            | 99.95%   | 99.40% |
| 8/4            | 99.69%   | 93.41% |

#### Table 4: Variation of Text Recognition Rates by varying the window and shift Size and States Number

| W/S   | Number of States | Accuracy | CRR | SRR |
|-------|------------------|----------|-----|-----|
| 2/0   | 7                | 74.78%   | 41.06% |
| 3/2   | 10               | 99.87%   | 97.80% |
| 4/1   | 6                | 99.76%   | 95.10% |
| 4/3   | 10               | 99.95%   | 99.40% |
| 5/2   | 6                | 99.79%   | 95.60% |
| 6/3   | 6                | 99.77%   | 95.20% |
Table 5 shows that the SAE codebook size affects the recognition accuracy. We observe that the proposed text recognition system provides its best performance with dictionary size = 500. We obtain an average accuracy of 99.95% for CRR and 99.40% for LRR.

4.3.4. Impact of the SAE Codebook Generation

SAE represents more flexibility than the hard clustering algorithm like K-means. The obtained results, as shown in Table 6, demonstrate a better performance of SAE to those derived via K-means.

With regards to the mono-font and mixed-font, the codebook generated with SAE reaches the best performance than the codebook generated with K-means. Furthermore, for Tahoma mono-font, a best average text recognition accuracy of 99.95% for CRR is achieved with SAE. It raises an improvement up to 3.25% comparing to k-means codebook.

4.3.5. Impact of different number of Gaussian Mixtures

The basic profit of the Gaussian Mixtures is their power to model complicated shapes of functions of probability density. They are modeled more precisely with increasing the Gaussians number. Figure 9 demonstrates the growth of the CRR and LRR rates as a function of the Gaussians number. Wehighlight that the CRR and LRR rates of Tahoma font text recognition are respectively increased from 97.90% and 70.35% with 1 Gaussian to 99.95% and 99.40% with 64 Gaussians. As indicated on the curve evolution, going more than 64 Gaussians does not ensure the enhancement of the obtained results.

4.4. Comparison to State of the Art

In Tables 7 and 8, we compare our results with state of the arts methods. The comparison proves the effectiveness and the robustness of our system. In fact, the system proposed by [29] is validated on the P-KHATT database. The comparison is assessed using mono-font and mixed-font. The extracted features with SAE show their contribution in solving the problem of morphological differences between the characteristics of characters belonging to different fonts.
Table 5: Effect of Hidden Neurons Number

| Hidden Neurons No | Tahoma CRR | Tahoma LRR | Mixed-Font CRR | Mixed-Font LRR |
|-------------------|------------|-----------|----------------|--------------|
| 50                | 99.83%     | 96.70%    | 95.80%         | 64.88%       |
| 250               | 99.90%     | 98.30%    | 98.04%         | 70.55%       |
| 500               | 99.95%     | 99.40%    | 98.92%         | 90.00%       |

Table 6: Comparison of Text Recognition Rates via K-means and SAE

| Codebook Generation | Tahoma CRR | Tahoma LRR | Mixed-Font CRR | Mixed-Font LRR |
|---------------------|------------|-----------|----------------|--------------|
| K-means             | 96.70%     | 95.18%    | 94.70%         | 85.33%       |
| SAE                 | 99.95%     | 99.40%    | 98.92%         | 90.00%       |

They allow a global and robust parametrization whatever the case of mono-font context or mixed-font context. The recorded performances are very promising in recognition of Arabic in unconstrained environments. The results are presented in Character Error Rate (CER) idiom.

In Table 9, we further compare our system to existing HMM based systems that are reported in the literature using APTI database. The Arabic Transparent is the font dependable in the comparison such that it is closed to the reference protocols for the text recognition competitions using the APTI database [71, 72]. A fully literal comparison is yet not feasible for multiple reasons. One of the further important reason is that set6, which is not publicly available, is used only to evaluate the systems in the competitions. For other systems that used the APTI database and that are available in the literature, each system built its particular training, development, and evaluation set. A few systems applied word lexicons and n-gram LM, whereas other systems did not use them. P-KHATT and APTI database share a fixed parameters of the overall system.
Figure 9: Growth of Recognition Rate (RR) by improving the number of Gaussians

Table 7: Comparison of mono-font text recognition using the P-KHATT database

| Font                | CER (%) | Irfan et al. [2016] | Ours |
|---------------------|---------|---------------------|------|
| Times New Roman     | 1.20    | 0.1                 |
| Andalus             | 1.35    | 0.04                |
| DecoType Thuluth    | 7.55    | 0.29                |
| Tahoma              | 1.04    | 0.05                |
| Traditional Arabic  | 4.35    | 0.23                |
| Naskh               | 3.06    | 0.24                |
| Akbaar              | 2.87    | 0.35                |
| Simplified Arabic   | 1.67    | 0.04                |

Table 8: Comparison of mixed-font text recognition using the P-KHATT database

| System                  | CER (%) | Mixed-font using samples from all fonts | Mixed-font using font identification |
|-------------------------|---------|-----------------------------------------|--------------------------------------|
| Irfan et al. [2016]     | 12.19   | 3.44                                    |
| Ours                    | 1.08    | -                                       |
Table 9: Comparison with HMM based Text Recognition using the APTI database

| System          | Training And Testing Set                  | CER% | WER% |
|-----------------|-------------------------------------------|------|------|
| Slimane et al.  | - Training: Set1 to Set5  
                 | - Testing: Set6                         | 0.30 | 1.10 |
| [2011]          |                                           |      |      |
| Slimane et al.  | - Training: Set1 to Set5  
                 | - Testing: Set6                         | 0.03 | 0.1  |
| [2013]          |                                           |      |      |
| Khoury et al.   | - Training: 12,000  
                 | - Testing: 3,000                        | 0.30 | 1.70 |
| [2013] [73]     |                                           |      |      |
| Awaida et al.   | - Training: 80,000  
                 | - Testing: 14,418                       | 3.35 | -    |
| [2012] [74]     |                                           |      |      |
| Irfan et al.    | - Training: Set1 and Set2  
                 | - Testing: Set5                         | 0.57 | 2.12 |
| [2016]          |                                           |      |      |
| Ours            | - Training: Set1 and Set2  
                 | - Testing: Set5                         | 0.05 | 0.17 |

5. Conclusion and Future Work

This paper is about the recognition of unlimited-vocabulary Arabic text images. A good analysis of literature review in Arabic text recognition lead us to develop a novel system to handle some of the current challenges. More specifically, the challenges of unlimited-vocabulary and mixed-font are addressed. We use BoF framework based on SAE for codebook generation. It enhances the quality of the extracted features and produces a robust statistical features for holistic text recognition system. Herein, the main advantage of BoF based on SAE is their ability to cope with the font identification where each input text is associated with the closet known font. Also, they demonstrate their ability to handle the specificities of fonts, showing complex shapes with ligatures and overlaps with the same parameters used to handle an easy font without ligature or overlap. Several critical parameters of the BoF are experimentally evaluated including the patch, the stride and the codebook size. In other words, we investigated the selection of HMM for training and recognition. An interesting feature of HMM is in the implicit segmentation that the system is able to perform automatically. This feature is especially interesting for Arabic script where a priori segmentation of the characters is hard due to the cursive nature of the scripts (being printed or handwritten). So, HMM are able to perform the segmentation and recognition simultaneously. The obtained results in this paper are encouraging future works. The recognition of text with degraded and highly complex documents, such as
administrative documents, could be investigated.

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