Unsupervised text line segmentation

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Abstract—We present an unsupervised text line segmentation method that is inspired by the relative variance between text lines and spaces among text lines. Handwritten text line segmentation is important for the efficiency of further processing. A common method is to train a deep learning network for embedding the document image into an image of blob lines which are tracing the text lines. Previous methods learned such embedding in a supervised manner, requiring the annotation of many document images. This paper presents an unsupervised embedding of document image patches without a need of annotations. The main idea is that the number of foreground pixels over the text lines is relatively different from the number of foreground pixels over the spaces among text lines. Generating similar and different pairs relying on this principle definitely leads to outliers. However, as the results show, the outliers do not harm the convergence and the network learns to discriminate the text lines from the spaces between text lines. We experimented with a challenging Arabic handwritten text line segmentation dataset, VML-AHTE, and achieved a superior performance even over the supervised methods.

I. INTRODUCTION

Text line segmentation is a classical document image analysis problem that has impact on the performance of subsequent analysis operations. The objective of text line segmentation is to recognize all the pixels that belong to a text line, as shown in Fig. 1(d). Text line segmentation contains both, text line detection and text line extraction. Text line detection roughly locates text line patterns, whereas text line extraction precisely assigns pixels to the text lines. Detection results can be represented by baselines or blob lines (Fig. 1(c)). Extraction can be represented by pixel labels (Fig. 1(d)) or bounding polygons. The final goal of a text line segmentation procedure is to provide text lines one by one into the next document analysis procedure.

Recently numerous deep learning based methods have been proposed for text line segmentation of handwritten documents. Learning based methods [1]–[4] can inherently handle the problems arising from complex layout of text lines and heterogeneity of documents. However, they require vast amount of labeling effort which consumes time not less than carefully designed ad-hoc heuristics [5]–[8]. Intuitively, labeling effort is favorable over designing ad-hoc heuristics because the former can be accomplished by human recognition skills, whereas the latter requires further mathematical skills.

This paper presents a simple but interestingly successful unsupervised convolutional network for text line segmentation (VML-UTLS). The input for the network is an unlabeled document image, and the output is segmentation of text lines. The main idea can be formulated that the visual discrimination

Fig. 1. Given a handwritten document image (a), VML-UTLS learns to extract representation vectors of image patches where the distances between these vectors are proportional to the similarity of patches. Three principal components of patch representation vectors are visualized as a pseudo-RGB image (b). The pseudo-RGB images are thresholded onto blob lines that hover text lines (c). Energy minimization with the assistance of detected blob lines extracts the pixel labels of text lines (d).
of number of foreground pixels in document image patches requires machine to learn features that represent proximity and similarity of the elements in the document image. According to the Gestalt principle, such relevance among the elements of a document image forms the basis of unsupervised segmentation of text lines. In the first phase we train a siamese network to learn that two document image patches with relatively same/distinct number of foreground pixels are similar/different. Certainly, this measurement assigns many pairs improperly. However, the outliers do not harm the convergence of the machine learning. Next, we extract representation vectors of document image patches using the penultimate layer of a single branch of the siamese network. Then, we reduce dimensions of these vectors into their three principle components, which enables producing pseudo-RGB images where similar pixels in the embedded space correspond to similar colors. The pseudo-RGB images are thresholded into blob lines that hover the text lines. In the last phase, text lines are labeled in pixel level using an energy minimization framework with the assistance of the detected blob lines. Experiments on Arabic Handwritten Textline Extraction (AHTE) dataset, which possesses challenges by crowded and cramped text lines, show that unsupervised VML-UTLS is more effective than supervised methods.

II. RELATED WORK

Text line detection and segmentation in historical document images have been widely studied during the last decades, but still remains an open problem for challenging documents.

During the years, numerous methods for text line extraction have been proposed. Between the early approaches are projection profiles based methods, which were first applied to documents with horizontal text lines, and subsequently adapted to document with skewed and multi-skewed text lines. Another wide class of methods are grouping or clustering methods that aggregate elements (such as pixels or connected components) in a bottom up strategy. Smearing based methods target to enhance the text line structure. Seam-carving methods build energy map and compute seams that separate text lines or seams that pierce through text lines. Recently, learning-based methods have shown promising results when applied for text line segmentation of handwritten documents. Renton et al. employed a variant of Fully Convolutional Network (FCN) with dilated convolutions for text line extraction. The model is trained to output an X-height pixel labeling as text line representation. Oliveira et al. presented a CNN-based pixel-wise predictor for addressing multiple tasks simultaneously: page extraction, layout analysis, baseline extraction, and illustration and photograph extraction. Their network is trained to predict the binary mask of polygonal lines that represent baselines. Kurar-Barakat et al. build a FCN to predict text line masks. Their method targeted challenging documents, which contain curved, multi-skewed and multi-directed text lines of different fonts types and sizes. Kiessling et al. presented method based on a fully convolutional encoder-decoder network to detect baselines in document images. The baseline definition was modified slightly towards manuscripts written in Arabic scripts. Mechi et al. and Neche et al. used an U-net and RU-net deep-learning models, which are variants of FCN. The models are trained for X-height based pixel-wise classifications of text lines.

All of the learning-based methods reviewed above are supervised methods. We are not aware of any unsupervised deep-learning approach for text line segmentation. In this paper we present an unsupervised deep-learning based method, VML-UTLS, for text line segmentation, and apply it on historical documents dataset which exhibits multiple challenges for text line segmentation. As we show in Section V, VML-UTLS outperforms supervised methods.

III. DATASET

We experiment with VML-AHTE (Arabic Handwritten Textline Extraction) dataset which is challenging in terms of rich diacritics, and touching and overlapping characters, as shown in Fig.2. It is a newly published dataset and available online for downloading. The dataset consists of 30 binary images from several historical manuscripts and is divided into 20 pages for training and 10 pages for testing.

![Fig. 2. Some samples of challenges in VML-AHTE dataset.](https://www.cs.bgu.ac.il/~berat/data/ahte_dataset)

IV. METHOD

We present a method for unsupervised text line segmentation (VML-UTLS) and show its effectiveness on handwritten document images. The method uses a siamese convolutional network to predict whether two given document image patches are similar or different, driven by the number of foreground pixels in the patches. After the training phase, a single branch of the trained network is used to extract features of document image patches, which are in turn visualized as pseudo-RGB images and thresholded into blob lines that hover text lines. Finally, we use an energy minimization framework to extract the pixel labels of text lines with the assistance of detected blob lines. This section provides the details of data preparation, training, visualization of blob lines and energy minimization procedures.

A. Data preparation

Data preparation consists of generating patches of the size $150 \times 150$ pixels, cropped randomly from document images and labeling every pair of patches either similar or different.
Patch size is estimated as three times of the average character height in the document images. This intuitive justification first appears as a special case but nevertheless generalize to heterogeneous cases with various text line heights. We have already observe validity of this assumption with heterogeneous text line heights (Fig. 3) but plan to present full results in another paper. Label of a pair of patches is derived from the number of foreground pixels in patches. Without loss of generality and by analogy with distance, we label similar pairs with zero and different pairs with one. We use three strategies to generate pairs of image patches with labels.

1) Patches similar by number of foreground pixels: Given randomly cropped two image patches, let \( a_i \) be the number of foreground pixels in patch \( i \) where \( i \in \{1, 2\} \). Our algorithm continues cropping two random patches until the similarity score \( s \) satisfies the following condition:

\[
s = \frac{\min(a_1, a_2)}{\max(a_1, a_2)} \leq 0.5
\]

Intuitively this strategy generates pairs where both centralize either a text line part or a part of space between text lines (Fig. 4). Because the number of foreground pixels in the spaces between text lines are relatively less than the number of foreground pixels in the text lines. We observed that the pairs of patches with \( s = 0.6 \) are mostly outliers. Hence we use \( s < 0.4 \) that enforces that the two patches of a pair are closer in feature space.

2) Patches different by number of foreground pixels: This strategy continues cropping two random patches until the similarity score \( s \) satisfies the following condition:

\[
s = \frac{\min(a_1, a_2)}{\max(a_1, a_2)} \geq 0.7
\]

Intuitively this strategy generates pairs where one centralizes a text line part and the other centralizes a part of space between text lines (Fig. 5). Because the number of foreground pixels in the spaces between text lines are relatively less than the foreground pixels in the text lines. TWe observed that the pairs of patches with \( s = 0.6 \) are mostly outliers. Hence we use \( s > 0.7 \) that enforces that the two patches of a pair are distant in feature space.

3) Patches different by background area: There also exist a significant difference between the background areas and the text areas in the document image. This strategy continues cropping two random patches until one of the patches is from background area and the other is from text area (Fig. 6). We assume a patch is from background area if more than half of it is from background area.

**B. Training**

The common deep learning practice for handwritten text line segmentation is to adapt an embedding from the text lines image into a blob lines image. The classifier is first trained
on a labeled set of text lines, and then expected to predict blob lines. Unlike these methods, VML-UTLS does not need labeled data for mapping the text line image into a blob line image. It is simply trained to distinct the text lines from the spaces between text lines.

The overall architecture is a siamese network with two identical branches. Each branch inputs an image patch and outputs a feature representation of that image patch. Consequently, these feature representations are concatenated and feed into fully connected layers in order to classify whether the two image patches are similar or different.

The branches of siamese network model is based on Alexnet [30] and through experiments we tune the hyperparameters to fit our task. The final architecture contains two branches of CNN, each of the branches has five convolutional layers (Fig. 7). Dotted lines indicate identical weights, and the numbers in parentheses are the number of filters, filter size and stride. All convolutional and fully connected layers are followed by ReLU activation functions, except fc5, which feeds into a sigmoid binary classifier. The learning rate is 0.00001 and the optimizing algorithm is ADAM.

![Network Architecture](image)

Fig. 7. Siamese architecture for pair similarity. Dotted lines stand for identical weights, conv stands for convolutional layer, fc stands for fully connected layer and pool is a max pooling layer.

We trained this model from scratch using 30,000 pairs that are generated and labeled according to the strategies described in section IV-A and reached a validation loss value of 0.29 after 11 epochs (Figure 8).

C. Visualization of blob lines for text line detection

Once the siamese network is trained, we use a single branch to extract the features of patches. This embeds every patch into a feature vector of 512 dimensions. To visualize the features of a complete document image, a sliding window of the size 20 × 20 is considered to eliminate the edge affect. We pad the document image with white pixels at its right and bottom sides if its size is not an integer multiple of the sliding window size, in addition to the padding at 4 sides of the document image for considering only the central part of the sliding window. As a result, a document image with the size \((r/20) \times (c/20) \times 512\). We project 512D vectors into their three principle components and use these components to construct pseudo-RGB image in which similar patches are assigned the similar colors (Fig.1(b)). Binary blob lines image (Fig.1(c)) is an outcome of thresholded pseudo-RGB image.

D. Energy minimization for text line extraction

We adopt the energy minimization framework [31] that uses graph cuts to approximate the minima of arbitrary functions. We adapt its function to be used with connected components for extracting the text lines. Minimum of the adapted function correspond to a good extraction which urges to assign components to the label of the closest blob line while straining to assign closer components to the same label.

Let \(L\) be the set of binary blob lines, and \(C\) be the set of components in the binary document image. Energy minimization finds a labeling \(f\) that assigns each component \(c \in C\) to a label \(l_c \in L\), where energy function \(E(f)\) has the minimum.

\[
E(f) = \sum_{c \in C} D(c, l_c) + \sum_{\{c, c'\} \in \mathcal{N}} d(c, c') \cdot \delta(l_c \neq l_{c'})
\]  

(3)

The term \(D\) is the data cost, \(d\) is the smoothness cost, and \(\delta\) is an indicator function. Data cost is the cost of assigning component \(c\) to label \(l_c\), \(D(c, l_c)\) is defined to be the Euclidean distance between the centroid of the component \(c\) and the nearest neighbour pixel in blob line \(l_c\) for the centroid of the component \(c\). Smoothness cost is the cost of assigning neighbouring elements to different labels. Let \(\mathcal{N}\) be the set of nearest component pairs. Then \(\forall\{c, c'\} \in \mathcal{N}\)

\[
d(c, c') = \exp(-\beta \cdot d_e(c, c'))
\]  

(4)

where \(d_e(c, c')\) is the Euclidean distance between the centroids of the components \(c\) and \(c'\), and \(\beta\) is defined as

\[
\beta = (2 \langle d_e(c, c') \rangle)^{-1}
\]  

(5)

\(\langle \cdot \rangle\) denotes expectation over all pairs of neighbouring components [32] in a document page image. \(\delta(l_c \neq l_{c'})\) is equal to 1 if the condition inside the parentheses holds and 0 otherwise.
V. EXPERIMENTS

We present the results on VML-AHTE dataset [11], a challenging text line segmentation dataset which exhibits crowded diacritics and cramped text lines. The results are presented using line segmentation evaluation metrics of ICDAR2013 [33] and ICDAR2017 [34].

A. ICDAR2013 line segmentation evaluation metrics

ICDAR2013 metrics calculate recognition accuracy (RA), detection rate (DR) and F-measure (FM) values. Given a set of image points \( I \), let \( R_i \) be the set of points inside the \( i^{th} \) result region, \( G_j \) be the set of points inside the \( j^{th} \) ground truth region, and \( T(p) \) is a function that counts the points inside the set \( p \), then the MatchScore\((i,j)\) is calculated by Equation 6:

\[
\text{MatchScore}(i,j) = \frac{T(G_j \cap R_i \cap I)}{T((G_j \cup R_i) \cap I)}
\]

(6)

The evaluator considers a region pair \((i,j)\) as a one-to-one match if the MatchScore\((i,j)\) is equal or above the threshold, which we set to 90. Let \( N_1 \) and \( N_2 \) be the number of ground truth and output elements, respectively, and let \( M \) be the number of one-to-one matches. The evaluator calculates the DR, RA and FM as follows:

\[
\text{DR} = \frac{M}{N_1}
\]

(7)

\[
\text{RA} = \frac{M}{N_2}
\]

(8)

\[
\text{FM} = \frac{2 \times \text{DR} \times \text{RA}}{\text{DR} + \text{RA}}
\]

(9)

B. ICDAR2017 line segmentation evaluation metrics

ICDAR2017 metrics are based on the Intersection over Union (IU). IU scores for each possible pair of Ground Truth (GT) polygons and Prediction (P) polygons are computed as follows:

\[
\text{IU} = \frac{I\text{P}}{U\text{P}}
\]

(10)

IP denotes the number of intersecting foreground pixels among the pair of polygons. UP denotes number of foreground pixels in the union of foreground pixels of the pair of polygons. The pairs with maximum IU score are selected as the matching pairs of GT polygons and P polygons. Then, pixel IU and line IU are calculated among these matching pairs. For each matching pair, line TP, line FP and line FN are given by:

- Line TP is the number of foreground pixels that are correctly predicted in the matching pair.
- Line FP is the number of foreground pixels that are falsely predicted in the matching pair.
- Line FN is the number of false negative foreground pixels in the matching pair.

Accordingly pixel IU is:

\[
\text{Pixel IU} = \frac{TP}{TP + FP + FN}
\]

(11)

where TP is the global sum of line TPs, FP is the global sum of line FPs, and FN is the global sum of line FNs.

Line IU is measured at line level. For each matching pair, line precision and line recall are:

\[
\text{Line precision} = \frac{\text{line TP}}{\text{line TP} + \text{line FP}}
\]

(12)

\[
\text{Line recall} = \frac{\text{line TP}}{\text{line TP} + \text{line FN}}
\]

(13)

Accordingly, line IU is:

\[
\text{Line IU} = \frac{\text{CL}}{\text{CL} + \text{ML} + \text{EL}}
\]

(14)

where CL is the number of correct lines, ML is the number of missed lines, and EL is the number of extra lines.

For each matching pair:

- A line is correct if both, the line precision and the line recall are above the threshold value.
- A line is missed if the line recall is below the threshold value.
- A line is extra if the line precision is below the threshold value.

C. Results

We compare our results with those of supervised methods, Mask-RCNN and FCN+EM and Human+EM. We run these supervised methods for our papers that are under review [10], [11]. Mask-RCNN method is fully supervised using the pixel labels of the text lines. The advantage of this method is that it directly outputs pixel labels of text lines and does not need an additional procedure. FCN+EM method is also fully supervised but using blob lines that pass over the text lines. Therefore it uses EM framework to extract the pixel labels of text lines. Human+EM method is supervised by blob lines that are drawn by a human and uses EM framework to extract the pixel labels of text lines.

The comparison in terms of ICDAR2013 metrics are reported in Table I

| Method            | DR    | RA    | FM    |
|-------------------|-------|-------|-------|
| VML-UTLS+EM       | 93.62 | 93.95 | 93.78 |
| Supervised        |       |       |       |
| Mask-RCNN         | 84.43 | 58.89 | 68.77 |
| FCN+EM            | 95.55 | 92.80 | 94.30 |
| Human+EM          | 95.15 | 95.15 | 95.15 |

The comparison in terms of ICDAR2017 metrics are reported in Table II

| Method | DR    | RA    | FM    |
|--------|-------|-------|-------|
| Unsupervised | VML-UTLS+EM | 93.62 | 93.95 | 93.78 |
| Supervised |       |       |       |
| Mask-RCNN | 84.43 | 58.89 | 68.77 |
| FCN+EM | 95.55 | 92.80 | 94.30 |
| Human+EM | 95.15 | 95.15 | 95.15 |

As validated by the results VML-UTLS successfully learns and discriminates between the text lines and the spaces among text lines. Moreover it outperforms all the supervised methods in terms of RA and line IU, and is competitive in terms of the other metrics. The error cases arise from few number of touching blob lines. Such errors can easily be eliminated but out of this paper’s focus.
VI. CONCLUSION

We presented an unsupervised text line segmentation method VML-UTLS, trained to discriminate the text lines from the spaces between text lines. VML-UTLS learn feature representations that are comparable or superior to other models trained with full supervision. In future, we plan to perform empirical experiments to study the effect of patch size and amount of training set size, and performance on multiply oriented and curved text lines.

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| Method                  | Line IU | Pixel IU |
|-------------------------|---------|----------|
| Unsupervised VML-UTLS+EM| 98.55   | 88.95    |
| Supervised Mask-RCNN    | 93.08   | 86.97    |
| Supervised FCN+EM       | 94.52   | 90.01    |
| Supervised Human+EM     | 99.29   | 91.49    |
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