Text Localization in Natural Scene Images based on Conditional Random Field

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Abstract

This paper proposes a novel hybrid method to robustly and accurately localize texts in natural scene images. A text region detector is designed to generate a text confidence map, based on which text components can be segmented by local binarization approach. A Conditional Random Field (CRF) model, considering the unary component property as well as binary neighboring component relationship, is then presented to label components as "text" or "non-text". Last, text components are grouped into text lines with an energy minimization approach. Experimental results show that the proposed method gives promising performance comparing with the existing methods on ICDAR 2003 competition dataset.

1. Introduction

With the widely use of digital image capturing devices, text localization/detection, as a key part of the image text information extraction system [3], has been studied intensively. Though many efforts have been devoted to, it remains a challenge due to variations of texts' size, font, array orientation and degraded images with the cluttered background and noises [5]. The existing methods can be categorized into two classes: region-based methods and connected component (CC)-based ones.

Region-based methods [3, 5, 14] are based on observations that text regions have distinct characteristics from non-text regions such as distinctive gradient distribution, texture and structure. These methods generally consist of two stages: text detection and text localization. For text detection, features of local regions are extracted to determine if they contain texts. Then specific grouping or clustering approaches are employed to localize text regions accurately.

CC-based methods [3, 5, 14] are based on observations that texts can be seen as sets of separate connected components, each of which has distinct intensity, color distri-

butions and enclosed contours. These methods generally contain three stages: 1) CC extraction to segment CCs from images, 2) CC analysis to determine whether or not they are text components by heuristic rules or classifiers and 3) post-processing to group text components into text regions (e.g. words, lines).

Although some existing methods have reported promising results, there still remains several problems difficult to be solved. For CC-based methods, text components are hard to be segmented accurately without prior information of text position and scale. Furthermore, designing fast and reliable CC analysis method is also difficult since there are too many text-like components in images. On the other hand, the performance of region-based methods is sensitive to the text orientation and cluster number. Most of these methods can only localize texts containing many characters in horizontal alignment.

To overcome these difficulties, we propose a hybrid method to robustly and accurately localize texts in natural scene images. A text region detector is designed to generate a text confidence map, based on which components are segmented with local binarization. Then a Conditional Random Field (CRF) model considering of both the unary component property and neighboring component relationship is presented for component analysis. Finally, a energy minimization based approach is used to group text components into text lines. We evaluate our method on ICDAR 2003 competition dataset and the results show that the text localization accuracy is improved.

2. System Overview

For scene texts localization, the process of our method consists of three stages: 1) pre-processing, designing a text region detector to generate the text confidence map, based on which text components can be segmented by local binarization, 2) CC analysis, presenting a CRF model to formulate component analysis into component labeling problem, which is solved by minimum classification error (MCE)

learning and graph cuts inference algorithm and 3) text line grouping, where component minimum spanning tree is built with a learned distance metric and inter-line edges are cut off with an energy minimization model. The flawchat of the proposed method is shown in Fig. 1 and detailed descriptions will be given in the following sections.
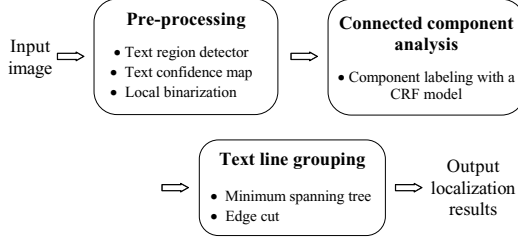

Figure 1. Flowchat of the proposed method.

3. Pre-processing

For utilizing region information, a text region detector is designed to measure confidences of containing texts for local image regions, based on which components can be segmented and analyzed accurately.

3.1 Text Region Detector

The color image is first converted into the gray-level image, on which image pyramids are built with nearest interpolation to capture texts with various sizes. Motivated by our previous work [8], a text region detector is designed by integrating Histograms of Oriented Gradients (HOG) feature extractor and boosted cascade classifier. For each local region in one image of pyramids, HOG features are extracted as an input to a variation of cascade boosting classifier, WaldBoost [10], to estimate whether this region contains texts. The major difference between WaldBoost and other cascade boosting classifiers is that it directly ensemble weak learners to build a strong classifier and each of them can be used to filter out negative objects individually.

3.2 Text Confidence Map

To measure the confidence that one region contains texts, we translate the Waldboost output, no matter accepted or rejected, into posterior probability based on a boosted classifier calibration method [12]. Posterior probabilities of the observation variable x, $x \in \{text,non\text{-}text\}$, conditioned on the state variable s, $s \in \{accept,reject\}$, at stage t can be estimated based on the Bayes' formula as

$$P_t(x|s) = \frac{P_t(s|x)P_t(x)}{\sum_x P_t(s|x)P_t(x)} = \frac{P_t(s|x)P_{t-1}(x|accept)}{\sum_x P_t(s|x)P_{t-1}(x|accept)},$$
(1)

where all likelihoods $P_t(s|x)$ are calculated on the validation set during the training procedure. In this way, each confidence map of the image pyramid can be calculated, whose pixel confidence and scale values are then projected back into corresponding pixels of the text confidence map for the original image which is used for subsequent stages.

3.3 Image Segmentation

Niblack's binarization algorithm [7] is adopted to segment connected components from the image. The formula to binarize each pixel is defined as

$$b(x) = \begin{cases} 0, & \text{if } gray(x) < \mu_r(x) - k \cdot \sigma_r(x); \\ 255, & \text{if } gray(x) > \mu_r(x) + k \cdot \sigma_r(x); \\ 100, & \text{other}, \end{cases}$$
(2)

where $\mu_r(x)$ and $\sigma_r(x)$ are the intensity mean and STD within a r radius window centered on the pixel x and the smoothing term k is set to 0.4 in practical. It is noted that the value of window radius r for each pixel is calculated based on the corresponding pixel value of the text confidence map. For a binarized image, components with 0 or 255 value are extracted as candidate text components while 100 ones are not considered further. An example of the pre-processing stage is shown in Fig. 3.

4. Connected Component Analysis

For CCA, a Conditional Random Field (CRF) model is proposed to label components as "text" or "non-text" by considering of both the unary component property and neighboring component relationship.

4.1 Brief Introduction to CRF

CRF [4] is a undirected graphical model to estimate probability distribution global conditioned on observations. Formally, Let $G = (X, E)$ be a graph constructed on random variables $X = (x_1, ..., x_n)$ with labels $Y = (y_1, ..., y_n)$. Then (X, Y) is a CRF when probability of Y conditioned on X obeys the Markov property: $P(y_i|x, y_j, j \neq i) = P(y_i|x, y_j, j \in n_i)$, where n_i is the neighborhood set (clique) for x_i.

In implementation, $P(Y|X)$ can be approximated by arbitrary real-valued energy function $E(X, Y, N, \Lambda)$ with clique set N and parameters Λ as

$$P(Y|X) = \frac{1}{Z(X)} exp(-E(X, Y, N, \lambda)),$$
(3)

where $Z(X)$ is the normalization constant which could not be considered if ignoring the probability explanation. Then the best label Y^* can be found from maximizing conditional probability $P(Y|X)$ to minimizing the total graph energy: $Y^* = \arg\max_Y P(Y|X) = arg\min_Y E(X, Y, N, \lambda)$.
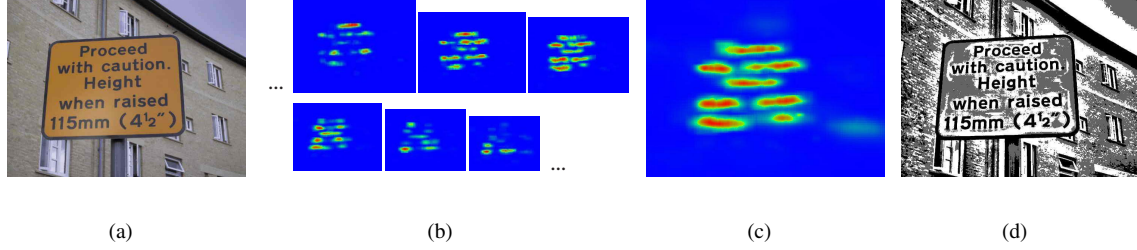
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| | (a) | | (b) | | (c) | | (d) |

Figure 2. Example of the pre-processing stage. (a) the original image. (b) text confidence maps for the image pyramid (brightness of pixels represents the probability as "text"). (c) the text confidence map for the original image. (d) binarized image.

4.2 CC labeling with CRF

Based on the definition of CRF, we formulate CC analysis into CC labeling problem: given the component set $X = (x_1, x_2, ...)$, on which a 2D undirected graph is constructed, the objective is to find the best component label $Y^* = (y_1^*, y_2^*, ...)$ to minimize the total graph energy E.

4.2.1 Neighborhood Graph

Considering the geometric and spatial relationship of components, we construct the neighborhood graph with a component linkage rule defined as

$$dist(x_i, x_j) < 2 * min(\ max(\ w_i, h_i\ ), max(\ w_j, h_j\ )\ ), \quad (4)$$

where $dist(\cdot, \cdot)$ is the centroid distance between two components and w and h are component width and height respectively. Any two components whose spatial relationship obeys this rule can be linked together by an edge.

4.2.2 Energy Function

Considering the effectiveness and efficiency, we utilize unary and binary cliques on the graph to construct the CRF model, where multi-layer perceptron (MLP) is selected to approximate the unary and binary energy function. The total energy function is defined as

$$E(X, Y, N, \lambda) = \sum_i (\ (E_{un}(x_i, y_i, \omega_{un}) +$$
$$\omega_c \cdot \sum_{c_i} E_{bi}(x_i, x_j, y_i, y_j, j \in n_i, \omega_{bi})\ )\ (5)$$

where values of $E_{un}(\cdot, \omega_{un})$ and $E_{bi}(\cdot, \omega_{bi})$ are outputs of two-class ("text", "non-text") and three-class (both texts, both non-texts and different style) MLPs on unary and binary features, and ω_c is a combination coefficient. Unary and binary features (defined in Table 1, refer to [11]), some of which are calculated with the text confidence map, are extracted to represent the component property and component neighboring relationship.

Unary feature	Binary feature
normalized width	centroid distance
normalized height	scale ratio
aspect ratio	shape difference
occupy ratio	(horizontal and vertical)
compactness	overlap degree
confidence	(horizontal and vertical)
contour gradient (R,G,B)	color difference (R,G,B)
average run-length	confidence
number	(minimum and maximum)

Table 1: Unary and binary features.

4.2.3 Learning and Inference

For parameter estimation of the CRF model, we use Minimum Classification Error (MCE) criterion [2] since it can be directly integrated with the MLP optimization. In MCE training, the misclassification measure can be approximated by $d(X, \Lambda) = -E(X, Y^c, N, \Lambda) + E(X, Y^r, N, \Lambda)$, where Y^c and Y^r are the true and rival label respectively and Λ represents CRF model parameters $\{\omega_{un}, \omega_{bi}, \omega_c\}$. The measurement can be transformed into loss function

$$L(X, \Lambda) = \frac{1}{1 + exp(-\xi(d(X, \Lambda)))}, \quad (6)$$

based on which parameters can be iteratively optimized by stochastic gradient decent algorithm as

$$\Lambda_{t+1} = \Lambda_t - \varepsilon_t \cdot \frac{\partial L(X, \Lambda)}{\partial \Lambda}|_{\Lambda = \Lambda_t}. \quad (7)$$

When energy function parameters are learned fixed, graph cuts (α-expansion) algorithm [1] is selected to find the best label Y^* of components to minimize the total energy since it can achieve approximate optimal results and is much efficient than other inference algrothms.

During the training procedure, we use coupling strategy to learn energy function parameters: at each time, the energy function is first fixed and graph cuts is used to label components, then the total energy value for fixed graph labels is used to optimize parameters based on MCE criterion. This updating process continues until the total energy only have very few changes. During the test procedure, to speed up the process, some apparent non-text components

are firstly filtered out based on unary feature thresholds before using the CRF model. Values of these thresholds are set very weak to accept all text components in the training set. Fig. 4 gives an example of the CC analysis stage.
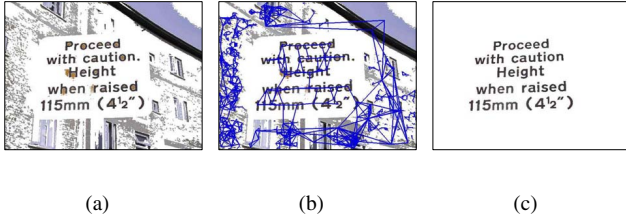

(a)   (b)   (c)

Figure 3. Example of the CC analysis stage. (a) components pass through unary thresholds. (b) component neighborhood graph (with blue edges). (c) components labeled as "text" with the learned CRF model.

5 Text Line Grouping

To group text components into text lines, we presented a learning based method by building neighboring components into minimum spanning tree (MST) and cutting off interline edge with an energy minimization model.

5.1 MST Building

Based on observations that components belonging to one text line are adjacent along specific orientation, we cluster text components into a MST. Motivated by Yin's work [13], we define a linear distance metric whose parameters are learned with the perceptron algorithm to estimate the similarity measurement between two components, where features are defined as Table 2. Then a MST can be built with the learned distance metric by Kruskal's algorithm [9].

Distance metric feature	Text line feature
centroid distance (horizontal and vertical)	line regression error
	line height
box boundary distance (horizontal and vertical)	line number
	cut edge score
shape difference	inter-line distance
color difference	(horizontal and vertical)

Table 2: Distance metric and text line features.

5.2 Edge Cut

To separate MST into text lines with irregular alignments, we formulate edge cut into edge labeling problem which is solved in the similar way as CC analysis in Section 4. Briefly, for a MST graph $G_{MST}(X, Y)$ on edges X with labels Y, a learned energy function is defined as $E_{MST}(X, Y) = \sum_i \omega_i \cdot f_i$, where $\{f_i\}$ are text line features

defined as in Table 2 (refer to [15]), and $\{\omega_i\}$ are classifier weight coefficients, whose values are learned with MCE criterion.

A recursive strategy is employed to inference edge labels: initially, edges are all labeled as "link". At each time, one edge is labeled as "cut" if the new energy is minimized and smaller than the last time. This process continues until the energy is minimal. Although this recursive approach can not be proved to find the optimal labels, experimental results are still satisfactory. Finally, text lines corresponding to sub-trees can be extracted and those containing too small components are removed. An example of the text line grouping stage is shown in Fig. 5.
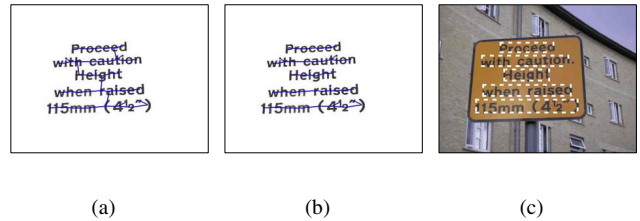

(a)   (b)   (c)

Figure 4. Example of the text line grouping stage (a) building MST with the learned distance metric. (b) edge cut with an energy minimization model. (c) final text localization results.

6 Experimental Results

To evaluate the performance of the proposed method, we have done experiments on ICDAR 2003 text locating competition dataset which includes 258 training images and 249 test images with English and Arab number texts.

For training text region detector, 5000 text samples were collected by manually and non-text samples are extracted randomly from training images. The size of detector was fixed to 16×16 and 4-orientation HOG were used to extract region features. Interval step was fixed to 1.2 to generate image pyramid and totally 612 weak learners were selected to build WaldBoost. For more details, please refer to [8].

4900 text components and 13000 non-text components were labeled from segmented images to train the CRF model. In order to achieve the optimal performance, parameters of two MLPs were initialized with standard back propagation algorithm and then the CRF model was jointly optimized with coupling training strategy. 10000 neighboring edges and 80000 non-neighboring edges were selected to train the MST distance metric and 550 text lines was labeled to train the energy function for edge cuts.

Our system was coded with C++ language and all experiments evaluated on a Pentium 4 3.4GHz desktop computer with Window XP OS.

To evaluate the proposed CRF model, we compared component classification performance with three different classifier settings: 1) MLP, only unary energy function is

used, 2) CRF-ω_c, unary and binary functions were all used but only combination coefficient ω_c was optimized with MCE criterion and 3) CRF-Λ, all energy function parameters $\Lambda(\omega_{un}, \omega_{bi}, \omega_c)$ were optimized with MCE criterion. Results in Table 3 shows that the CRF model is better than unary MLP as considering relationship between neighboring components and parameters fully learned with MCE is better than only optimizing the combination coefficient.

	Recall rate(%)	Precision rate(%)
MLP	79.04	78.61
CRF-ω_c	80.77	82.81
CRF-Λ	83.12	83.77

Table 3: Component classification results for different classifier settings.

To evaluate the proposed text localization method, we compared our method with several existing methods: the top two participants of ICDAR 2005 text location competition [6] and our previous method [8]. We adopted the performance evaluation criterion by defining precision rate and recall rate based on area matching ratio as the ICDAR 2005 competition. As shown in Table 4, the proposed method is still comparative with the existing methods and the recall rate is improved than our previous region-based work, even there are different test images and evaluation units (word *vs.* line) between ours and competition methods.

	Recall rate(%)	Precision rate(%)
1st ICDAR'05	62	67
2nd ICDAR'05	60	60
Our previous method	68	67
The proposed method	71	67

Table 4: Text localization results of different methods.

7 Conclusions

In this paper, we present a hybrid method to localize scene texts by using region as well as component information. Furthermore, the neighboring component relationship, in addition to the unary component property, is used to construct a CRF model for CC analysis, whose model parameters are optimized with MCE learning and graph cuts inference algorithms. Experimental results have demonstrated that our method is meaningful for unconstrained scene text localization. However, until now, we just implemented a primary version of the proposed method which need to be investigated and improved further.

8 Acknowledgements

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