Approach for document detection by contours and contrasts

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Abstract—This paper considers the task of arbitrary document detection performed on a mobile device. The classical contour-based approach often mishandles cases with occlusion, complex background, or blur. Region-based approach, which relies on the contrast between object and background, does not have limitations, however its known implementations are highly resource-consuming. We propose a modification of a contour-based method, in which the competing hypotheses of the contour location are ranked according to the contrast between the areas inside and outside the border. In the performed experiments such modification leads to the 40% decrease of alternatives ordering errors and 10% decrease of the overall number of detection errors. We updated state-of-the-art performance on the open MIDV-500 dataset and demonstrated competitive results with the state-of-the-art on the SmartDoc dataset.

Index Terms—document detection, quadrangle detection, smartphone-based acquisition, mobile document recognition, image segmentation.

I. INTRODUCTION

Problem of quadrangle detection (see Fig. 1) quite often occurs in a computer vision tasks. This is not surprising since rectangular objects are widespread in the urban scenes and four points are enough to form a homography basis for a planar part of the scene and perform a local rectification. That is why quadrangle detection is used, for example, in automatic processing documents [1], signboards [2], whiteboards [3], vehicle license plates [4], road signs [5], paintings [6], beds in hospital [7] and in other possible applications. Another application is an estimation of an observer orientation in a scene’s coordinate system specified by a rectangular object, for example, by a truck body [8] or by corners of an evacuation plan [9]. In this paper, we will consider the quadrangle detection problem in the case of flat document detection.

A classical contour-based approach to solve this problem is based on the following steps: edge detection, borders candidate selection, quadrangles candidate construction, and, finally, ranking of those alternatives in order to choose the best one [3], [11]–[14]. The key assumption of this approach is that borders of the target object form consistent and unambiguous strong polyline contour on the image. In other words, contour-based algorithms usually have difficulties when sought contour not entirely fits the image or is partially occluded, when contrast between the object and background is low, in the presence of strong lines crossing object or background, in poor lighting conditions, or when the image is blurred.

Another well-known approach is based on exploiting of a known object’s structure: feature points [15], sets of line segments [16] or maps of local contrasts [17], [18]. These methods are hardly applicable if there are no a priori infor-
mation about object structure.

In the lack of knowledge about object structure alternative for the contour detection is region-based approach. Its main difference with edge detection is reliance on areal contrast between object and background rather than differential characteristics of the border. Algorithms based on this approach was proposed in [19] and [20], combining region-based segmentation and shape analysis. Solution considered in [19] is quite elegant. The image is segmented by watersheds of filtered colour gradients and then segments contours are analysed as candidates for sought quadrangle shapes. Though being very fast, this algorithm shows not very good performance, and later the same authors proposed much slower but more precise algorithm [29]. It is interesting that the article [21] with similar approach was proposed earlier but it did not show such good quality performance.

A different strategy is proposed in [1]: a hypothetical position of the document is optimised in such a way that the color distributions in the internal and external areas of the quadrangle would differ maximally. An advantage of contrast-based approach is robustness for background lines presence and image blurring. However, the computational complexity of such algorithms is usually high and their usage on mobile processors is limited.

In addition to contour and region approaches to the detection of quadrangles with unknown internal structure, there are works in which the quadrangle is detected as a set of vertices [3, 22, 23]. The disadvantage of this approach is the assumption of the visible vertices. Therefore, high quality should not be expected when they are obscured or are outside the frame. In [24] a combination of the contours and the vertices is used. And despite the fact that it makes the system more robust, the criticism of contour-based methods to such algorithms remains valid.

The problem of document detection can be simplified not only to the quadrangle detection, but also to a semantic segmentation problem. This strategy was used in region-based algorithms [20], [21], which were mentioned above. And works which use modification [25], [26] or original [27] Unet architecture networks.

In this paper a combination of the contour and region-based approaches is proposed. Its main idea is that competing algorithms remains valid.

The rest of the paper consists of 3 main sections: in section II our algorithm is proposed and section III is devoted to the experimental evaluation.

II. STATEMENT OF A RANKING PROBLEM

Let us consider an image $I$, a set of quadrangles $\{q_i\}_{i=0}^N$ (the explanation of how we generate baseline set of quadrangles see in paragraph IV-A) and a ground truth quadrangle $m$ which describes a position of an object in the image. It is required to define a function $F(q, I)$ in such way, that the quadrangle with the highest score $q^* = \arg\max_{q} F(q, I)$ fits the ground truth quadrangle $m$ according to a binary quality metric $L(q, m)$. If the tested quadrangle $q$ is correct $L(q, m) = 1$, otherwise $L(q, m) = 0$.

III. PROPOSED ALGORITHM

Function $F$ should take into account both contour and contrast features of the quadrangle. We will search the solution in following form:

$$F(q, I) = kC(q, I) + R(q, I),$$

where $C$ is a contour score, which will be described in paragraph III-A, $R$ is a contrast score (par. III-B), $k$ is a combination coefficient (par. III-C).

A. Determining contour-based score

In classical contour based algorithms the quadrangle $q$, composed of four borders $B(q) = \{b_i\}_{i=1}^4$, is usually estimated using edges (for example, Canny edges [28]). For instance, in [3] a consistency score $\sum_{b \in B(q)} c(b)$ of all edges is calculated, where the consistency $c$ is a ratio of non zero edges along the border $b$. In paper [11] the function $F$ is estimated as $\min_{b \in B(q)} c(b)$.

In our score we will taken into account not only consistency but also a strength and penalty for corners like in [12]:

$$C(q) = \frac{\sum_{b \in B(q)} w(b)}{1 + \sum_{b \in B(q)} (1 - c(b))} - \sum_{b \in B(q)} w'(b),$$

where $w(b)$ is a total intensity of edges along the border and $w'$ is a penalty equal to the total intensity of the edges that are on a straight line outside the border $b$ (see [12] for more details).

B. Determining contrast-based score

An assessment of the correspondence of the inner region of the found quadrangle to the internal structure of the target object is possible only under the assumption that the texture of the object is different from the background. The degree of difference between two regions may be used for scoring the quadrangle. To assess the degree of difference between two regions, for example, intensity [29], color [11] or both characteristics [20] of the image may be used.

In our case the contrast score of $q$ was based on color difference, measured by the Chi-square distance, which was used in [20]. For this purposes two regions were obtained: external region $A = \{a_j\}_{j=1}^n$ and internal $B = \{b_j\}_{j=1}^n$ (see Fig. 3). Then two histograms $H^A$ and $H^B$ computed on the quantized colors of all pixels in the regions $A$ and $B$ was obtained and normalized. With two histograms the final score was calculated as:

$$R(q) = \frac{\sum_{j=1}^{N_b} (H^A(j) - H^B(j))^2}{H^A(j) + H^B(j)},$$

where $N_b$ is a number of bins in each histogram.
C. Optimization of the combination coefficient

The combination coefficient of the two score functions was optimized on the training data. Let the training dataset consist of $M$ samples. For each sample the ground truth quadrangle $m$ and the $N$ alternatives $\{q\}$ as well as their contour $I$ and contrast $I$ scores is calculated. It is required to determine the combination coefficient $k$ at which the number of successful detection of a quadrangle according to the metric $L$ reaches a maximum:

$$k^* = \arg \max_k \sum_{i=0}^{M} L(q^*_i, m_i). \quad (4)$$

A solution to this problem is equivalent to finding all intervals on a line with maximal number of segment intersections.

In further experiments we used $k$, optimised on all images of MIDV-500 [10] dataset.

IV. EXPERIMENTS

A. Baseline quadrangles generation

For baseline set of quadrangles $\{q\}^N_{i=0}$ generation we used an algorithm derived from the classical contour/line method [12].

Let the image is portrait oriented. In [12] it was assumed that the objects’ borders in the image lie in known regions of interest. In our case, more relaxed restrictions on the permissible positions of the quadrilateral in the image were used – the opposite sides are either ”mostly horizontal” (tangent belongs to $[-1; 1]$) or ”mostly vertical” otherwise (assumption *). This assumption is taken into account on all stages of obtaining quadrangles. The result of edge extraction are two edge maps: with ”mostly horizontal” and ”mostly vertical” edges respectively. After that each edge map is blurred with a Gauss filter in a direction of gradient. The vertical edge map is divided into three equal parts by horizontal cuts before finding the strongest lines. This is done to improve the quality of detection of short sides. Then for obtaining line candidates from edge maps the Fast Hough Transform (FHT) [30] was applied. As a result of the line finding 15 extreme points from the horizontal FHT image and 45 from the vertical (15 from each part) were obtained. Next a brute-force search of two pairs of lines (vertical and horizontal) were performed. In [12] while searching for the best image of the rectangular object some geometry tests were checked, however in this paper they have not been used, due to the fact that our study primarily aimed to analyse the contour and contrast features. In the end, all quadrangles were sorted in the descending order of the contour score $I$ and the best $N$ were left.

B. Datasets and evaluation

All of our quality metrics were based on Jaccard index, which was used in SmartDoc challenge [31]. As was mentioned above, $q$ is a found (or predicted) quadrangle, $m$ is a ground truth image of a rectangle object and $t$ is a template of the rectangle object. Let $H'$ represents a homography such that $H'm = t$. Then Jaccard index between predicted and ground truth quadrangles calculates as follows:

$$JI(q, m, t) = \frac{\text{area}(q' \cap t)}{\text{area}(q' \cup t)} \quad (5)$$

where $q' = H'q$.

To check that the predicted quadrangle $q$ is correct or incorrect, quality metric $L(q, m, t)$ was used.

$$L(q, m, t) = \begin{cases} 1, & JI(q, m, t) \leq \gamma \\ 0, & JI(q, m, t) > \gamma \end{cases} \quad (6)$$

where $\gamma$ – threshold coefficient that equals 0.945.

We have tested proposed algorithms using 2 open datasets: MIDV-500 [10], which contains images with identification documents of different types and backgrounds, and SmartDoc [31], which was created specially for A4 page detection challenge. The first dataset, as it was mentioned above, contains of 15000 images or 500 video clips (10 clips for each of 50 unique identical documents), the ground truth quadrangle $m$ for each frame and information about the template sizes $t \in \{(856; 540), (1050; 740), (1250; 880)\}$. The feature of MIDV-500, that we want to draw attention, is that it does not guarantee that the document is entirely in the frame. So in our next experiments we consider several subsets of the images: first subset contains images in which all 4 vertices of the document lie inside the frame (9791 images), second subset contains images with at least 3 vertices inside the frame.
(11965 images) and the last one contains the entire MIDV-500 (all 15000 images).

In contrast to MIDV-500, SmartDoc [31] dataset has the guarantee that the document is fully inside the frame. This dataset has its own separation into subsets, in particular it has 5 subsets with different backgrounds: from the easiest one to the most complex.

And before we move on to the experiments we would like to note some implementation details. First, to reduce operating time, the original image resolution was decreased to $240 \times 427$. And second, in equation (3) the histograms with 512 bins (by 8 on each of RGB channels) were used.

$$\text{area}(M(q) \cup M(m)) + \text{area}(M(q) \cap M(m))$$

with $q$ and $m$ as the binary masks for the ground truth and predicted contours, respectively.

Fig. 3. Dependence of the system performance quality on $N$. The two compared versions are marked with red dots.

C. Results and analysis on MIDV-500

In the beginning of this paragraph we will evaluate the quality performance of our proposed algorithms on MIDV-500 and classify the errors in each case. Then we will measure the time performance on the mobile device.

The percentage of correctly [6] localised quadrangles while using only the contour score [2] on entire MIDV-500 was 71%.

All localisation errors can be divided into 4 classes: (i) less then 20% of at least one the ground truth quadrangle’s borders $b(m)$ is presented within the frame, (ii) no lines were found in the neighbourhood of $b(m)$, (iii) ranking system error and (iv) the assumption (*) is violated. Let us note that the errors of the third class are our target. The distribution of errors by class is as follows: 65% correspond to the first class, 15% to the second and 20% to the third. The percentage of the fourth class is negligibly small (2 errors). The number of errors for each first three classes while using only the contour score is shown in the first row of Table I.

Using the combined score (1) several experiments were performed with different numbers $N$ of considered alternatives. For each $N$ the optimal value of the combination coefficient $k$ was selected independently (par. III-C). As it was mentioned above, all 15000 images from the MIDV-500 were used for $k$ optimisation. With increasing of $N$ the quality also increases up to 73% until $N = 11$ (see Fig. 3). With large $N$ the quality changes only slightly, thus version with $N = 11$ was used for comparison with the contour score.

The number of errors while using the combined score decreased by 10% comparing to the total number of errors of the algorithm with contour score. More than 80% of all corrected errors belong to the target class (iii) (see the second row in Table I). The main achievement of this work is that by using combine score we managed to reduce the number of class (iii) errors by 40% (see the fourth row in Table I).

As it was expected the proposed algorithm were able to fix cases when following two conditions was performed: (i) the quadrangle with the highest contour score was formed by background lines and (ii) its difference between foreground and background was small (see Fig. 4a and 4b). More than that, the proposed algorithm sometimes was able to fix cases with strong background and foreground difference (see Fig. 4c) and cases with occlusion of the object (see Fig. 4d).

The runtime of the system was also measured on iPhone 6 in single-threaded mode. For this experiment, 100 random images from the dataset were selected. The system with only contour score required 82 ms per image, while the runtime of the system with the combined score of 11 alternatives was 88 ms per image, which is 6% slower.

D. Comparison with state-of-the-art

For comparison on MIDV-500 we have tested two algorithms which have an open access code. Both of them use neural network. In [22] recursive CNN for corner detection was applied. Pretrained model that we use in this experiment was optimised on SmartDoc dataset, so we were able to validate the results of our measurements. The second neural network from paper [25] is based on Unet architecture. Proposed model uses by an order less parameters then original Unet [33] and have similar quality performance of semantic segmentation on their synthetic private dataset. Unfortunately, in the paper there are no results of quality performance on an open dataset, so we were not able to validate the correctness of our experiments on MIDV-500 and SmartDoc.

To evaluate quality performance we used averaged across all frames Jaccard index (3).

Results of quality performance evaluation are illustrated in Table III. As we can see, our algorithm with modification reaches the highest quality performance. Low quality of other methods can be explained by the fact that we use pretrained models which did not see documents and background from MIDV-500.

Also we would like to compare our algorithm with system from [26]. It use Unet-like neural network with Fast Hough Transform layers. And unlike other works, they trained their model on the subset of MIDV-500 where at least 3 vertices are within the frame. Only in this experiment for the comparison we had to measure our algorithm quality performance by the average value across the subset of another variation of Jaccard index:

$$0.5 \left( \frac{\text{area}(M(q) \cup M(m))}{\text{area}(M(q) \cap M(m))} + \frac{\text{area}(M(q) \cup M(m))}{\text{area}(M(q) \cap M(m))} \right)$$

(7)
TABLE I

Comparison of two versions of the score function with error classification.

<table>
<thead>
<tr>
<th></th>
<th>(i) Out of frame</th>
<th>(ii) No line</th>
<th>(iii) Ranking err.</th>
<th>Total err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contour</td>
<td>2850</td>
<td>660</td>
<td>854</td>
<td>4366</td>
</tr>
<tr>
<td>Combined</td>
<td>2803</td>
<td>627</td>
<td>509</td>
<td>3941</td>
</tr>
<tr>
<td>Improvement</td>
<td>47</td>
<td>33</td>
<td>345</td>
<td>425</td>
</tr>
<tr>
<td>Relative improvement</td>
<td>1.65%</td>
<td>5.0%</td>
<td>40.4%</td>
<td>9.73%</td>
</tr>
</tbody>
</table>

Fig. 4. Example of resolved errors. Red quadrangle corresponds to the top contour alternative, blue one – to the top combined alternative.

TABLE II

Comparison with state-of-the-art on SmartDoc.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Background 1</th>
<th>Background 2</th>
<th>Background 3</th>
<th>Background 4</th>
<th>Background 5</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>[Our]: Contour</td>
<td>0.980</td>
<td>0.974</td>
<td>0.982</td>
<td>0.966</td>
<td>0.294</td>
<td>0.906</td>
</tr>
<tr>
<td>[Our]: Combined</td>
<td>0.983</td>
<td>0.974</td>
<td>0.983</td>
<td>0.970</td>
<td>0.319</td>
<td>0.910</td>
</tr>
<tr>
<td>SEECS-NUST-2 [22]</td>
<td>0.988</td>
<td>0.976</td>
<td>0.984</td>
<td>0.974</td>
<td>0.948</td>
<td>0.978</td>
</tr>
<tr>
<td>JCD+CSR [23]</td>
<td>0.988</td>
<td><strong>0.984</strong></td>
<td>0.983</td>
<td><strong>0.984</strong></td>
<td><strong>0.961</strong></td>
<td><strong>0.982</strong></td>
</tr>
<tr>
<td>GOP [21]</td>
<td>0.961</td>
<td>0.944</td>
<td>0.965</td>
<td>0.930</td>
<td>0.412</td>
<td>0.896</td>
</tr>
<tr>
<td>LRDE-2 [19]</td>
<td>0.905</td>
<td>0.936</td>
<td>0.859</td>
<td>0.903</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>LRDE-3 [20]</td>
<td>0.985</td>
<td>0.982</td>
<td>0.987</td>
<td>0.980</td>
<td>0.848</td>
<td>0.970</td>
</tr>
<tr>
<td>DBSCAN [32]</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Smart Engines [24]</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SmartDoc (Average) [31]</td>
<td>0.947</td>
<td>0.903</td>
<td>0.938</td>
<td>0.812</td>
<td>0.404</td>
<td>0.855</td>
</tr>
</tbody>
</table>

TABLE III

Comparison of quadrangle detection on MIDV-500. The results in the bottom part of the table are calculated by (7).

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>MIDV-500</th>
<th>MIDV-500</th>
<th>MIDV-500</th>
<th>MIDV-500</th>
<th>MIDV-500</th>
<th>MIDV-500</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4 vertices in</td>
<td>at least 3 in</td>
<td>full</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[Our]: Contour</td>
<td>0.968</td>
<td>0.955</td>
<td>0.861</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[Our]: Combined</td>
<td>0.972</td>
<td><strong>0.961</strong></td>
<td><strong>0.87</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEECS-NUST-2 [22]</td>
<td>0.739</td>
<td>0.705</td>
<td>0.626</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OctHU-PageScan [26]</td>
<td>0.403</td>
<td>0.374</td>
<td>0.319</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[Our]: Combined</td>
<td>-</td>
<td><strong>0.974</strong></td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HoughEncoder [26]</td>
<td>-</td>
<td>-</td>
<td>0.96*</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

where $M(.)$ is a binary mask with the same size as input image $I$. This metric takes into account not only the overlay of the object, but also the background. The algorithm from [26] had reached 0.96 by metric (7), while our algorithm with contrast score reached 0.974 (see, Table III). So we updated state-of-the-art performance on MIDV-500.

Let us consider the performance of the proposed algorithm on SmartDoc [31] dataset as well as all available statistics from algorithms that have their open published papers in Table II. As we can see both of our algorithms have competitive results on first 4 backgrounds. Cause of failure on the fifth part is complex: (i) low contrast of the document boundaries, especially in our scale, (ii) similarity of the internal and external region of the target document, (iii) presence of other documents within the frame with much stronger boundaries.
V. CONCLUSION

In this paper an improvement of a classical contour approach for the problem of document detection was proposed. In particular, a scoring function in a ranking of quadrangle candidates was modified in such a way that it takes into account not only contour characteristics but also the degree of difference between internal and external regions of the candidate. This reduced a number of the ranking errors by 40% on the one hand, and retained applicability on the mobile phones on the another. Also proposed algorithm was tested on the open source datasets. It has shown the highest quality on MIDV-500 dataset and competitive results on four out of five parts of SmartDoc dataset.

VI. FUTURE WORK

To increase the quality performance of our algorithm in the future works we are going to take into account geometric properties of the document and its interframe transformation in the video stream. Also we would like to test proposed modification with other contour-line methods of quadrangle detection.

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