Multi-Oriented Text lines Detection and Their Skew Estimation

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Abstract

There are some documents where text lines are not parallel to each other i.e. different text lines of a single page may have different inclinations (orientations) with the horizontal lines. To enhance the ability of document analysis system, we need text line extraction in multiple orientations. In this papers we propose a robust technique (a) to detect text lines of arbitrary orientation in a single document page, and (b) to detect skew angle of individual text line. We use here a bottom-up approach where the connected components are at first labeled. They are then clustered into word groups. Text lines of arbitrary orientation are segmented from the estimation of these word groups. From an experiment of 3045 text lines we obtained an accuracy of 97.7% by the proposed method.

1. Introduction

With the remarkable progress in computer technology, and with the rapid spread of OCR software and hardware, the computers aim to automatically recognize, read and store documents having very complex layout. In general, a document analysis system requires text line extraction before subjecting it to character recognition process. When the text lines in a document are parallel to one another a simple algorithms using global projection profile is good enough to identify them [3]. The 'Docstrum method' [4] based on nearest neighbor technique can also extract text lines of single orientation. But there are some documents where text lines are not parallel to each other. They have different inclinations. Examples of such documents are shown in Fig.1. Extraction of individual line in these documents is very difficult. Simple projection profile or Docstrum methods [4] will not work for these documents. Pieces of published work on this area are few. Goto and Asu [2] proposed a technique to identify such text lines where document image is split into some small sub-regions of constant width chosen randomly, and the local orientations are estimated in each sub-region. They tried to discriminate the number of possible orientations from the extended linear segment linking estimation on the sub-regions. This method has some limitations since it cannot handle variable sized text. Fletcher and Kasturi [1] proposed a method which can extract text lines in arbitrary orientations from region mixed with text and graphics. The character bounding box and the Hough transform are used in the method. Their method too can not handle text lines of arbitrary size since they assumed that the average height of the largest character is not greater than five times the average height of the smallest character. Also, the Hough transform may not detect desired peak if the components in a document are sparsely distributed. Recently, we proposed a robust multi-skew detection techniques for two Indian scripts Bangla and Devnagari [5]. Most Bangla and Devnagari characters have horizontal line at the top. When two or more characters sit side by side to form a word, these horizontal lines touch and generate a long line called 'Matra' or Shirorekha. Detection of Matra/Shirorekha and its orientation gives orientation of script. This method will not work on English because of the absence of Matra/Shirorekha.

In this paper, we propose a robust technique which extracts English text lines of arbitrary orientations with variable sizes and styles, and detects the skew of individual text line. Here individual text lines are assumed straight in arbitrary orientation. The procedure is as follows. At first, connected component labeling is done. Next, characters of individual words are grouped based on a size independent association rule. Next, grouping of words with respect to individual lines is done based on the normal distance among the base-lines (reference line) of grouped words.

2. Component grouping technique

Since characters in English text are mostly isolated, our method starts with component labeling. During component labeling, lowermost point, the left candidate point, right candidate point and the component height for

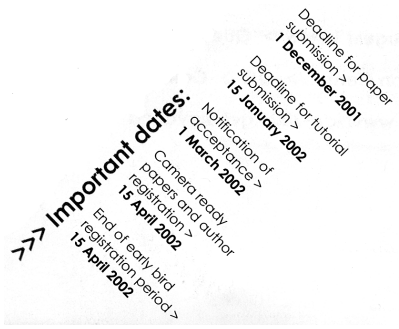
each labeled object are computed for faster processing in future steps. If multiple lowermost pixels are there then the leftmost one is chosen as lowermost point of the component. Left (right) candidate point of a component is the intersection point of the leftmost (rightmost) column and lowermost row of the component. In other words, left and right candidate points of a component are two lower corner points of the bounding box of the component. Candidate points (marked by small circles) of two characters 'T' and 'o' are shown in Fig.2. Based on these candidate points and the height of the components, labeled components are merged into groups of individual words. For a group two *anchor* components (left and right anchor components) are maintained and average height (H) of the components in the group is computed. The left (right) anchor component is the leftmost (rightmost) component of the group.

The grouping is done as follows. First, an arbitrary component is chosen (here we choose the topmost component of the document) and a group is formed using this component. Initially, the left anchor component and right anchor component are set as the same because the number of component in this group is only one now. Next, for grouping a component, say C, we check (a) whether at least one of the candidate points of the component is situated in the candidate region (candidate region is described later) of an existing group and (b) whether the height of the bounding box of C is greater than half of H of the group. If for the component C the above conditions are satisfied by an existing group G_i, then C is merged with G_i. The anchor components and the average height of the components of the group G_i are modified, accordingly. Otherwise, a new group is created by the component C.

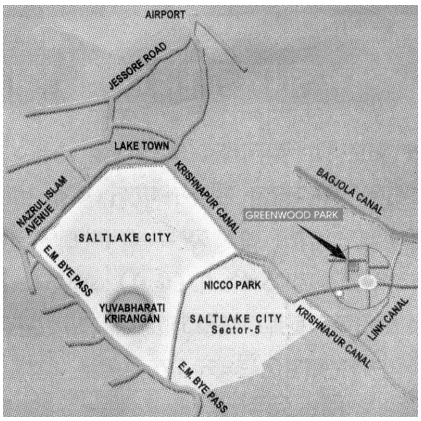
Modification of anchor components is done as follows. If the left candidate point of C is in the right side of the left candidate point of the right anchor component of the group G_i then C is assigned as the right anchor component of G_i. Similarly, modification of left anchor component is done if the left candidate point of the newly included component is in the left side of the left candidate point of the left anchor component of the group.

In a similar way, the grouping of all the components of the document is done. Generally, we get N groups if there are N words in a document.

Note that components like dots of 'i' and 'j', comma(,) and fullstop (.) etc. are not included in the word grouping because of their smaller height. These components will be kept as isolated components. Because of the size independent technique, which is dynamic in nature, we are able to isolate these small components. If we use average height of all components of a document as a threshold for component selection then we may be able to isolate these dots and punctuation marks but some components with smaller height may also be isolated if a document contains text line of variable size. For example, see Fig.1(c). Here all components of the word 'institute' will be isolated along with the dots and fullstop if we consider all components of the document for average component height computing.



(a)



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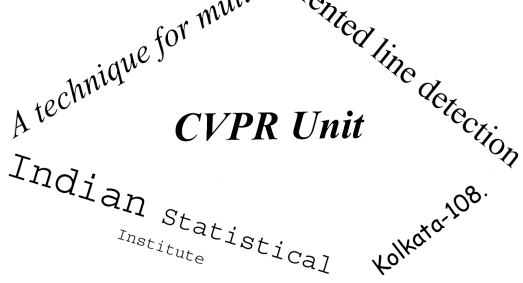

(c)

Fig.1: Examples of multi-oriented documents (a) from ICPR-2002 call for papers (b) from map (c) synthetic document.

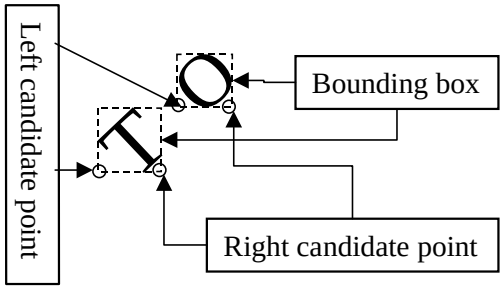

Fig.2: Candidate points of two characters are shown.

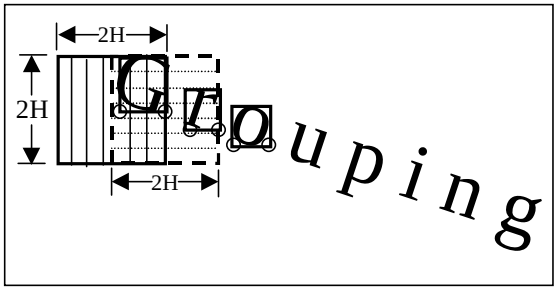

Fig.3: The approach of candidate region detection

Candidate Region detection:

From left candidate point of the left anchor component of a group, a H neighborhood (a square of side 2H, H is the average height of the components in the group) is selected considering the left candidate point as centre. H neighborhood of the right candidate point of the left anchor component is also selected. These H neighborhoods of the two candidate points of a group are the candidate region of the left anchor component of the group. Similarly, candidate region selection of the two candidate points of the right anchor component is done. The candidate region of the left anchor component 'G' of a word 'Grouping' is shown in Fig.3. Here candidate region for the left (right) candidate point is shown by solid (dotted) lines. Note that the area of candidate region is not same always. Depending on the present average height of the components of a group the candidate region is selected. Because of this dynamic nature our proposed method can handle text lines of arbitrary size and orientations.

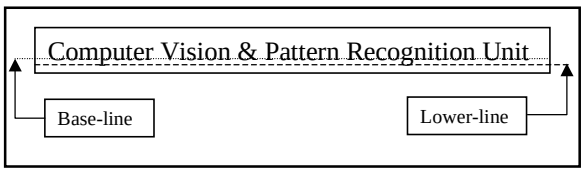

Fig.4. Base-line is shown.

3. Proposed line extraction techniques.

Our line identification approach is based on the detection of base-lines of word groups. Base-line of a text line is shown in Fig.4. If a text line is horizontal then its base-line extraction is very simple. The imaginary line which passes through the maximum number of lowermost points of the components is the base-line. If a text line is not horizontal then its base-line detection is difficult. Here we propose a robust technique for base-line detection of a line segment of arbitrary orientation. Take lowermost points A and B of any two components of a group and find the perpendicular distances of the lowermost points of the other components of the group from the line AB. If AB is the base-line then generally we can group these distances into two classes. Length of distances of one class will be very small (nearly zero). This will happen for those characters whose lowermost points lie on or near the line AB. Length of distances of other class will be higher because of the characters having descender. Individual variance of these two classes of distances will be nearly zero, and hence the sum of these variances will be nearly zero. For an illustration see Fig.5. The word image shown in this figure has six characters and hence we can get ${}^{6}C_{2}$ =15 combination of two characters. We compute the variance of the distances obtained by considering two components of each of these combinations as A and B. The combination for which sum of individual variances of the two classes will be minimum is noted and the line passing through the lowermost points of the components of this combination is the base-line. For example, consider the lowermost points of two components 'u' and 'e' of Fig.5(a) as A and B. The line drawn through A and B is shown in Fig.5(a). Length of perpendicular distances of the lowermost points of the other components are shown by small line segments. It can be noted that these length of perpendicular distances of different characters can be grouped into two classes. Length of one class of such distances is very small. This small distance is available because of the characters 'u', 'r', 'e' and 'l'. The other type of distances are obtained for the characters 'p' and 'y' of the line. If we compute variance of this individual class it will be nearly zero. Thus, the line through the line A and B is the base-line. If we consider the lowermost points of 'p' and 'y' then also we get two classes of distance with zero individual class variance (see Fig.5(b)). Thus, the line passing through lowermost points of 'p' and 'y' of Fig.5(b) may also be considered as base-line. It may be noted that in Fig.5(a) the line passes through two characters without descender and in Fig.5(b) the line passes through the two characters with descender. Thus, the line passing through two characters without descender or the line passing through

two characters with descender will be treated as base-line. The line passing through two characters of which one of them has descender will not be considered as base-line because in this case we will get different distances for different characters in the group (as shown in Fig.5(c)) and we cannot group these distances into two classes of nearly zero variance. Although we may get two base-lines (as discussed above) we consider the line which is above the other as the actual base-line. Thus the line passing through the lowermost points of two components 'u' and 'e' of Fig.5(a) will be considered as the base-line.

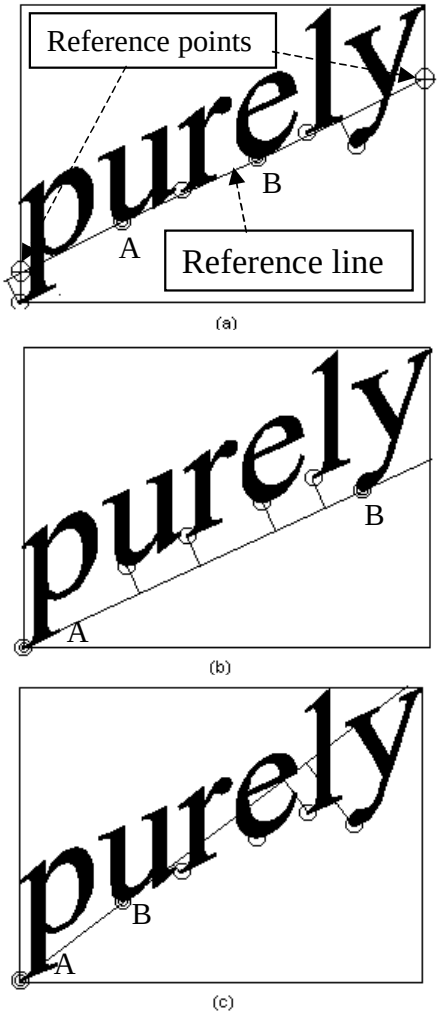

Fig.5: The approach of base-line (reference line) detection.

This base-line is extended both-ways in such a way that its two ends lie on the bounding box of the group. We call this extended base-line as *reference line*. The leftmost and rightmost extreme points (we call these points as reference points) of this line are stored for future use. Thus for a group we have a reference line and two reference points. The reference line and reference point of a group is marked in Fig.5(a). Let S be the set of all such reference lines (RL) obtained from individual groups.

Note that if there are three components in a group then by the above definition, a line obtained by any two points may behave as a base-line. To get rid of such situations we consider only those groups having 4 or more characters. Groups of 3 or less components will be considered as isolated groups.

To extract individual text lines, we have clustered the members of S corresponding to individual text lines. The clustering of S into groups of individual text lines is done as follows. Let C_L be the reference line of S obtained from a group having maximum number of components. From C_L or its continuation find the perpendicular distances to the left and right reference points of other RLs in S. The RLs corresponding to the text line containing C_L will have nearly equal distances from both the reference points. The RLs obtained from this criteria can be clustered in terms of these distances.

The co-ordinates of the left reference point (x_{lc},y_{lc}) of the leftmost group and the right reference point (x_{rc},y_{rc}) of the rightmost group of each cluster are also maintained for future convenience. To get the next cluster corresponding to another line, same procedure is used on S omitting those RLs which have already been clustered from S. At the end, K clusters are usually produced if there are K text lines in the document.

The clustering approach may be viewed as filling parametric space bins as in the Hough transform. For a reference line of S, perpendicular distances of its two reference points are computed from the C_L. Those RLs for which the distance of both the reference points is less than D are placed in a bin along with C_L. At the same time, the co-ordinates of the left reference point (x_{lc},y_{lc}) of the leftmost group and the right reference point (x_{rc},y_{rc}) of the rightmost group of individual clusters are updated accordingly. For example, suppose a new group q enters in an existing cluster, say E, with left reference point (x_{lc},y_{lc}) and right reference point (x_{rc},y_{rc}) of a text line. If the left reference point (x_q, y_q) of q is to the left of (x_{lc},y_{lc}) of E i.e. if $x_q < x_{lc}$ then we make $x_{lc} \leftarrow x_q$, and $y_{lc} \leftarrow y_q$. Else, no modification is done. The right reference point (x_{rc},y_{rc}) of the cluster E is treated similarly. The angle of the line joining (x_{lc},y_{lc}) and (x_{rc},y_{rc}) with the horizontal direction is computed to get the angle of orientation of the individual text line.

The value of D can be estimated as follows. For most text documents, the character size is not smaller than 6 points. Then, the minimum spacing between two lines is 6 points (single spacing). If the document is digitized at p dpi then the minimum distance between two text lines

will be p× 6/72 pixels = p/12 pixels (since 72 points = 1 inch). For a document digitized at 300 dpi, we get minimum distance between two text lines as 300/12 = 25 pixels. Based on this estimation we choose the value of D as 25.

Now we merge all the isolated component (elements of isolated groups are also considered as isolated components) which are not considered earlier for grouping. For isolated component merging we follow three steps. In the first step we check whether the middle point (by middle point of a component we mean the middle point of the bounding box of the component) of an isolated component falls in the Core Area (CA) of a cluster or not. By CA of a cluster L we mean the rectangular region bounded by four lines L_b, L_t, L_l, L_r, where L_b is the reference line of L, L_t is parallel to L_b and passing through the top of the component having highest bounding box height among all components in L. L_l (L_r) is the line perpendicular to L_b and passing through the left (right) candidate point of the group. These four lines of a group is shown in Fig.6. If the middle point of an isolated element falls in CA of a cluster we merge the isolated element with that cluster. For example, in Fig.6 isolated component 'a' and isolated group 'is' fall in the CA of the first line and hence we merge them with the line. Note that except 'a' and 'is' other words of this line are merged in a single cluster by the clustering technique stated above. In the second line isolated component 'A' does not fall in its CA. In the second step we compute the normal distance of the lowermost point of the components (which are not grouped by the first step) to the reference lines of the existing clusters. If the distance of an isolated component is less than the height of the CA of a cluster then the component is marked as a possible candidate for merging with that cluster. If a component is marked by two or more clusters for possible merging candidate we proceed for the third step. Else, the component is merged with the respective cluster. In the third step we merge a component by nearest neighbor principle from CA. We compute Euclidean distance of the lowermost point of the component from the CA of each cluster. The component is merged with that cluster from which this distance is minimum. To compute the distance of a component from a cluster we compute Euclidean distance of the lowermost point of the component from the four corner points (shown by small circle in Fig.6) of the rectangular CA of the cluster. Minimum among these four distances is the distance of the component from the cluster. For example, the component 'A' of the second line of Fig.6 is identified by the two lines as the distance of the lowermost point of this component from the reference lines of the two lines is very small. By nearest neighbor technique this component is merged with the second line.

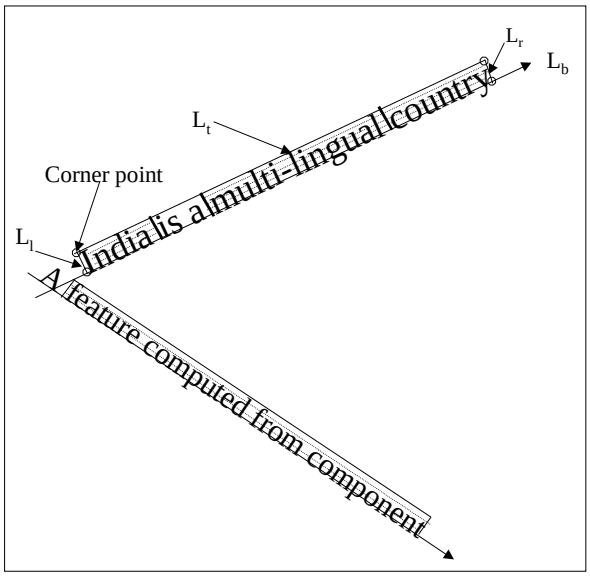

Fig.6. Isolated elements grouping. Words of a line cluster are marked by dotted lines.

Algorithm:

1. Find connected components in the binary document image and compute the lowermost point, left and right candidate points of each component.
2. Make initial grouping of the components.
3. For each initial group find its reference-line by the procedure discussed above. Form the set S of reference lines.
4. Compute the longest reference line in S. Let the longest reference line in S be C_L.
5. From the line C_L or its continuation find the perpendicular distances to the two reference points of other reference lines of S. Let d_{il} and d_{ir} denote these distances for the reference points of i-th reference line. Select the reference lines for which $|d_{il}| \prec D$ and $|d_{ir}| \prec D$. The word groups corresponding to these selected reference lines are clustered for individual text line.
6. Find the leftmost reference point (x_{lc},y_{lc}) of the leftmost group and the rightmost reference point (x_{rc},y_{rc}) of the rightmost group of an individual text line.
7. Consider the rest of the reference line of S which have not been clustered. If no reference line remains in S go to step 8. Else, go to Step 4 and execute the same procedure on the remaining reference lines in S.

8. For each individual text line cluster find the angle of the line obtained by joining two reference points (x_{lc},y_{lc}) and (x_{rc},y_{rc}) with the horizontal direction. This gives the skew angle (angle of orientation) of an individual text line.
9. Merge isolated elements with their respective text lines by the procedure discussed above.

4. Results and Discussion

For experiment, 3045 text lines were considered from different documents like magazines, newspapers, advertisements, computer printouts etc. Both the single and multi-oriented documents were considered for experiment. Among these 3045 text lines 810 lines were taken from multi-oriented documents (like Fig.1) and 2235 lines are from single oriented documents (where all text lines of a document have similar orientation). The images were digitized by flatbed scanner at a resolution of 300 dpi. For the experiment we consider single column document pages.

To check whether text lines are extracted correctly or not we connect all components of individual cluster by line segments (as shown in Fig.7). These lines are drawn through the mid point of the components of the clusters. By viewing the results on the computer display we check the line extraction result manually. If all components of a text line are extracted by the algorithm we say line extraction is correct. From the experiment is it observed that overall accuracy of the proposed method is about 97.7%. Distributions of results on single and multi-oriented text lines are shown in Table 1.

Table 1: Distributions of the results:

Document type	Data size (in lines)	Correctly extracted line	Accuracy
Multi-oriented	810	769	94.9%
Single oriented	2235	2208	98.7%
Total	3045	2977	97.7%

From the experiment we also note that most of the errors occur due to one or two characters having ascenders or descenders.

We also noted that our angle detection technique can detect the angle of orientation of each line with a tolerance of $\pm$ 0.5 degree in 98.2% cases.

One of the significant advantages of the proposed method is its flexibility. Our scheme is independent of font, size and style of the text line. For the flexibility testing, text lines with different popular fonts, sizes and styles (bold and italics) were considered. An example is shown in Fig.7. From the Fig.7, it can be noted that some text lines in this figure have different sizes, fonts, and styles. Also, we consider different word with different sizes within a single line, as it can be seen from the figure. There was no effect of these on our scheme.

The main draw back of the proposed method is that it can not extract a text line properly if the total number of components in the text line is two or less. But in real documents this situation is rare.

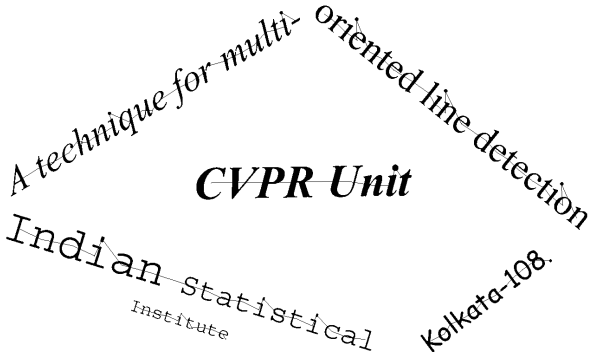

Fig.7: The line extraction result of the image shown in Fig. 1(c).

At present our method can not handle mixed text graphics documents automatically. In future we plan to develop a more general system to handle mixed text-graphics and curved text documents.

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