ICR DETECTION IN FILLED FORM & FORM REMOVAL

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Abstract: This paper presents methods to enhance accuracy rates of ICR detection in structured form processing. Forms are printed at different vendors using a variety of printers and at different settings. Every printer has its own scaling algorithm, so the final printed forms though visibly similar to naked eyes, contains considerable shift, expansion or shrinkage. This poses problems when data zones are close together as the template reference points refer to the neighbouring identical zones, impeding data extraction accuracy. Moreover, these transformational defects result in inaccurate form removal leaving behind line residues and noise that further deteriorates the extraction accuracy. Our proposed algorithm works on filled forms thereby eliminating the problem of difference between template and actual form. Template data can also be provided as an input to our algorithm to increase speed and accuracy. The algorithm has been tested on a variety of forms and the results have been very promising.

1 INTRODUCTION

World over, paper-based forms are a popular medium for capturing data in a concise, organized and consistent manner. However, for this data to be used and subjected to further analysis, it has to be converted into the electronic form. This can be done either manually or through automatic form processing (Liu et al., 1995). Manual data entry is excessively time consuming and error prone. Automatic form processing is fast and cost effective but the results are rarely 100 percent accurate. Automatic form processing solutions work best on structured forms. Structured forms are static forms that have precisely defined page layouts such that templates can be built to geometrically identify and extract needed data.

In traditional template-based approach (Mathur et al., 1999) for structured form processing, the template serves as the reference to specify the location of the data fields to be captured from each form. This approach uses vector distances of data zones from some artefacts on the template, known as registration marks, to locate the data fields on the filled form. This approach works fine when the quality of printed forms and scanning is very good. In practical scenario, neither holds true. Forms are printed from different printers at different points in time and scanning is done in large batches at different scan stations. This introduces multiple distortions such as broken lines, skew, noise, black borders, shrinkage/expansion, and shifting between template and filled form. Some of these distortions like noise, skew and black borders can be removed using a number of available techniques (Pitas et al., 1990) (Chih-Hong et al., 200) (Shi et al., 2003) (Le et al, 1996). But in the presence of other distortions like broken lines, shrinkage/expansion, and shifting, reference vector distances of template cannot be used to accurately locate data fields (Fig. 1).

Contents of a typical form are barcodes, OCR, ICR and OMR data. OCR (Optical Character Recognition) generally involves recognition of machine printed characters. ICR (Intelligent Character Recognition) is an extension of OCR, which explicitly includes handwritten characters. OMR (Optical Mark Recognition) entries are in the form of a check mark, a cross or a scribble. Of these, ICR data extraction is very challenging as ICR engines work best on small and accurate zones. These zones should not contain noise, line residuals or static text like legends; otherwise it will hamper the recognition rate. The most desirable situation is providing the ICR engine with only the ICR characters. Therefore, form removal becomes a very

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important step for ICR data extraction. Previous systems relied on colored dropout boxes to remove the form, but this needs the form to be printed in color, which substantially increases the cost. If printing and scanning quality is good and consistent, template data can be used for form removal. However, in presence of distortions as described earlier, form removal is achieved by line detection and removal from the filled form. ICR cells are rectangular boxes present on the forms that serve as guideline for the users to properly fill data in the boxes. In most of the cases, characters written by users are touching the bounding boxes or cutting across two boxes. Line removal becomes a daunting task in presence of boundary-touching characters. If parts of character are erased, or if there are leftover line residuals, the ICR engine may give erroneous results.

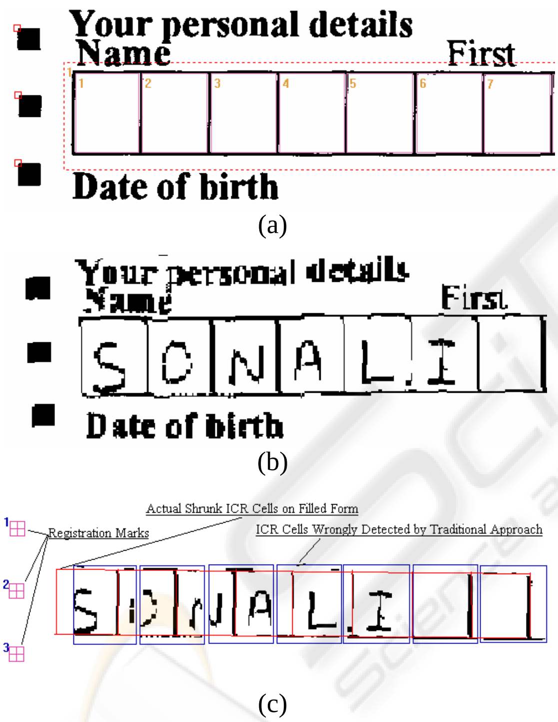


Figure 1: Traditional Template Based Approach (a) Registration marks and ICR cells defined on Template (b) Shrunk ICR cells present on the filled form (c) ICR cells not formed out properly due to a slight shrinkage in the filled form.

In this paper we present a novel algorithm to overcome these two problems. ICR cell detection, and line removal with character preservation is done on filled forms to substantially increase the accuracy rate. The algorithm has been tested and verified on multitudes of form data, and the processing time involved has been found to be considerably less.

The remainder of this paper is organized as follows: Section 2 discusses the ICR cells detection algorithm using an improved line detection algorithm; Section 3 talks about accurate form removal and ICR character preservation; and we present some results and conclusion in Section 4.

2 ICR CELLS DETECTION

Locating ICR cells on filled forms having distortions using traditional template-based approach (Mathur et al., 1999) is unfeasible. ICR detection technique, which was only applied on templates before is now to be applied on filled forms also.

ICR cells are generally present as a collection of multiple ICR cells. They can be described by some common characteristics such as minimum width and height, equidistant lines and L-shaped corners. ICR cells are detected using equidistant, orthogonal nodes formed by intersecting lines.

ICR detection is far more complex on filled forms than on templates. Filled characters in ICR cells give a false impression of ICR cell due to detection of spurious lines in them. ICR characters generally cut across cells or touch ICR cell boundaries. This gives rise to the following three problems:

1. Bounding lines of the ICR cell are not detected at all.
2. During form removal, part of the character gets removed.
3. Line residue is left.

Our algorithm is aimed at handling each of the above-mentioned problems and achieving better extraction accuracy. Line detection plays an important role in ICR cells detection. A number of line-detection algorithms have been proposed (Illingworth et al, 1998) (Rosito Jung et al., 2004) (Zheng et al., 2003) in the past but most of these algorithms are either too slow for large sized documents or do not necessarily support line removal. After much research we selected line-detection algorithm (Gattani et al., 2003). This line-detection algorithm, apart from being fast and accurate, can also be used for high precision line removal. Using this algorithm, lines connected or intersected by characters can also be easily detected and removed. Lines are detected using a set of specifications that are obtained in the form of user input and is known as *hyposet*. The algorithm represents a line using *accumulators*, *collections* and *buckets*. Each line is formed by small *segments* of continuous black-pixel runs along the same scan line. These *segments* are stored in the *accumulators* and the *collection* of such segments that form a line is known as a *bucket*. A *bucket* holds information about the whole of the line such as the average thickness, skew and orientation. Using these *accumulators*, *collections* and *buckets* we generate an exact bitmap of the line that can be used for further analysis while performing line removal.

Some changes were made to the line detection algorithm (Gattani et al., 2003) to suit our needs. These changes are aimed at better line detection/removal and character preservation after line removal. A new specification is added to the *hyposet*, known as minimum *segment length*, as it was observed that the '*minimum line length*' was insufficient for accurate detection of lines. Segment length is used to detect even jagged lines in the form (Fig. 2). The algorithm is also modified to preserve characters (Yoo et al., 1995) that are cut by lines while removing lines. Previously, when these detected lines were removed using (Gattani et al., 2003), the characters were broken and the ICR engine's accuracy was reduced. To overcome this, smearing of the line-surrounding neighbourhood is done with a threshold equal to the thickness of the line. Horizontal smearing is done for vertical line as is vertical smearing for horizontal lines. This is followed by OR-ing this with the original image. This achieves character preservation (Fig. 3).

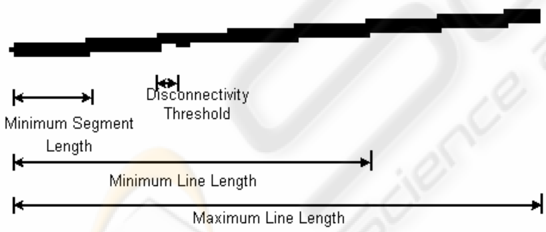
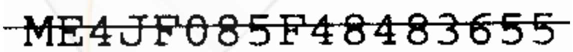
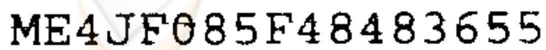


Figure 2: Minimum segment length in line specifications.



(a)



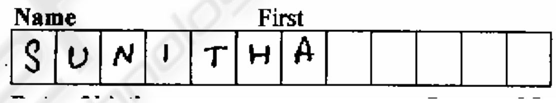
(b)

Figure 3: (a) Characters cut by lines (b) Characters get preserved after line removal using improved line removal algorithm.

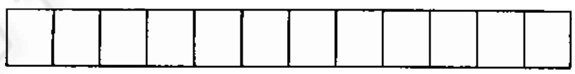
Template information, if provided, can improve the performance and accuracy of the algorithm. Template information will generally be in terms of number of cells, coordinates, minimum width and height of the ICR cells, average thickness of lines, etc.

2.1 Algorithm

As the first step, we smear the image, both horizontally and vertically, by a resolution-dependent threshold so as to join the broken components. An eight-neighbour connected component-labeling algorithm (Dillencourt et al., 1992) is then used to get the connected components. We create a bitmap of each component for further processing (Fig. 4). Further analysis is done on the component bitmap as doing so helps us eliminate all the character components that lie inside the ICR cells and are not touching the ICR cell boundaries. This helps in eliminating most of the spurious lines detected in the characters that might confuse or complicate our ICR cell-detection analysis.



(a)



(b)

Figure 4: (a) ICR cells on the filled form to be detected (b) Component Bitmap of ICR cells obtained by connected component labelling.

Candidate components for ICR cells are defined as those components that have dimensions greater than the minimum ICR cell width and height. For each such candidate component, we detect lines on that component's bitmap using the improved line detection algorithm (Fig. 8(c)).

Once we have all the lines information of the component, we assume that the component is an ICR cell, and filter lines based on the characteristics of ICR cells. First, we estimate the average width and height of the ICR cells using the equidistant lines and equidistant orthogonal nodes formed by them. Average width and height of ICR cells obtained from template can be directly used, if available. In ICR cells, the valid boundary lines must all lie at a distance of average width from their predecessor. Using this fact and the average width and height, we determine the valid ICR cell lines (Fig. 8(d)). All other invalid lines are rejected at this stage. Once we have the valid lines and the nodes formed by them, we verify whether the lines and the nodes form a valid ICR cell. To verify the ICR cell, the type and orientation of each node is determined (Fig. 5).

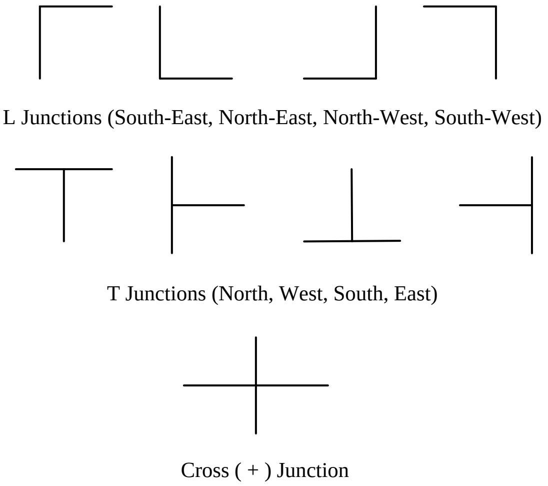


Figure 5: Different types and orientations of nodes.

Based on type, orientation of each node and distance between successive nodes, ICR cells are determined.

In case some of the ICR cells are distorted and are not detected, we estimate them using the template information and Tied Strings probabilistic estimation approach (Mathur et al., 1999). To estimate the ICR cells, first we determine the *scaling factor* (SF) between template and filled form. SF is the ratio of average width of ICR cells on template to that on the filled form. SF is calculated by

$$SF = \left(\sum_{i=1}^{n} W^t_i / n \right) / \left(\sum_{j=1}^{m} W^f_j / m \right)$$

where

n is the number of ICR cells detected on template.

m is number of ICR cells detected on filled form. (m < n and n-m cells are to be estimated).

W^t_i is width of i^{th} ICR cell of template.

W^f_j is width of j^{th} ICR cell of filled form

Each detected ICR cell on filled form is mapped onto the corresponding ICR cell on template using SF and vector distances to determine the corresponding unmapped cells of the filled form (Fig. 6).

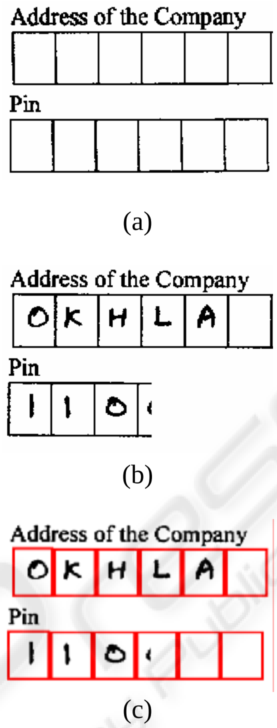
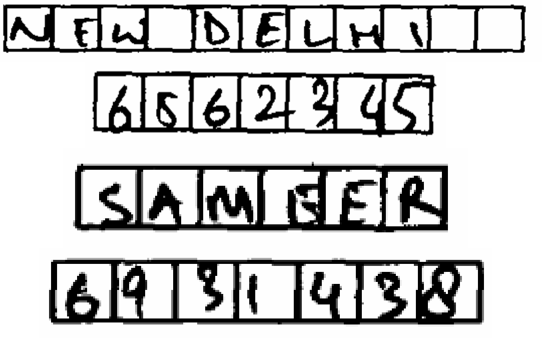


Figure 6: (a) ICR cells present on the template (b) Some of the ICR cells not present on the filled form (c) ICR cells on the form are estimated and properly formed out using template information.

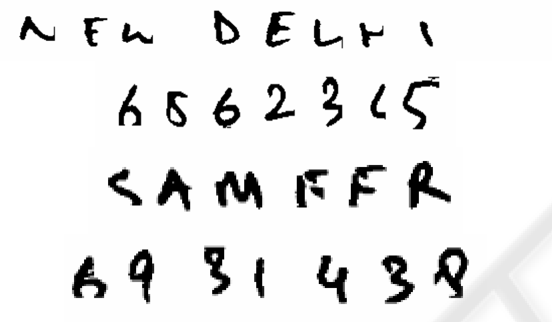
3 FORM REMOVAL

After detection of ICR cells, the next task is form removal. Form removal is the task to properly remove ICR boundary lines (Yoo et al., 1995) so that final image contains only ICR characters for better ICR extraction. We do this by traversing the accumulators given by improved line removal algorithm. However, the algorithm may still remove some parts of ICR characters that are touching ICR cell boundaries. Also, the line removal algorithm may leave some line residues.

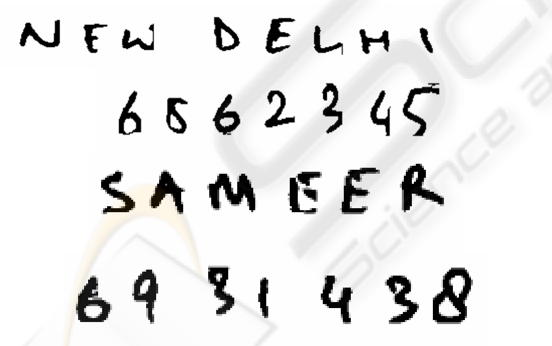
To prevent erosion of touching characters, we use the information of valid ICR lines. First of all, we try to detect those lines that are attached to characters. To do so we remove the valid ICR lines from the component bitmap using *accumulators*, *collections* and *buckets*. On this updated component bitmap, we do component labeling to find the connected components. These components are the part of the characters attached to the ICR cell boundary (Fig. 8(e)). We scan the original and updated component bitmap one row at a time to select the lines that are attached to the ICR character components, the direction of attachment (i.e. left, right or both for vertical lines or top, bottom or both for horizontal lines) and projection profile of each line on both directions using the *accumulators*.



(a)



(b)



(c)

Figure 7: (a) Filled ICR cells (b) Form Removal after ICR detection without character preservation (c) Form Removal after ICR detection with character preservation. Note that no line residue is left in both the cases.

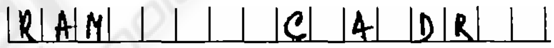
We now have two disjoint sets C and U of lines, one having lines that are connected to the characters (C) and other having the ones that are Unconnected (U). We have to reduce the thickness of each line of set C so that the part of the character attached to it is not removed. To do so, we first determine the maximum thickness of lines of set U. Then we update the *accumulators* and corresponding *bucket* of each line of set C from the direction opposite to the direction of attachment. In case the direction of attachment is both, we have to preserve the character present on the critical side. Critical side is decided on the basis of the standard deviation of projection profile for both directions. The side having more standard deviation is always the critical one (Fig. 7).

Finally, we remove small line residues by applying eight-neighbour connected component labeling and removing very small, noise-like components that are close to the ICR boundaries (Fig. 8(f), 8(g)).

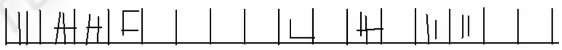
4 RESULTS AND CONCLUSION

The intermediary results and the flow of the algorithm are summarized below through pictorial depiction.

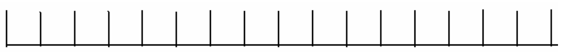
(a) ICR cells on a filled form



(b) Component Bitmap of ICR cells obtained by connected component labeling



(c) Lines detected on component bitmap



(d) Filtered lines on component bitmap

(e) Filtered lines removed from component bitmap to preserve characters

(f) Filtered lines finally removed from original image after preserving characters

(g) Bitmap after form removal. Line residues removed

Figure: 8 Results during intermediate stages in our algorithm.

We tested our algorithm on a mix of several educational and business forms containing different types of ICR cells used in different layouts. Our batch consisted of 918 different images, which were further divided into two separate sets based on whether template information is present. We used Newgen OmniExtract Form Processing Engine to run our tests. Caere engine was used for ICR.

On a batch size of 500 images, structured form processing approach was followed that used template information. We tested using both the approaches; the traditional vector distance mapping and our proposed approach. The image dataset had a collection of images with skew (+ 3 degrees), shift and shrinkage. Out of the 500 images, 10% of the set had images that contained broken or missing cells and required estimation. We recorded a 77% improvement in data extraction using the proposed algorithm. We calculated the number of correctly extracted ICR cells for both the approaches to get a measure of the improvement in data extraction. The improvement was due to the accurate ICR cell detection and estimation and better form removal (Fig. 8).

On a batch size of 418 images, we followed the unstructured form processing approach by passing the whole image to our engine as input without any template information. The results were again very promising with a total data extraction accuracy percentage of 97.9%.

The experiment results show that our approach, even when not using the template information, brings in highly accurate data extraction results when compared to the traditional form processing approach. The result also underscores the fact that the proposed solution can be applied to unstructured form processing where ICR cells can be detected and used for document understanding, classification, and segmentation.

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