

# An Automatic Closed-Loop Methodology for Generating Character Groundtruth for Scanned Documents

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**Abstract**—Character groundtruth for real, scanned document images is crucial for evaluating the performance of OCR systems, training OCR algorithms, and validating document degradation models. Unfortunately, manual collection of accurate groundtruth for characters in a real (scanned) document image is not practical because (i) accuracy in delineating groundtruth character bounding boxes is not high enough, (ii) it is extremely laborious and time consuming, and (iii) the manual labor required for this task is prohibitively expensive. In this paper we describe a closed-loop methodology for collecting very accurate groundtruth for scanned documents. We first create ideal documents using a typesetting language. Next we create the groundtruth for the ideal document. The ideal document is then printed, photocopied and then scanned. A registration algorithm estimates the global geometric transformation and then performs a robust local bitmap match to register the ideal document image to the scanned document image. Finally, groundtruth associated with the ideal document image is transformed using the estimated geometric transformation to create the groundtruth for the scanned document image. This methodology is very general and can be used for creating groundtruth for documents in typeset in any language, layout, font, and style. We have demonstrated the method by generating groundtruth for English, Hindi, and FAX document images. The cost of creating groundtruth using our methodology is minimal. If character, word or zone groundtruth is available for any real document, the registration algorithm can be used to generate the corresponding groundtruth for a rescanned version of the document.

**Index Terms**—Automatic real groundtruth, document image analysis, OCR, performance evaluation, image registration, geometric transformations, image warping.

## 1 INTRODUCTION

CHARACTER groundtruth for real, scanned document images is crucial for evaluating the performance of OCR systems, training OCR algorithms, and validating document degradation models [5], [10], [9], [6]. Unfortunately, manual collection of accurate groundtruth for characters in a real (scanned) document image is not practical because:

- 1) accuracy in delineating groundtruth character bounding boxes is not high enough,
- 2) it is extremely laborious and time consuming, and
- 3) the manual labor required for this task is prohibitively expensive.

In this paper, we present a closed-loop methodology for collecting very accurate groundtruth for scanned document images.

Although work on document registration has been reported in the past, most of this literature pertains to the case where a fixed

ideal form has to be registered to a scanned, hand-filled form. The general idea is to extract the information inserted by a human in the various fields of the form. A common method is to extract features from the scanned forms and match them to the features in the ideal form [1], [2]. Unfortunately, we cannot use this body of work since there are no universal landmarks that appear at fixed locations in each type of document. Image registration is also studied in the area of sensor fusion where the objective is to align images of 3D scenes taken from different sensors [13]. The work reported here was presented at ICPR96 [7]; more recently, others have used optimization methods to match images [4].

## 2 THE GROUNDTRUTH GENERATION METHODOLOGY

In the document image analysis community, *groundtruth* refers to the correct identity, location, size, font (Helvetica, Times Roman, etc.), language, and bounding box coordinates of the individual symbols on the document image. More global groundtruth associated with a document image could include layout information (such as zone bounding boxes demarcating individual words, paragraphs, article and section titles, addresses, footnotes, etc.) and style information (general information regarding number of columns, right justified or not, running head, etc.). The groundtruth information, of course, needs to be 100 percent accurate, otherwise the systems being evaluated or trained are penalized incorrectly.

Our groundtruth generation method is as follows:

- 1) Generate ideal document images and the associated character groundtruth. We accomplish this by starting with documents typeset in LaTeX, creating the corresponding bitmap images, and generating the ideal groundtruth from the DVI files. Any other typesetting system can be used instead.
- 2) Print the ideal documents and then scan them again.
- 3) Find corresponding feature points  $p_1, \dots, p_n$  and  $q_1, \dots, q_m$  in the ideal and real document images.
- 4) Establish the correspondence between the points  $p_i$  and  $q_j$ .
- 5) Estimate the parameters of the transformation  $T$  that maps  $p_i$  to  $q_j$ .
- 6) Transform the ideal groundtruth information using the estimated transformation  $T$ .

The transformation  $T$  mentioned in the procedure above is a  $2D$  to  $2D$  mapping—that is,  $T: R^2 \rightarrow R^2$ . Thus, if  $(x, y) = T(u, v)$ , where  $(u, v)$  is the ideal point and  $(x, y)$  is the scanned point,  $x$  in general may be a function of both  $u$  and  $v$ ; and same is true regarding  $y$ .

Generation of the ideal document image and the corresponding groundtruth is achieved by the synthetic groundtruth generation software DVI2TIFF, which was described in [5], [10]. The software is available with the UW English Document Database [3]. Given a transformation  $T$ , transforming the groundtruth information is trivial—all that needs to be done is transform the bounding box coordinates of the ideal groundtruth using the transformation  $T$ . Thus, there are two main problems: finding corresponding feature points in two document images, and finding the transformation  $T$ .

## 3 ESTIMATION OF GEOMETRIC TRANSFORMS

Suppose we are given the coordinates of feature points  $p_i$  on an ideal document page, and the coordinates of the corresponding feature points  $q_j$  on the real document page. (How these feature points are extracted and matched is described in Section 4.) The problem is to hypothesize a functional form for the transformation  $T$  that maps the ideal feature point coordinates to the real point coordinates, and a corresponding noise model. To ensure that the transformation  $T$  is the same throughout the area of the document page, we choose the points  $p_i$  from all over the document page.

The possible candidates for the geometric transformation and

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pixel perturbation are similarity, affine, and projective transformations. In this article we describe the projective transform; a discussion of affine and similarity transforms can be found in [8].

We assume that the real image is a perspective projection of an image on a plane onto another nonparallel plane. The functional form that maps the ideal point  $(u, v)$  onto the real point  $(x, y)$  is

$$\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \frac{1}{w_i} \begin{pmatrix} a_1 u_i + b_1 v_i + c_1 \\ a_2 u_i + b_2 v_i + c_2 \end{pmatrix} + \begin{pmatrix} \eta_i \\ \psi_i \end{pmatrix} \quad (1)$$

where  $w_i = a_3 u_i + b_3 v_i + 1$ ,  $(u, v)$  is the ideal point,  $(x, y)$  is the transformed point,  $(\eta, \psi)^t \sim N(0, \sigma^2 I)$  is the noise, and  $a_1, b_1, c_1, a_2, b_2, c_2, a_3, b_3$  are the eight transformation parameters. Since there are eight unknowns, we can solve for them using the least squares method if we have at least four corresponding points. This parameterization accounts for rotation, translation and the center of perspectivity parameters. In the above discussion,  $\sigma$  can be assumed to be known and a function of the spatial quantization error and the image processing algorithm that is used to detect the feature points.

If there are  $n$  corresponding points, the projective transformation equations given in (1) can be rearranged as  $\mathbf{y} = \mathbf{A}\mathbf{p} + \mathbf{W}\mathbf{n}$  where  $\mathbf{y} = (x_1, \dots, x_n, y_1, \dots, y_n)^t$ , the parameter vector  $\mathbf{p} = (a_1, b_1, c_1, a_2, b_2, c_2, a_3, b_3)^t$ ,  $\mathbf{n} = (\eta_1, \dots, \eta_n, \psi_1, \dots, \psi_n)^t$ ,

$$\mathbf{A} = \begin{bmatrix} u_1 & v_1 & 1 & 0 & 0 & 0 & -u_1 x_1 & -v_1 x_1 \\ u_2 & v_2 & 1 & 0 & 0 & 0 & -u_2 x_2 & -v_2 x_2 \\ \vdots & \vdots \\ u_n & v_n & 1 & 0 & 0 & 0 & -u_n x_n & -v_n x_n \\ 0 & 0 & 0 & u_1 & v_1 & 1 & -u_1 y_1 & -v_1 y_1 \\ 0 & 0 & 0 & u_2 & v_2 & 1 & -u_2 y_2 & -v_2 y_2 \\ \vdots & \vdots \\ 0 & 0 & 0 & u_n & v_n & 1 & -u_n y_n & -v_n y_n \end{bmatrix}$$

$\mathbf{W}$  is the diagonal weight matrix  $\text{diag}(w_1, \dots, w_n, w_1, \dots, w_n)$ ,  $(u, v)$  are the ideal points,  $(x, y)$  are the transformed points on the scanned image, and  $w_i = a_3 u_i + b_3 v_i + 1$ . The weighted least squares estimate of the parameter vector is given by  $\hat{\mathbf{p}} = (\mathbf{A}^t \mathbf{W}^{-2} \mathbf{A})^{-1} \mathbf{W}^{-1} \mathbf{y}$ .

Since the  $w$ s are initially unknown, we can solve for  $\mathbf{p}$  iteratively: Initialize  $\hat{\mathbf{p}} = \mathbf{0}$  and then in each iteration compute  $\mathbf{W}$  using the estimate of  $\mathbf{p}$  from the previous iteration.

#### 4 FINDING CORRESPONDING FEATURE POINTS

In a document image with text, figures, and mathematics, there are no universal feature points in the interior of the document that are guaranteed to appear in each type of document. However, most documents have a rectangular text layout, whether they are in one-column format or in two-column format. We use the upper-left (UL), upper-right (UR), lower-right (LR), and lower-left (LL) corners of the text area as feature points.

The four feature points  $p_1, \dots, p_4$  are detected on the ideal image as follows (assume the origin at the top left corner of the image and a row-column coordinate system).

- 1) Compute the connected components in the image.
- 2) Compute the upper-left ( $a$ ), upper-right ( $b$ ), lower-right ( $c$ ), and lower-left ( $d$ ) corners of the bounding box of each connected component.
- 3) Find the four feature points using the following equations:

$$p_1 = \arg \min_{a_i} (x(a_i) + y(a_i))$$

$$p_2 = \arg \max_{b_i} (x(b_i) - y(b_i))$$

$$p_3 = \arg \max_{c_i} (x(c_i) + y(c_i))$$

$$p_4 = \arg \min_{d_i} (x(d_i) - y(d_i))$$

Integrating indefinite sum variables were proposed [20]. Implemented in MACSYM acts occurring in the analysis [21].

In section, we introduce the for the stability analysis (role of symbolic computation) the objects concerning Section III In Section IV

Fig. 1. A scanned image with groundtruth overlaid. A perspective transform was used to register the ideal document image to the scanned image. It can be seen that there is a large error in the groundtruth.

The above equations compute the upper-left ( $p_1$ ), upper-right ( $p_2$ ), lower-right ( $p_3$ ), and lower-left ( $p_4$ ) feature points on the ideal image.

The above algorithm is also used to compute the corresponding four feature points  $q_1, \dots, q_4$  on the real image. Since sometimes noise blobs can appear in a real image, we check to see that the bounding box sizes of the components are within a specified tolerance. Furthermore, a potential problem can arise when two bounding boxes have their corners on a 45 degree line. A transformation  $T$  can be estimated using the corresponding points  $p_1, \dots, p_4$  and  $q_1, \dots, q_4$  by the methods described in Section 3.

#### 5 REGISTRATION RESULTS ON SCANNED IMAGES

The geometric transformation described in Section 3 does not model the transformation very accurately. That is, there is a nonlinear displacement between the real points and the ideal transformed points. To investigate further, we drew a rectangle on a blank image, and then printed and scanned it. The opposite sides of the scanned figure were no longer equal in length. In fact, all four sides were of different length, suggesting a projective transform, which could arise because the image plane and the original document plane are not parallel to each other. If the projective transform does not model the transformation adequately, the mismatch must arise from nonlinearities in the optical and mechanical systems. These nonlinearities could be either in the printer, the photocopier, the scanner, or in any combination of the three. We suspect that the nonlinearities in the sensor motion account for most of the mismatch. Small perturbations around the nominal position could be due to spatial quantization.

In Fig. 1, we show a subimage of a scanned image with the groundtruth (character bounding boxes) overlaid. We see that there is a lot of error. This error is not systematic over the entire page.

To confirm the fact that there are nonlinearities in the printing-photocopying-scanning processes, we set up a calibration experiment and performed a statistical test to prove that the projective transform alone does not model the transformation adequately. In the experiment we created an ideal calibration image consisting of only "+" symbols arranged in a grid. We printed this document and then scanned it back. The crosses in the ideal image were then matched to the crosses in the scanned image. This set of corresponding points were then used to estimate the geometric transform parameters. The sample mean and sample covariance matrix of the registration error vectors were then computed. Since the population mean and population covariance matrix of the error vectors can be theoretically derived, we tested whether the theoretically derived distribution parameters are close to the experimentally gathered sample parameters. The calibration experiment is described in [8], [5]. In Fig. 2, we show the images used in the calibration experiment.

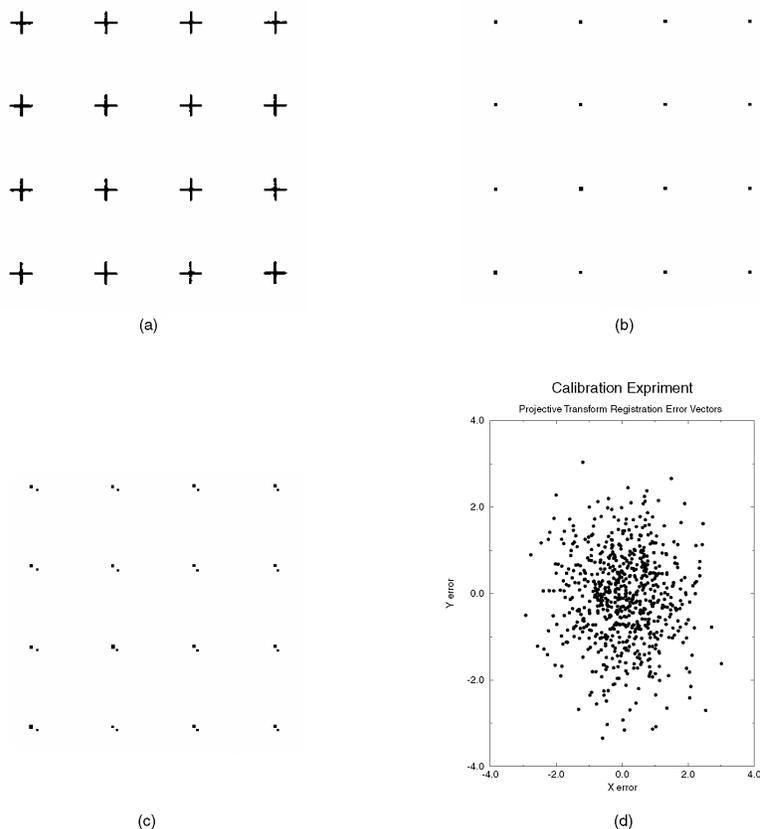


Fig. 2. (a) A subimage of the scanned calibration document. The detected calibration points are shown in (b). (c) The ideal calibration points are transformed using the estimated projective transformation and overlaid on the real calibration points. (d) A scatter plot of the error vectors computed between the real calibration points and ideal calibration points after they have been transformed using the estimated projection parameters.

## 6 DEALING WITH NONLINEARITIES

Due to nonlinearities in the scanning process, the estimated groundtruth bounding boxes for the characters in a scanned image are not correct. Our solution to this problem is as follows. We first transform the ideal document image using the perspective transformation. The groundtruth associated with the ideal image is also transformed using the estimated perspective transform parameters. Next, each character bitmap in the perspective transformed image is locally translated and matched (using Hamming distance) with a same-size subimage in the scanned document image. Thus, if the nonlinearity gives rise to a (2, 3) translation error in pixels, our template matching process gives the best match (minimum Hamming distance) when the translation is (2, 3). The size of the search window is decided by the calibration experiment. If the error vectors are large, the search window is made large. This local search process gives us a highly accurate groundtruth, and the potential errors are within a pixel.

## 7 DEALING WITH OUTLIERS: ROBUST REGRESSION

At times, when two very similar characters (for example, two "i"s or one "i" and one "l") are physically close to each other, the template matching process can match the perspective transformed character to the wrong scanned character. This typically happens if we use a large search window size. This means that the error translation vector associated with the wrongly matched character is off. Our procedure for detecting such outliers is as follows. Once the error vectors are computed, we can fit a multivariate function to the  $x$  and  $y$  translation errors associated with characters in a small area of the image. We assume that within this small area the error vectors do not vary much. Next we perform a robust regres-

sion, detect the outlier error vectors, and then correct them. For the regression we use a piece-wise bilinear function. A discussion of bilinear function fitting and image warping can be found in [15].

Let the function  $f: R^2 \rightarrow R^2$  be an image-to-image nonlinear function. We are given the ideal calibration points  $p_1, \dots, p_n$  and the corresponding observed points  $q_1, \dots, q_n$ . That is,  $q_i = f(p_i) + \eta$ . The problem is to construct a piecewise bilinear function that approximates  $f$  in the sense that

$$\sum_{k=1}^n \|q_k - f(p_k)\| \quad (2)$$

is minimized.

The piecewise bilinear function is represented as follows. First, a grid of points  $g_{ij}$ , with  $i = 1, \dots, l$  and  $j = 1, \dots, m$  on the first image are identified. The grid points are such that the  $y$ -coordinates of the points along any row of grid points are the same and the  $x$ -coordinates of points along any column of grid points are the same. That is,  $y(g_{ij}) = y(g_{ik})$  for  $j = 1, \dots, m$ ,  $k = 1, \dots, l$ . Furthermore, there is a natural ordering of the grid point coordinates:  $x(g_{ij}) < x(g_{i+1,j})$  and  $y(g_{ij}) < y(g_{i,j+1})$ . Note that the number of grid points is much less than the number of calibration points:  $l \times m < n$ .

We represent the nonlinear function  $f$  by representing the transformation on the grid of points  $g_{ij}$ . Let  $g_{ij} + \Delta g_{ij}$  be the grid point after the function  $f$  transforms the grid point  $g_{ij}$ . Let the point  $p$  lie within a grid cell whose four corner grid points are  $a = g_{ij}$ ,  $b = g_{i+1,j}$ ,  $c = g_{i+1,j+1}$ ,  $d = g_{i,j+1}$ . The transformation of the point  $p$  is then approximated as follows. Let

$$t = (x(p) - x(a)) / (x(b) - x(a)), \quad (3)$$

$$s = (y(p) - y(d)) / (y(d) - y(a)). \quad (4)$$

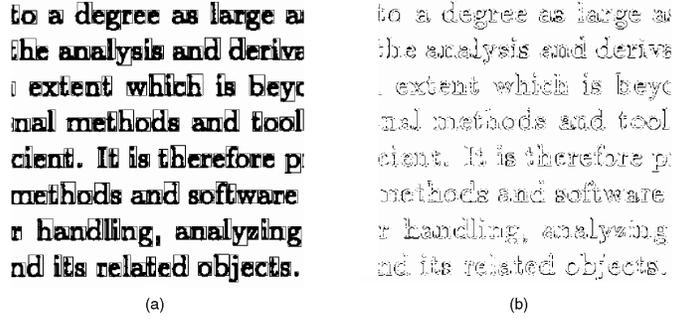


Fig. 3. Groundtruth for real documents. (a) A subimage of a document with the estimated bounding boxes of each character. (b) The result of exclusive-OR between the real document and the registered ideal document. The exclusive OR image shows that the groundtruth for each character is centered on the character and the differences are at the character edges. These differences, due to the image point spread function of the printing and scanning, are what is expected.

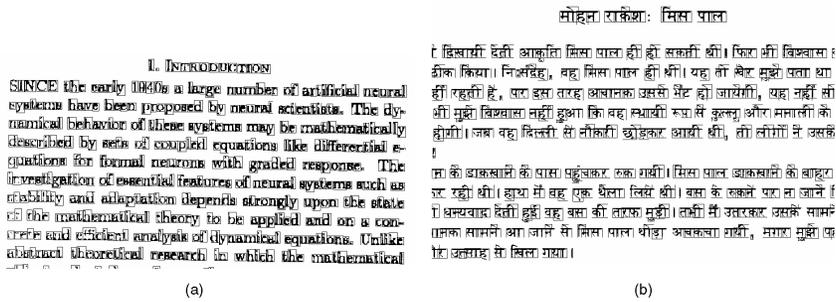


Fig. 4. (a) A subimage of a faxed document with the groundtruth overlaid. Notice that the characters in the bottom left of the image are hardly legible. Manual groundtruth for these type of documents would be prone to errors. In contrast, our software has produced correct groundtruth without any error. (b) A subimage of a LaTeX formatted Hindi document in Devanagari script with the groundtruth overlaid. The bounding boxes of the symbols are overlapping because the Devanagari symbols are arranged in that manner.

Then the point  $q = f(p) + \eta$  after transformation is given by

$$q = p + (1-t)(1-s)\Delta a + t(1-s)\Delta b + ts\Delta c + (1-t)s\Delta d + \eta, \quad (5)$$

where  $\Delta a = \Delta g_{i,j}$ ; and  $\Delta b, \Delta c,$  and  $\Delta d$  are defined similarly.

Let  $a_k, b_k, c_k, d_k$  be the corner points of the grid cell within which the point  $p_k$  lies, and let  $t_k$  and  $s_k$  be constants calculated using (3) and (4). Equation (2) can be stated as: Find  $\Delta a_k, \Delta b_k, \Delta c_k, \Delta d_k$  that minimize

$$\sum_{k=1}^n \left\| q_k - \left[ p_k + (1-t_k)(1-s_k)\Delta a_k + t_k(1-s_k)\Delta b_k + t_k s_k \Delta c_k + (1-t_k)s_k \Delta d_k \right] \right\| \quad (6)$$

In the above equation, out of the  $n \times 4$  elements  $\Delta a_k, \Delta b_k, \Delta c_k, \Delta d_k, k = 1, \dots, n$ , only  $l \times m$  elements are unique. For example,  $\Delta c_9$  and  $\Delta d_{20}$  both might represent the same grid point variation,  $\Delta g_{4,5}$ :  $\Delta c_9 = \Delta d_{20} = \Delta g_{4,5}$ . We can now give unique labels to the grid differences, set up a system of linear equations, and solve for the unique elements in a least squares sense.

## 8 EXPERIMENTAL PROTOCOL AND RESULTS

### 8.1 Data Collection

The ideal data is a LaTeX formatted document [11], [12]. For the English documents, the IEEE Transactions style is used for typesetting the document Hindi documents. in Devanagari fonts are formatted using public-domain LaTeX macros [14]. The ideal binary image and character ground truth is created using the DVIT2TIFF software. The ideal document is created at  $300 \times 300$  dots/inch resolution and the size of the binary document in pixels is  $3,300 \times 2,550$ . This document is printed using a SparcPrinter II. Next, the original printed document is photocopied five times

using a Xerox photocopier—once at the normal setting, twice with darker settings, and twice with lighter settings. Finally, the five photocopied documents are scanned using a Ricoh scanner. The scanner is set at  $300 \times 300$  dots/inch resolution. The rest of the scanner parameters are set at normal settings. The scanned binary image is of size  $3,307 \times 2,544$ .

### 8.2 Protocol for Generating Real Groundtruth

Once the real scanned documents have been gathered as described in the previous section, we use the registration algorithm described in Section 1 to:

- 1) transform the ideal binary documents so that it registers to the scanned document and
- 2) create the groundtruth corresponding to the scanned document.

The transformed groundtruth also forms the groundtruth for the transformed ideal document. The local nonlinearities of the transformation are accounted for by searching in a local neighborhood for a good match between the ideal character symbol and the real character symbol. The local template match window size is determined by the calibration experiment we performed earlier. Since the maximum error in the registration is  $\pm 4$  pixels, we used a window with  $-7 \leq \Delta x, \Delta y \leq 7$ . The groundtruth generated by our algorithm is highly accurate.

### 8.3 Results and Discussion

In this section, we show a few sample outputs of our automatic groundtruth generation algorithm. A subimage of the scanned image with the overlaid bounding box is shown in Fig. 3. An exclusive or-ed image of the real scanned document and the registered ideal document is shown in Fig. 3. The exclusive OR images shows that the groundtruth for each character is centered on the

character and the differences are at the character edge. These differences due to the image point spread function of the printing and scanning are what is expected. The time needed for this procedure on a Sun Sparc 5 is two minutes.

In Fig. 4a, we show automatically generated groundtruth for a faxed document. In this case the ideal bitmap was generated on the computer and then printed. The printed document was then faxed and the fax output was scanned using a Ricoh scanner. It is interesting to note that in many cases even though the scanned documents are highly degraded, our algorithm produces the correct groundtruth.

Finally, in Fig. 4b, we show a Hindi document written in Devanagari script. The document was typeset in LaTeX using macros made available by Frans Velthuis (velthuis@rc.rug.nl). We can see that our methodology is general enough to handle documents in any language. We have also used this methodology to groundtruth Arabic and music documents [5].

In addition, we used the groundtruth generation software to groundtruth 33 English document pages consisting of over 62,000 symbols. The algorithm takes about five minutes to groundtruth each page on a Sun Sparc 10. Some of these documents had numerous mathematical equations.

A few of the limitations of our algorithm are:

- 1) It is sensitive to the feature points that are used for registration; more robust methods need to be explored.
- 2) If the scanned image is from a bound book, our procedure will not perform well.
- 3) The population of documents one can generate by printing and scanning ideal documents is a subset of the population of document images in the real world.

## 9 SUMMARY

In this paper, we have presented a closed-loop method for producing character groundtruth for real document images. The method starts by generating ideal noise-free document images using document typesetting software like LaTeX. These binary document images are printed, photocopied/faxed, and then scanned. Feature points are extracted from the ideal and the scanned document images, and their correspondences established. We showed that the projective transformation alone cannot be used to represent the transformation between the ideal and the scanned documents. This fact was confirmed by using test images specially designed for calibration, and verifying that the statistical distribution of the registration errors is not what the theory predicts. The local nonlinearities that exist are accounted for by performing a local template match using the ideal character as the template, and searching a small neighborhood in the real image for the best match. The size of the local search neighborhood is decided by the calibration experiment. The calibration experiment gives us the maximum deviations that can occur between the ideal feature points after they have been transformed using the estimated transformation and the feature points on the scanned image. We used this methodology to groundtruth 33 documents consisting of over 62,000 symbols. The procedure took approximately five minutes to groundtruth each page on a Sun Sparc 10. Furthermore, we used the method to groundtruth Hindi documents without any modification to our procedure. If character, word, or zone groundtruth is available for any real document, the registration algorithm can be used to generate the corresponding groundtruth for a rescanned version of the document.

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