EDGE ENVELOPE BASED RECONSTRUCTION OF TORN DOCUMENT

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ABSTRACT

The paper proposes a new algorithm for reconstruction of torn document ripped-up by hand using a unique feature, E*dge Envelope*. The essence of the paper is to match the edges using high curvature points and edge variations as human visual system does while reconstructing the document. Moreover the ambiguity created during the matching of edges due to shearing can be overcome by smoothing the edge envelopes using a filter. Further, a newly defined parameter *Normalized Edge Envelope Difference* can be used as an effective quantitative measure for matching the edges of torn pieces, which exploits property of human visual system. The effectiveness of the algorithm is demonstrated through preliminary results by taking limited amount of torn pieces.

Keywords

Track-Map, Corner Points, Edge Envelope, Normalized Edge Envelope Difference.

1. INTRODUCTION

Recovery of ripped-up document is a problem that often arises in archival study, forensics, defence and investigation sciences. Document may be ripped-up by hand or shredded by a machine [14]. The reconstruction of a torn or shredded document is a puzzling, complex and painstaking task to be performed by a human operator, and often becomes intractable even for a small number of fragmented pages. In both cases, the automatic reconstruction of the original document is a challenging task. In this paper, we deal with automatic reconstruction of torn document ripped-up by hand.

In case of machine shredding of pages, each fragment piece of paper has straight edge only and hence the problem may be considered as a variety of jigsaw puzzle [13]. But the reconstruction of torn document by hand is considerably different from the referred jigsaw problem [13]. This is because, a paper when torn creates uneven edges bearing undesired shears containing tiny paper fibers, which gives rise to ill-defined physical contours when compared to jigsaw puzzle which have smooth edges with well defined corners. The method reported in [12] has a priori knowledge of outer frame of the puzzle and strict restrictions on the shape of the puzzle pieces. In [13], it is assumed that there exist four corner points for the canonical jigsaw puzzle piece, and the piece boundary curve can be separated into four edges at the four corner points. In the case of document fragments, however, there are no restrictions on the shapes of the fragments and corners are usually hard to identify. The act of ripping often produces irregularities in the fragment contours, which make it difficult to get a perfect curve matching [4, 10]. Moreover, no a priori knowledge about the original content exists for the document reconstruction. Further, due to limitations in the imaging mechanism, the torn piece after being scanned may contain digital imperfections and unpredictable rigid transformations [1]. In that case, the unevenness of the torn edges pose severe problem in automatic reconstruction of a document.

In literature, many methods [10, 14] use polygonal approximation to represent the contours of the torn pieces as a preprocessing phase. The matching of the torn pieces is done through partial curve matching using turning function [14] or matching the edges of the torn pieces using the space-domain parameters [1, 10] like Chain Code, Chain Length, Euclidean Distance. Further, [8] deals with reconstruction of ripped-up documents using fragment stack analysis with the assumption that, the relative stacking order of torn pieces is never changed neither during the tearing process, nor during the on-site recovery, nor during transportation etc. Nevertheless, approaches like this might be interesting for small sized instances provided the on-site recovery is perfect, i.e., almost no change in stacking order of torn pieces, but in most cases there will be too many concurrently arising issues [6].

In the proposed scheme, the matching of edges is through time-domain parameter *edge envelope* rather than space-domain parameters and is independent of stacking order. Most of the document reconstruction procedure involves three phases: Preprocessing, Feature extraction and Matching. Among these, second and third phases i.e., feature extraction and matching are very crucial and time consuming. Reducing the processing time by restricting to only one unique feature rather than relying on many features and resolving the ambiguity in matching of edges due to shearing is the key approach of this paper.

The paper is organized as follows: Section 2 discusses the proposed algorithm in detail. Section 3 deals with results and discussions followed by conclusion and future work in Section 4.

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2. PROPOSED ALGORITHM

The proposed algorithm has four phases as shown in Fig. 1. Initially, each piece of ripped-up document is pre-processed to obtain single pixel width contour. Then, a feature *edge envelope* is extracted from contour in order to carry out the matching and joining process. In the following section, we describe each of the phases in detail.

2.1. Preprocessing Phase

The aim of the preprocessing phase is to estimate outline/contour of the torn pieces. The application of conventional algorithms like canny, sobel, prewitt which work on gray level images results in unwanted details (like edges of the text, image etc.) present within the torn piece in addition to the required contour as in Fig. 2 (a). These unwanted details make the tracking of the outlier/contour difficult. Hence, the scanned image of torn piece is converted to binary image before applying conventional edge detection algorithm.

The torn piece is scanned such that it is well within the boundary of the scanned image. This makes sure that the background is well estimated and it is used for computation of a threshold value using histogram [2]. The computed threshold is used to binarize the image. The binary image is then passed through canny/sobel edge detector to get the single pixel width contour. From Fig. 2 (b) it is observed that, the proposed way of getting the contour is free from multiple and spurious contours compared with that of direct application of edge detection algorithms (Fig. 2 (a)).

The scanned image of each torn piece P_t, t = 1,2,3,…,p, where p

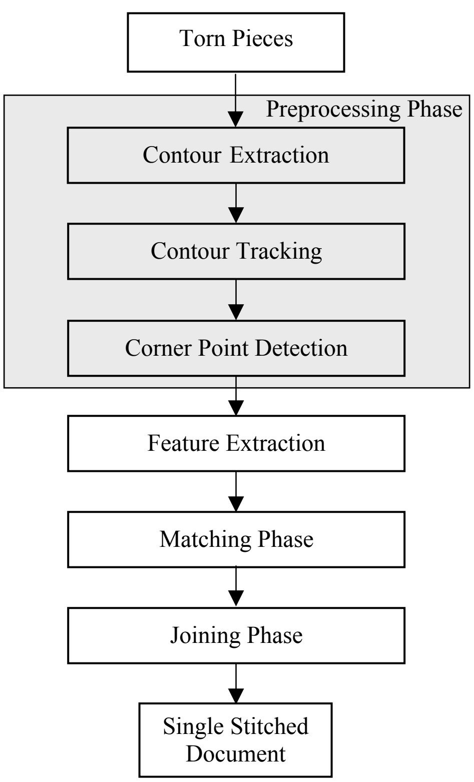

Fig.1 Overview of the Proposed Algorithm.

Fig. 2 (a) Contour extracted using Canny Edge Detector
(b) Contour extracted after Binarization

is total number of torn pieces, is converted to binary image. The binary image is then passed through canny/sobel edge detector to get the single pixel width contour C_t. The coordinate locations of points on a contour C_t are very important information in pattern recognition and other applications. They can be obtained by using a contour tracking algorithm. It scans an image from left to right, and up to down to locate the first point on a given C_t as the tracking point. Once the first point has been located, then 8-connected neighbors are checked in clockwise to find the next tracking point. This procedure is repeated until all the points on C_t have been traced. The contour C_t can then be expressed in terms of track-map T_t which has coordinate locations of points on a contour C_t.

To match the torn pieces it is required to extract each edge of the torn pieces. The extraction of edges is based on points with high curvature values or with discontinuity of the slopes, because of their significance in visual perception [5]. These high curvature points are extracted using corner detection algorithms. Among the different corner detection algorithms like Bending value [11], Harris [3], SUSAN [9], Bending value method is used in this approach. Because, the calculation of bending value only requires (integer) addition, subtraction, and comparison operations, thus it is simple in computation.

Corner point detection using bending value involves break point detection and it's bending value computation. The point under consideration is a break point if it doesn't form a straight line with its two immediate neighboring points. By this, points which form a straight line are eliminated thereby reducing the competitors for corner points. Hence, it is more efficient than those algorithms evaluating all the points on a given curve and involving more complex computations, such as division and tangent operations [11].

In this approach, instead of computing break points after extraction of T_t, it is computed during extraction of T_t. The extracted break points are used to find the bending value as in [11]. Now the break point with maximum bending value is considered as the probable candidate for corner point.

The above procedure of corner point detection results in many unwanted corners (Fig. 3), which creates a lot of ambiguity at matching phase of the torn pieces. These spurious corners are removed if the angle at the corner point between the corners

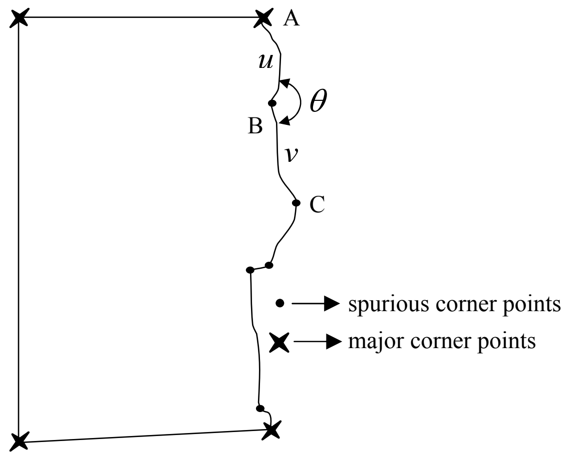

Fig. 3 Removal of spurious corner points.

exceeds a predefined threshold. From Fig. 3, the angle at the corner point B is calculated using the following equation,

$$\theta = cos^{-1}\left(\frac{u\,.\,v}{|u||v|}\right) \quad \ldots (1)$$

where, u is a distance vector between present corner point B under consideration and its immediate previous corner point A.
v is a distance vector between present corner point B under consideration and its immediately following corner point C.

In conventional methods, a polygonal approximation [7] is applied to each contour as a preprocessing step. It is a nonparametric and a recursive method to get the best representation of the contour [10, 14]. This recursive nature of polygonal approximation makes the contour tracking complex compared to the method discussed in present section, which is a non recursive.

2.2. Feature Extraction

Human visual system is one of the most sophisticated and versatile systems in nature. This complicated system uses the edge variations of torn pieces for matching with its counterpart. This concept of human visual system is groundwork for the proposed feature extraction.

In the feature extraction phase, the edge variation between the two corner points is captured and is referred as *Edge Envelope*. From

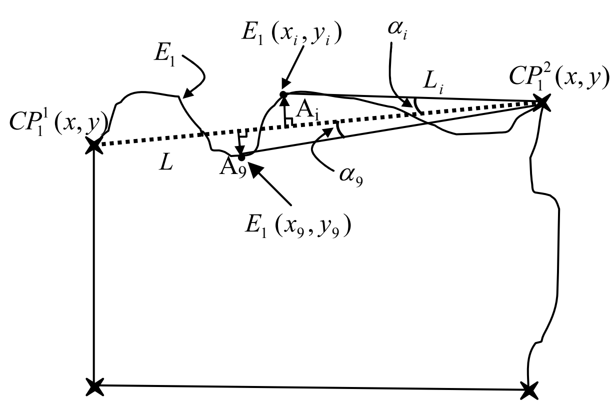

Fig. 4 Edge Envelope Extraction.

Fig. 4, CP_1^1 and CP_1^2 are the two corner points of piece P_1, L is the line joining these two corner points, E_1 is the edge between these two corner points and the points along the edge E_1 are denoted by $E_1(x_i, y_i)$, where i varies from 1 to total number of points t_p defining the edge. The mapping of the two-dimensional spatial co-ordinate points $E_1(x_i, y_i)$ to its one-dimensional *Edge Envelope* is as follows:

1) Consider a straight line L between two corner points $CP_1^1(x, y)$ and $CP_1^2(x, y)$. Further, L_i is a straight line between two points $CP_1^2(x, y)$ and $E_1(x_i, y_i)$.

2) In order to capture the edge variations, the *perpendicular distances* A_i between straight line L and the points $E_1(x_i, y_i)$ corresponding to edge E_1 are computed using following Eqns. (2) and (3).

$$\alpha_i = \tan^{-1}\left(\frac{CP_1^2(y) - CP_1^1(y)}{CP_1^2(x) - CP_1^1(x)}\right) - \tan^{-1}\left(\frac{CP_1^2(y) - E_1\,(y_i)}{CP_1^2(x) - E_1\,(x_i)}\right) \quad \ldots (2)$$

$$A_i = sqrt\left(\left[CP_1^2(y) - E_1\,(y_i)\right]^2 + \left[CP_1^2(x) - E_1\,(x_i)\right]^2\right) * \sin(\alpha_i) \quad \ldots (3)$$

where, $i = 1,\ldots, t_p$

α_i is the angle between the lines L and L_i,

3) The procedure of *Edge Envelope* extraction is repeated for all the edges.

2.3. Matching Phase

The human visual system finds the one-to-one similarity by comparing the edge patterns of the torn pieces. In a similar way, the degree of similarity between the edge patterns of torn pieces is computed by comparing the extracted *Edge Envelopes*. To find the one-to-one similarity like human visual system does, a new parameter *Normalized Edge Envelope Difference (NEED)* is introduced and is given by,

$$NEED = \frac{1}{M}\sum_{j=1}^{M}\left|S_1^a(j) - S_2^b(j)\right|, \quad \ldots (4)$$

where, M is $\max\left(length\left[S_1^a(j)\right], length\left[S_2^b(j)\right]\right)$,

$S_1^a(j)$ is the a^{th} edge envelope signal of the torn piece P_1,

$S_2^b(j)$ is the b^{th} edge envelope signal of the torn piece P_2.

$P_1, P_2 \in \{P_t\}$, and P_1, P_2 are mutually exclusive.

The value of NEED thus computed is used as the measure of one-to-one matching between the *Edge Envelopes* of the torn pieces and lower the value of *NEED*, the better is the degree of similarity between the *Edge Envelope* under consideration. The corners for a torn piece may be topologically different from those of its counterparts, depending on the nature of hand movements during torn process and behavior of the corner detection process. Because of this, total number of points t_p of edge envelope under consideration and its counterpart will be different. To take care of this, the edge envelope with the shorter t_p is interpolated to the length of the longer edge envelope. The outcome of the matching phase is the matched edges of the torn pieces that are to be joined to get a single reconstructed document.

Due to limitations in the imaging mechanism, the torn piece having a shear, after being scanned, may contain digital imperfections and unpredictable rigid transformations. This creates a lot of ambiguity in matching phase and it can be overcome by smoothing the *edge envelope* by filtering.

2.4. Joining Phase

The matched edges of the torn pieces may have different orientations because of the positioning of the torn pieces during scanning. Now in order to join the pieces, it is required to rotate and translate the pieces under consideration. This requires the computation of rotation and translation parameters.

Let $CP_1^1(x,y)$ and $CP_1^2(x,y)$ be the corner points of the edge E_1 for the torn piece P_1 which has its matching counterpart in torn piece P_3, whose edge is represented by E_2 with the corner points $CP_3^2(x,y)$ and $CP_3^3(x,y)$. The rotation angle RA between the edges E_1 and E_2 is calculated using Eqn. (5).

$$RA = \tan^{-1}\left(\frac{CP_1^2(y) - CP_1^1(y)}{CP_1^2(x) - CP_1^1(x)}\right) - \tan^{-1}\left(\frac{CP_3^3(y) - CP_3^2(y)}{CP_3^3(x) - CP_3^2(x)}\right) \quad \dots (5)$$

The corner points $CP_3^2(x,y), CP_3^3(x,y)$ of P_3 are updated by an angle RA to $RCP_3^2(x,y)$, $RCP_3^3(x,y)$ respectively. These new corner points are used to find the translation parameters T_x, T_y as in Eqns. (6), (7)

$$T_x = \frac{1}{2}\left(\left[CP_1^2(x) + CP_1^1(x)\right] - \left[RCP_3^3(x) - RCP_3^2(x)\right]\right) \quad \dots (6)$$

$$T_y = \frac{1}{2}\left(\left[CP_1^2(y) + CP_1^1(y)\right] - \left[RCP_3^3(y) - RCP_3^2(y)\right]\right) \quad \dots (7)$$

The torn piece P_3 is rotated by an angle RA and then translated by T_x, T_y. The updated torn piece P_3 is joined with its matched counterpart P_1 to make a larger piece P_{13}. This new piece P_{13} with its updated corner points replaces P_1, P_3 and the above procedure is repeated for the remaining torn pieces P_t.

3. RESULTS AND DISCUSSION

For our experiments, we have used torn pieces of document and book. Two set of such scanned images of torn pieces are shown in Fig. 5 (a) and 6 (a) for illustration. Fig. 5 (a) shows scanned images of four torn pieces of a page taken from a book and Fig. 6 (a) shows six torn pieces of a document. For background estimation of all the scanned images of the torn pieces, border pixels of width four are used. The computed histogram from these border pixels is used to find the pixel value which has resulted in maximum count. This pixel value with a deviation of three is used for Binarization of the scanned image of torn pieces. The canny edge detector with a threshold on 0.6 is used to get single pixel width contour. In corner detection phase, the points with an angle greater than 135 degrees are considered as spurious corners and are not considered for further analysis.

The proposed unique feature *Edge Envelope* is extracted for all the edges of the torn pieces. It is observed that, the scanned torn pieces of the document shown in Fig. 5 (a) and 6 (a) have reasonable shear associated with them. This creates a lot of ambiguity in matching phase and it is overcome by smoothing the edge envelopes using 5-point moving average filter. The typical edge envelope S^1, with its matched S^2 and unmatched S^3 counterpart are shown in Fig. 7. From Fig. 7, it has been found that the degree of similarity between S^1, S^2 is more compared with that of S^1, S^3. Also, the newly defined *NEED* value between S^1, S^2 is lower compared to that of S^1, S^3. Thus the *NEED* can be used as an effective quantitative measure for matching the edges of torn pieces, which exploits the property of human visual system. The reconstructed documents of scanned images are shown in Fig. 5 (b) and 6 (b) respectively. It is observed from Fig. 5 and 6 that, the reconstructed documents from the torn pieces matches with that of the original documents.

4. CONCLUSIONS AND FUTURE WORK

A new novel technique for reconstruction of document ripped-up by hand is proposed, which uses a unique feature, *edge envelope* that helps in successful matching of torn pieces. As human visual system uses high curvature points and edge variations for finding match between the edges, a feature that captures these edge variations using high curvature corner points is proposed. The ambiguity created during the matching of edges due to shearing is overcome by smoothing the *edge envelopes* through filtering. From the results, a newly defined parameter *NEED* is indeed an effective quantitative measure for matching the edges of torn pieces. Even in-spite of using a single feature, the proposed algorithm is able to reconstruct the document ripped-up by hand very effectively.

Automatic reconstruction of a document from lager number of torn pieces from single and multiple pages is the scope of future work.

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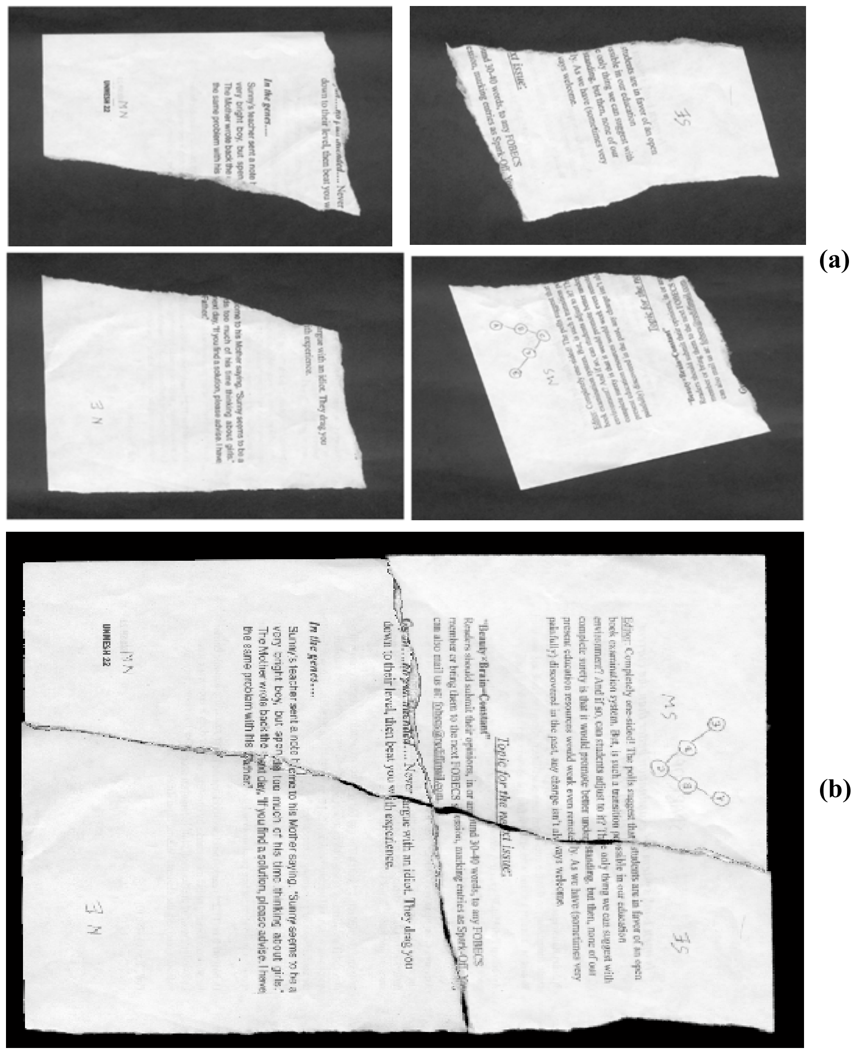
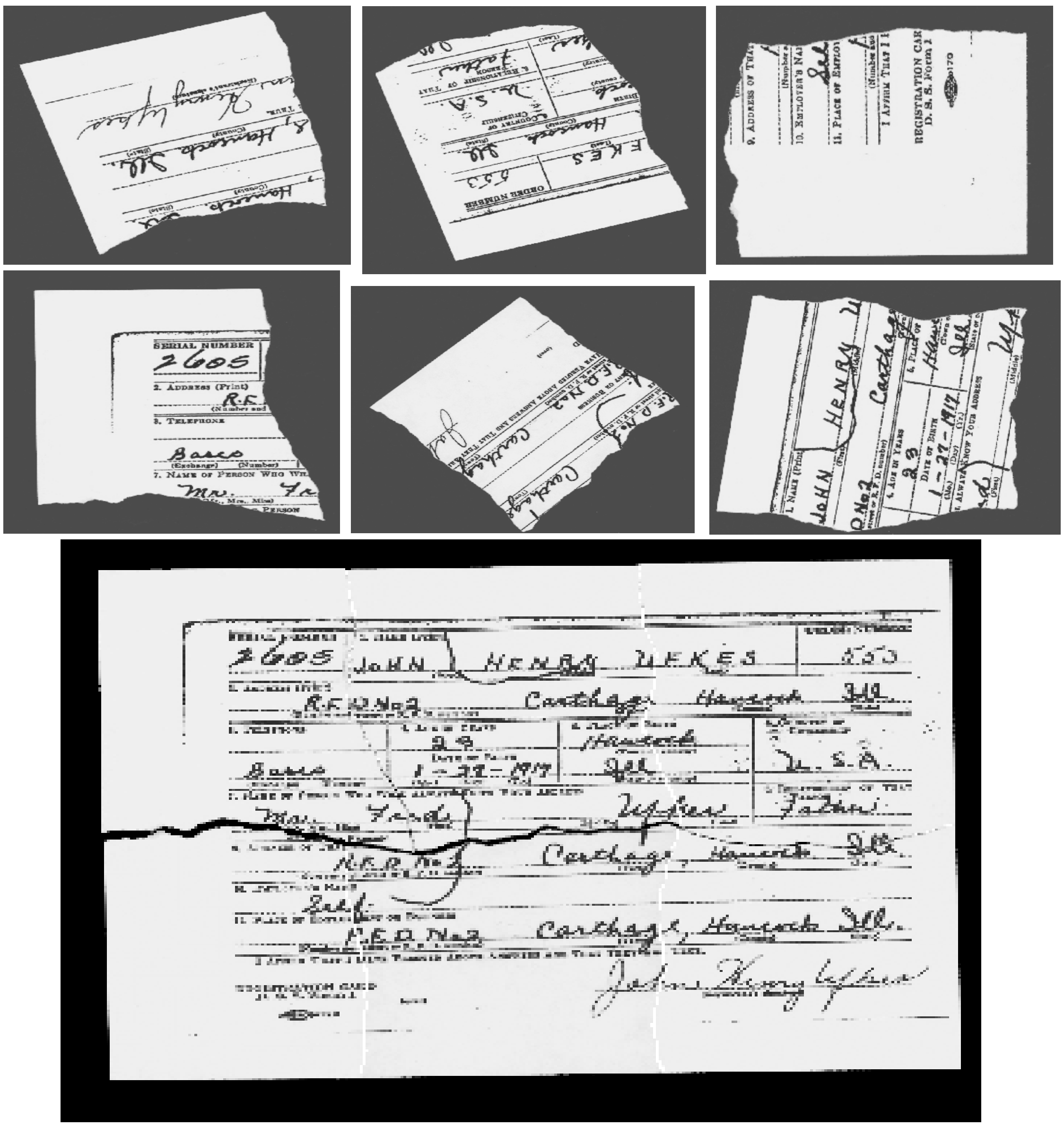


Fig. 5 (a) Scanned images of torn pieces of a page from a book and (b) its reconstructed page



(a)

(b)

Fig. 6 (a) Scanned images of torn pieces of a document and (b) its reconstructed document

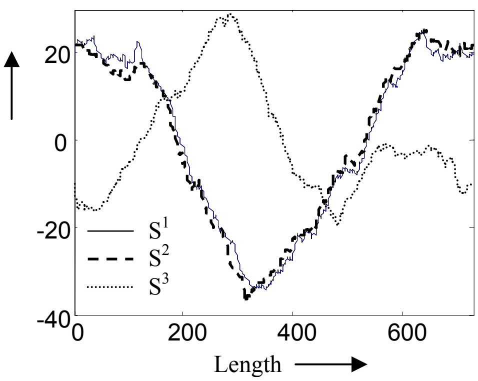


Fig. 7 Edge Envelopes of torn pieces.

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