COLOR AND SHAPE BASED REASSEMBLY OF FRAGMENTED IMAGES

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Abstract-
The manual execution of reassembling a fragmented image is very difficult. To overcome this difficulty a new technique was introduced in the existing system called "The novel integrated color based image fragments reassembly technique". This technique is divided into four steps, which is based on color. Initially, the spatial adjacent image fragment is discovered. The second operation is to discovery of matching contour segments of adjacent image fragments. The next step is to find the appropriate geometrical transformation for an image fragments contour alignment. Finally the overall image assembly is done via novel based algorithms. In proposing system, the same reassembly technique is applied but additionally the shape alignment algorithm is used to utilize the shape of the fragment contours in order to perform matching. This will produce very satisfactory reassembly results and also it can lead to more efficient, significant reduction in human effort.

Keywords- **Fragmented image, spatial adjacent image fragments, color quantization contour segments, geometrical transformation.**

1. INTRODUCTION

The problem of reassembling image fragments arises in many scientific fields such as forensics and archaeology. The manual execution of reassembly is very difficult as it requires great amount of time, skill and effort. Thus the automation of such a work is very important and can lead to more efficient, significant reduction in human effort involved. In our work, the automated reassembly of images from fragments follows a four step model, similar to the one presented in [10] for 3-D object reconstruction.

The first step of our approach is, the identification of probable adjacent image fragments, in order to reduce the computational burden of the subsequent steps. There, several color based techniques are employed. This step will produce higher performance. The second step is the identification of the matching contour segments of the image fragments. The corresponding step employs a neural based color quantization approach for the representation of the image contours, followed by a dynamic programming technique that identifies their matching image contour segments. Once the matching contour segments are identified, a third operation takes place. Here, the geometrical transformation, which best aligns two fragment contour along their matching segments, is found. A very popular registration technique is the Iterative Closest Point (ICP) is used to limit the effects of noise. Here in this module we are proposing a new approach of shape alignment method based on the Fourier coefficient.

The last step in solving the fragment reassembly problem is the reassembly of the overall image from its constituent fragments. Here, a novel algorithm is proposed. It is clear that it is essential that each step of the algorithm feeds the next one with correct results; otherwise the image reassembly may contain errors, or may even fail completely. Our goal is to investigate and propose the most robust techniques in order to produce accurate results at each intermediate step. In this paper the integrated method for automatic color based 2-D image fragment reassembly is presented. To summarize, the main steps of the proposed method are shown in Figure. 1.

The main steps are as follows:

1) Discovery of spatial adjacent image fragments
2) Discovery of matching contour segments of adjacent image fragments
3) Image fragments contour alignment
4) Overall image assembly

This paper is organized as follows. Section 2 discusses the related work. Section 3 describes the discovery of the spatial adjacent fragments. Section 4 presents the identification of the matching contour segments of the spatial adjacent image fragments, while Section 5 describes the derivation of the optimal geometrical transformation that aligns contours along their matching segments. Section 6 presents the overall image assembly algorithm. Experimental results are presented in Section 7 and Conclusions are drawn in Section 8.

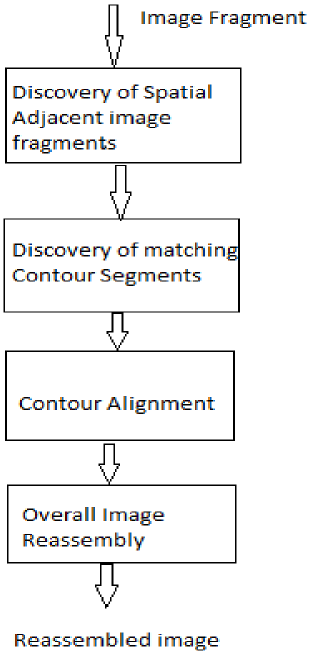

Figure.1. Overall image reassembly approach

2. RELATED WORKS

2.1. Two Dimensional Paper Document Reassembly

Similar to 2-D image fragment reassembly, in paper document reassembly, torn paper fragments must be assembled to form the image of an entire page of a paper document. The above employ shape representations of the paper fragments, in order to reassembly the original documents. In [4], polygonal approximation is initially applied to reduce the complexity of the paper fragment contours and geometrical features are extracted from these polygonal curves. Then, a method based on [7] is used to assemble the entire document from its constituent paper fragments. In [11], shape features, namely turning functions, are estimated from every fracture contour and are utilized to discover matching contour segments. After that, each matching is assigned a confidence score. The alignment transformation of the fragments is simultaneously found during matching. After the discovery of matching contour segments, the final reassembly step performs two actions, namely matching relaxation and fragments merging. During matching relaxation, every pair of aligned input fragments is checked for overlap along their matching contour segments. If they overlap, this matching is discarded. Otherwise, the neighbouring fragments of this pair are identified. A score, called support, is assigned to the neighbourhood of each pair of non-overlapping fragments. This score increases as the number of neighbouring fragments as well as the matching confidence assigned to pairs of fragments increase. The fragments that have neighbourhoods with maximum support are merged into new fragments and the whole procedure starts again, i.e., the matching contour segments are identified for all pairs of fragments, and so on.

2.2. Two Dimensional Puzzle Reassembly

Many methods were also proposed for the 2-D puzzle reassembly problem. In [6], color and textural features of the puzzle pieces are utilized. The matching and alignment of puzzle pieces is carried out using an FFT-based image registration technique. In [5], the puzzle reassembly process consists of two steps; frame and interior assembly. A travelling salesman problem (TSP) is formulated for frame assembly, while backtracking and branch&bound techniques are employed for interior assembly. The puzzle pieces are matched employing (L_2) the distance of their contours curves. In [9], the overall puzzle assembly is done using a Best-First procedure. There, two criteria are utilized to sort matching contour segments. The first one is the residual error of corresponding contour pixels after the discovery of the optimal geometrical transformation, while the second criterion is the arc-length of the matching contour segments. It is clear that the problem of 2-D puzzle assembly does not meet the major difficulty of the image and object reconstruction problems; that is the missing or highly damaged image (or) object fragments. Thus, in general, the algorithms proposed in this field would be inadequate to solve such problems.

2.3. Three Dimensional Object Reconstruction

Regarding 3-D object reconstruction, an automatic method for matching and alignment of 3-D, free-form archaeological fragments is proposed in [8]. The input fragments are not pre-processed. The matching is performed utilizing only the 3-D points of the whole surfaces of the objects. The output matching-alignment minimizes the distance between the 3-D surface points of the two fragments. Andrews *et al.* [1] propose an automatic method for the reconstruction of pairs or triplets of 3-D symmetric archaeological fragments. The matching is found through a two-phase method. During the first phase several matching's-alignments are estimated for every pair of fragments. The 3-D points of the fracture curves in the outer and inner surface of the fragments as well as the axis of rotation of the fragments are utilized to this end. In the second phase, these matching's are refined using the quasi-Newton method, and evaluated according to several criteria namely the angle formed by the fragments rotation axes, the perpendicular distance between the rotation axes and the distance of the matched fracture curves points. Eventually, one matching is retained for every pair of fragments. Finally, in the overall object reconstruction step, a greedy merge strategy selects pairs of fragments to form triplets. A human-supervised collaborative reconstruction system is described. The aim of the system is to propose a potential matching between any pair of input fragments. The matching is found by utilizing shape feature estimated from all 3-D points in the fracture curves of the fragments. The shape similarity of the fracture curves is ranked with a cyclic distance algorithm. Each matching defines correspondences between 3-D points in the fracture curves. Then the users select to merge or not the proposed fragments. The fragments alignment is performed interactively by the users. The object reconstruction procedure follows the merge-update paradigm.

3. DISCOVERY OF SPATIAL ADJACENT IMAGE FRAGMENTS

In this step a basic approach for identifying the spatial adjacent image fragments are presented using content based image retrieval. Color quantization is used to find the normalized quantized color image histograms, which can be used for color image retrieval. The Spatial Chromatic Histogram, which provides information both of color presence and color spatial distribution. The Spatial Chromatic Histogram [3].

$$\mathbf{S_I=(h(i),b(i),\sigma(i)),\ i=\{1,\ldots..C\}}$$

In this equation h denotes the normalized color histogram, i.e**., h(i)** is defined as the number of pixels having color i divided by the total number of pixels**, b(i)** is a 2-D vector expressing the center of mass and **σ(i)** is the standard deviation of the color label. Histogram Intersection measures and scaled them to the range [0, 1], with 1 denoting a perfect similarity. The utilized matching measures are the following:

1) Scaled L_1 norm

$$d_{L1}(h_1,h_2)=1-0.5\sum_{i=1}^{c}|h_1(i)-h_2(i)|$$

2) Scaled L_2 norm

$$d_{L1}(h_1,h_2)=1-1/\sqrt{2}\sum_{i=1}^{c}(h_1(i)-h_2(i))^2$$

3) Scaled Histogram Intersection

$$d_{HI}(h_1,h_2)=\sum_{i=1}^{c} min(h_1(i),h_2(i))(1-|h_1(i)-h_2(i)|)$$

h_1, h_2 denote the normalized color histograms, extracted from images I_1 ,I_2 respectively.

4. DISCOVERY OF MATCHING CONTOUR SEGMENTS OF ADJACENT IMAGE FRAGMENTS

In this step a Smith Waterman algorithm is presented in order to match the colors appearing in the contours of adjacent image fragments. Various color similarity criteria are being evaluated. Based on such similarity criteria, for each image fragment, one matching contour segment with other image fragments is retained. In order to avoid comparing directly contour pixel colors that may contain noise, a color quantization pre-processing step is utilized, which takes pixel samples from the contours of all image fragments.

A Kohonen neural network (KNNs) is used for color quantization purposes. KNNs belong in the class of unsupervised neural networks. They can cluster input vectors without any external information, following an iterative procedure based on competitive learning. KNNs consist of two node layers; the input and the output layer. In the former, the number of nodes equals the dimension of input vectors, while in the latter the number of nodes equals the amount of produced clusters. The nodes in the output layer are organized by means of a lattice. In KNNs, each node in the input layer s_i has a connection w_{ik} with every node in the output layer. For a network with n input nodes, the weight vector ending at an output node w_j = [w_{1k}, w_{2k}, ... , w_{nk}], is the center of a cluster. In KNNs, given an input vector, the output node with the highest response (winning node) for that as well as all "neighboring" nodes that belong to an area around it, update their weight vectors.

5. IMAGE FRAGMENTS CONTOUR ALIGNMENT

The purpose of this step is to find the appropriate geometrical transformation of one fragment relative to its adjacent one, in order to align them along their matching contour segments. Many variants of the ICP algorithm [2] are employed and evaluated to this end.

The ICP algorithm generally starts with two point sets (contour segments in our case) and an initial guess of their relative rigid body geometrical transformation. It then refines the transformation parameters, by iteratively generating pairs of point correspondences and by minimizing an error metric. Additionally we are proposing a new approach of shape alignment method based on the Fourier coefficient. The aligned fragments of the images will assemble to obtain the required resultant output image.

5.1. Proposing Work

5.1.1. Shape Alignment Using Fourier Coefficient

A new approach of shape alignment method based on the Fourier coefficient will propose to match the contour segments. In this method, the closest contour of a planar object can be represented by a parametric equation γ: [0; 2π] → C

$$l \to x(l) + i\,y(l)$$

With i^2= -1. For latter use, the Fourier Coefficients of γ is given by

$$C_k(\gamma) = \int_0^{2\pi} \gamma(l)\, e^{-ikl}\, dl,\ \ k\epsilon Z$$

Now let γ_1 and γ_2 be centered (according to the center of mass) and normalized arc length parameterizations of two closed planar curves having shapes F_1 and F_2. Hence, scale factor and translation between the two curves can be ignored.

Ghorbel shown that the following quality is a metric between shapes:

$$d(F_1, F_2) = \inf_{(l_0, \theta)} ||\gamma_1(l) - e^{i\theta}\gamma_2(l + l_0)||$$

Where T = [0; 2π] is the range of the rotation angle θ, and of the difference between the starting description points for the two curves l_0. By using the shift theorem in the Fourier domain, computing such a distance comes down to the minimization of

$$f(\theta, l_0) = \sum_{k\epsilon Z} |C_k(\gamma_1) - e^{i(kl_0+\theta)}C_k(\gamma_2)|^2$$

Persoon & al. proposed a solution to compute l_0 and θ. First, l_0 is one of the zeros of the function

$$g(l) = \sum_k \rho_k \sin(\varphi_k + kl) \sum_k k\rho_k \cos(\varphi_k + kl) - \sum_k k\rho_k \sin(\varphi_k + kl) \sum_k \rho_k \cos(\varphi_k + kl)$$

6. OVERALL IMAGE ASSEMBLY

Once the matching contour segments of couples of input image fragments are identified and properly aligned, the remaining step is the reassembly of the overall image. In this module we are presenting the overall assembling of the image fragments obtained from the previous approach. Since the criteria that are based on the contour matching do not suffice for the overall image reassembly, a novel feature, namely the alignment angles found during the process in module is introduced. Here an integrated method for automatic color based 2-D image fragment reassembly is presented. Consider three image fragments f_i, f_j and f_k each one having one matching contour segment with the rest ones. We denote by Θ_j the rotation angle by which the individual fragment f_i must be rotated, in order to be correctly placed inside the overall reassembled image. The alignment angle, by which we must rotate fragment f_i to align it with the matching contour segment of fragment f_j (before fragment f_j is rotated by Θ_j), is denoted by Θ_{ij} . In order to align fragments f_i and f_j with respect to each other and place them correctly in the reassembled image, the following steps must be performed:

1) Rotate fragment f_j by Θ_j to correctly orient it in the assembled image.

2) Rotate fragment f_i by $\Theta_{ij}+\Theta_j$ to correctly align its matching contour segment with the corresponding matching contour segment of fragment. This procedure will simultaneously align fragment f_i with fragment f_j. and provide its correct orientation inside the entire image.

7. IMAGE REASSEMBLY EXPERIMENTS

To evaluate the performance of the reassembly method, the camera image (fig.2.) was taken and it was fragmented into six pieces that were taken as an input for reassembling the image (fig.3.) While executing, the histogram of the original camera image was displayed (fig.4.) and the adjacent images were identified at the very first step.

Figure.2. Camera image

Figure.4. Fragments of the camera image

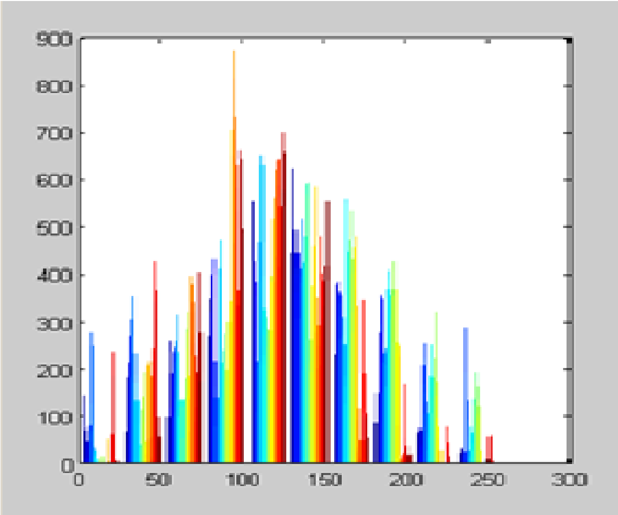

Figure.3. Histogram of the original camera image

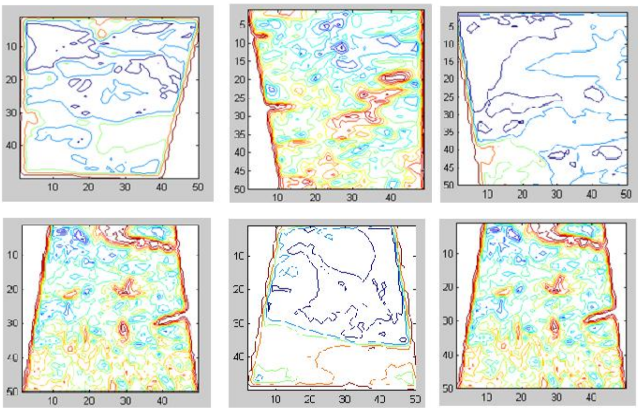

Figure.5. Contour Segments of the fragments

Three sets of the adjacent image were found based on the distance of the color pixels. After that, the matching contour segments were discovered (fig.5. and fig.6.) for each fragment by using smith waterman algorithm. This algorithm was used to match the color appearing in the contours of adjacent image fragments. It must be properly aligned before reassembly of the overall image. For aligning the correct matching contour segments, the Iterative Closest Point algorithm was employed. At the end of the reassembly method, the matched fragments were reassembled (fig.7.)

(1) Fragment 1 and 3

(2) Fragment 2 and 4

(3) Fragment 6 and 5

Figure.6. Alignment of fragments with contour segments

Figure.7. Automatically reassembled image produced from the fragments of fig.4.

8. CONCLUSIONS AND FUTURE WORK

In this paper, we have introduced a novel integrated color based image fragments reassembly method that consists of several distinct novel algorithms, which produced satisfactory reassembly results. The shape alignment algorithm will be used to improve the matching contour segments of the original camera image fragments.

REFERENCES

[1] S. Andrews and D. H. Laidlaw, "Toward a framework for assembling broken pottery vessels," in *Proc. 18th American Conf. Artificial Intelligence*, 2002, pp. 945–946, American Association for Artificial Intelligence(AAAI).

[2] Y. Chen and G. Medioni, "Object modelling by registration of multiple range images," *Image Vis. Comput.*, vol. 10, no. 3, pp. 145–155, 1992.

[3] L. Cinque, G. Ciocca, S. Levialdi, A. Pellicano, and R. Schettini,"Color based image retrieval using spatial chromatic histograms," *Image Vis. Comput.*, vol. 19, pp. 786–979, 2001.

[4] E. Justino, L. S. Oliveira, and C. Freitas, "Reconstructing shredded documents through feature matching," *Fores. Sci. Int.*, vol. 160, pp.140–147, 2006.

[5] Kalvin, E. Schonberg, J. Schwartz, and M. Sharir, "Two dimensional model based boundary matching using footprints," *Int. J. Robot. Res.*,vol. 5, no. 4, pp. 38–55, 1986.

[6] W. Kong and B. B. Kimia, "On solving 2D and 3D puzzles using curve matching," in *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2001, vol. 2, pp. 583–590.

[7] H. C. G. Leitao and J. Stolfi, "A multiscale method for the reassembly of two dimensional fragmented objects, " *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 9, pp. 1239–1251, Sep. 2002.

[8] G. Papaioannou, E. A. Karabassi, and T. Theoharis, "Reconstruction of three-dimensional objects through matching of their parts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 1, pp. 114–124, Jan.2002.

[9] M. S. Sagiroglu and A. Ercil, "A texture based matching approach for automated assembly of puzzles," in *Proc. 18th Int. Conf. Pattern Recognition (ICPR)*, 2006, vol. 3, pp. 1036–1041.

[10] R. Willis and D. B. Cooper, "Computational reconstruction of ancient artifacts," *IEEE Signal Process. Mag.*, pp. 165–183, Jul. 2008.

[11] L. Zhu, Z. Zhou, and D. Hu, "Globally consistent reconstruction of ripped-up documents," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 1, pp. 1–13, Jan. 2008.