Determination of the Spatial Adjacent Image Fragment for Reassembly of Fragmented Images

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ABSTRACT
An integrated method for automatic reassembly of fragmented images is developed in this paper. The problem of reassembling image fragments arises in many fields, such as archaeology and forensics. Here the spatial chromatic histogram of each fragment, histogram intersection and spatial chromatic distance are calculated. The automation of such a work is important and can lead to faster, more efficient fragment reassembly method.

Keywords
Fragmented image, spatial chromatic histogram, histogram intersection, spatial chromatic distance.

1. INTRODUCTION
The reassembly of fragments to recompose images and objects is a problem occurring in a number of fields: in archeology, in art restoration, and in other disciplines including forensics, computer-aided design, chemistry, and medicine. In the field of archaeology, the pictorial excavation findings are almost always in the form of painting fragments. In this paper, an integrated method for automatic color based 2-D image fragment reassembly is presented. A method that applies polygonal approximation to reduce the overall complexity is proposed by Edson in [1].

In [2], an analogous algorithm is presented, for the discovery of the matching contour segments of 2-D fragmented objects. However, the fragment contour comparison is based on the shape of the input 2-D object fragments, while a dynamic programming technique is employed in order to identify their matching segments. Aminogi *et al.* [3] presented an algorithm based on both the shape and the color characteristics of the input 2-D image fragments contours. There, one contour pixel sequence is overlaid on another one and, for each such "placement", the curvature and color differences of the corresponding contour pixels are estimated. If their total sum is less than a user defined threshold, the contour segments are considered to match. In the experimental results section, the latter approach is compared with the one proposed here. The results show that the latter has better performance. Regarding 3-D object reconstruction, an automatic method for matching and alignment of 3-D free-from archaeological fragments is proposed in [4].

In [5],a pattern matching algorithm for comparison of digital images implemented by discrete circular harmonic expansions. Fast, robust, and accurate digital image pattern recognition algorithm which is independent of mutual rotation and displacement. The accuracy and the robustness of the procedure are realized by exploiting the independent information. In [6], the development of automatic reconstruction systems capable of coping with the realities of real-world geometric puzzles that anthropologists and archeologists face on a daily basis. Such systems must do more than find matching fragments and subsequently align these matched fragments; these systems must be capable of simultaneously solving an unknown number of multiple puzzles where all of the puzzle pieces are mixed together in an unorganized pile and each puzzle may be missing an unknown number of its pieces.

The automated reassembly of fragmented images addresses the problem of reassembly of images from a collection of their fragments. The image reassembly problem is formulated as a combinatorial optimization problem and image assembly is then done by finding an optimal ordering of fragments. The implementation results showing that images can be reconstructed with high accuracy even when there are thousands of fragments and multiple images involved. Pattern recognition is the act of taking in raw data and taking an action based on the category of the pattern. Pattern recognition aims to classify data based either on a priori knowledge or on statistical information extracted from the patterns.

2. BLOCK DIAGRAM

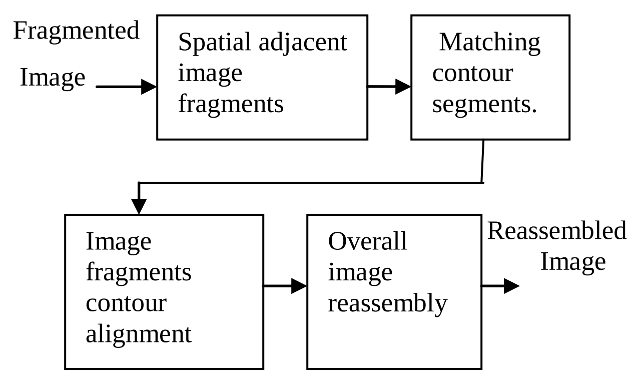

Figure1.Block diagram

Figure 1 shows the block diagram of automated reassembly of images from fragmented image. 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. The second operation is the identification of the matching contour segments of the image fragments. The corresponding step employs a neural network 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 contours along their matching segments, is found. The last step in solving the fragment reassembly problem is the reassembly of the overall image from its constituent fragments.

3. DETERMINATION OF THE SPATIAL ADJACENT IMAGE FRAGMENT

The spatial adjacent image fragments identification by using their probable high color similarity. The spatial adjacent image fragment procedure involves the quantization of the image colors and calculation of color histograms based on the resulting colors. Computing distance measures based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. The techniques that are widely employed in CBIR systems are utilized in order to identify these similarities. The content-based image retrieval systems aim to provide an automatic way to extract information from images that depends only on the content of the image. CBIR system receives an image or an image description as input and retrieves images from a data base that are similar to the query image.

Color quantization involved the use of a palette based on a commercial color chart known as the Gretag Macbeth Color Checker. The Macbeth Palette is a standard used to evaluate color reproduction systems and it consists of 24 colors that are scientifically chosen to represent a variety of naturally occurring colors. Color quantization is used to find the normalized quantized color image histograms, which can be used for color image retrieval [7]. We have also experimented with the Spatial Chromatic Histogram, which provides information both of color presence and color spatial distribution [8].

The Spatial Chromatic Histogram S_I of image I having C quantized colors is given by $S_I(i)=(h(i),b(i),\sigma(i))$ where $i=\{1,\ldots,C\}$, $h(i)$ 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 $\sigma(i)$ is the standard deviation of the ith color label respectively. After estimating the spatial chromatic histogram of each fragment we are calculating the histogram intersection.

Histogram intersection using the equation given by

$$dc(1,2)= \sum_{i=1}^{C} \min\big(h1(i), h2(i)\big) * \left(\frac{\sqrt{2}-d(b1(i),b2(i))}{\sqrt{2}} + \frac{\min(\sigma1(i),\sigma2(i))}{\max(\sigma1(i),\sigma2(i))}\right) \quad (1)$$

If the histogram intersection of two fragments is greater than or equal to a predefined threshold value, then the two fragments will be added to the set of image fragment couples. Once this step is finished, we select to retain, for every image fragment, a list of the most chromatically similar fragments.

4. METHODOLOGY

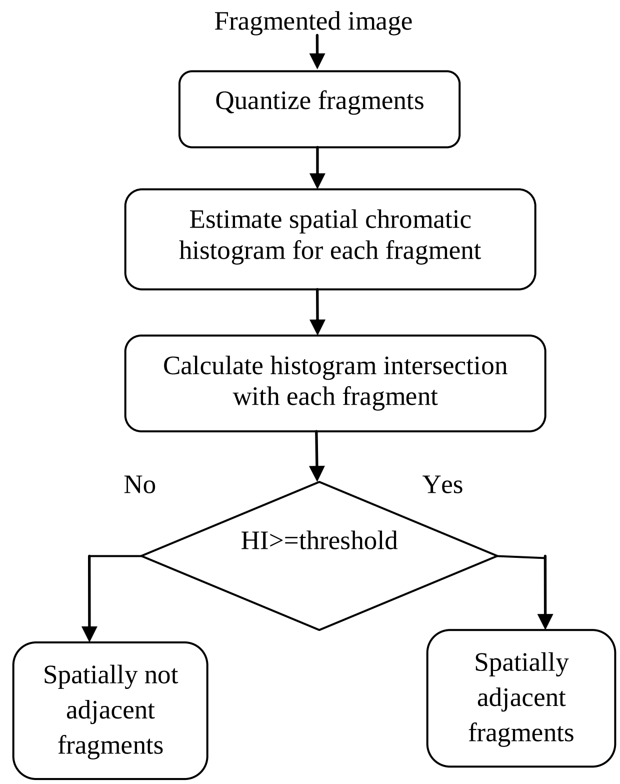

Figure 2. Discovery of spatial adjacent image fragments

5. IMPLEMENTATION RESULTS

The input given is a set of image fragments.

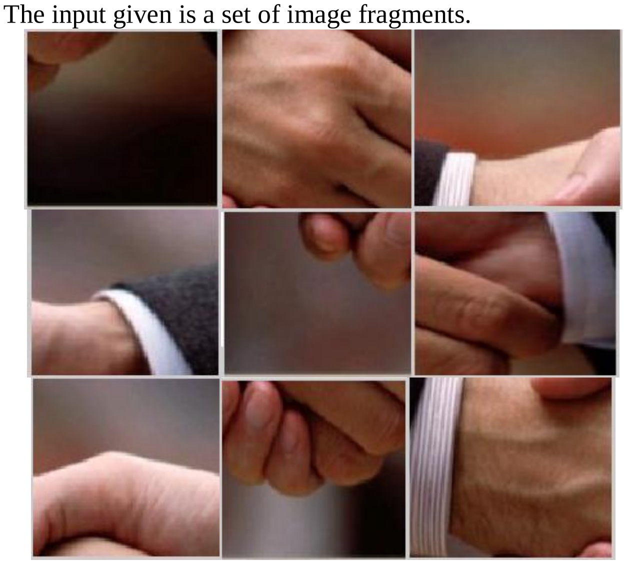

Figure 3. Input Fragments

Figure 4. Quantized input fragments

Each fragment is quantized based on a commercial color palette. Color quantization is used to find the normalized quantized color image histograms, which can be used for color image retrieval.

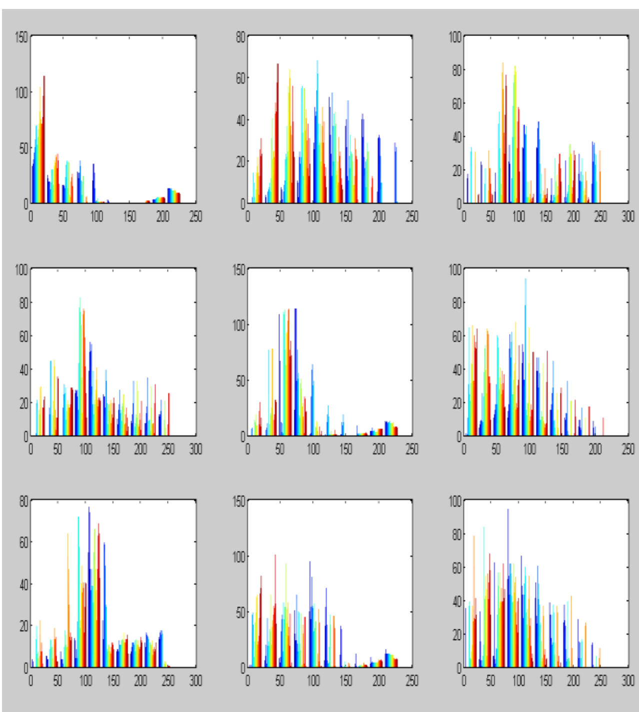

Figure 5. Quantized color image histogram

After estimating the spatial chromatic histograms, the histogram intersection is calculated. If the histogram intersection of two fragments is greater than or equal to a predefined value, then the two fragments are said to be spatially adjacent.

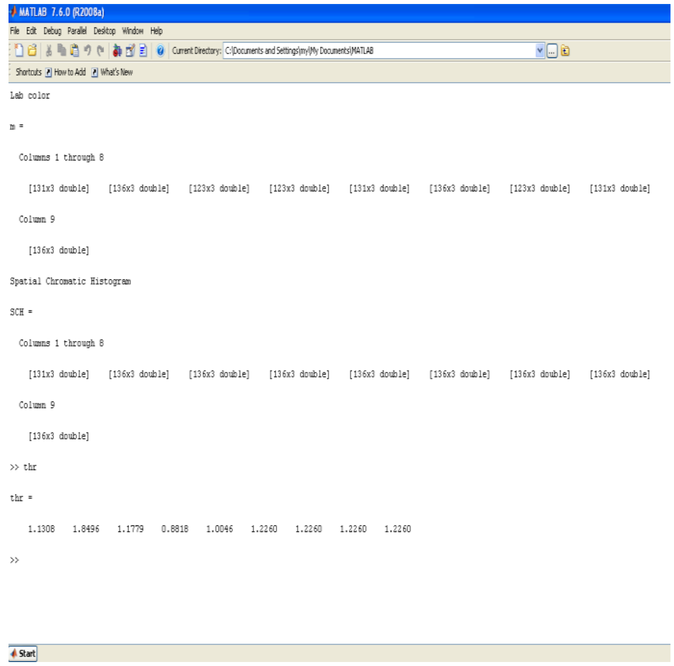

Figure 6.Result

6. CONCLUSION

A faster and efficient color based image fragments reassembly method is described in this paper. It involves the discovery of spatial adjacent image fragments of each fragment. A significant reduction in human effort can be achieved by using this fragment reassembly technique. Experiment is conducted with various image fragments and satisfactory results are obtained. Overall reassembly of discovered adjacent image fragments will be doing as future work.

7. REFERENCES

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