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Enhanced Graph-Based Optimization Algorithm For Fragmented Image Reassembly

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ABSTRACT

The problem of reassembling image fragments arises in many scientific fields, such as forensics and archaeology. In the field of archaeology, the pictorial excavation findings are almost always in the form of painting fragments. The manual execution of this task 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 faster, more efficient, painting reassembly and to a significant reduction in the human effort involved. In this paper, an integrated method for automatic color based 2-D image fragment reassembly is presented. The proposed 2-D reassembly technique is divided into four steps. Initially, the image fragments which are probably spatially adjacent are identified utilizing techniques employed in content based image retrieval systems. The second operation is to identify the matching contour segments for every retained couple of image fragments, via a dynamic programming technique. The next step is to identify the optimal trans-formation in order to align the matching contour segments. Finally, the overall image is reassembled from its properly aligned fragments.

Keywords:- Windows based Application, Html, CSS and java Script Security used, Fragmented image reassembly, Fragmented data restoration, Shape matching.

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I. INTRODUCTION

In image processing, the collection of small piece of fragments are combined together reassemble image. This type of reassembly fragmented images are used in archaeology and forensics. The form of painting fragments are from pictorial excavation. These fragments of murals, mosaics or pottery are assembled into original complete painting. A related aspect of the problem is the development of a generative model for fractures and cracks as proposed in[4]. Suppose there was an accident could be happened, if in that case image of face structure was destroyed then that time it should not be possible to reassemble the image. So, that help of this project we can easily reassemble image very efficiently. Sometimes Because of destruction,the cases where the form of original object is known but has to be reassembled. By using discrete circular harmonic expansion a pattern matching algorithm for the comparison of digital images are implemented[5].In previous system is time consuming, lots of efforts are required. The proposed system is very efficient, faster and to a significant reduction in the human effort involved. In our project, The reassembly of images from fragmented images are of four step model [6].The first step is pairwise matching, groupwise matching, graph based optimization matching, overall graph based optimization reassembly.

II. BASIC CONCEPT

In this section, a brief introductionabout the concept of the pairwise matching, groupwise matching, graph based optimization matching, overall graph based optimization reassembly is provided.

1. Pairwise matching

Pairwise matching is first step of module. They can work on the adjacent pair is to identify and their initial alignment is also matched and then couple of image is form.Content

based image retrival(CBIR) algorithm is used for pairwise matching in which adjecent contour are matched and form couple of image. In this way reduce computational burden. The shape of boundary curve contour can be analyzed by geometry based matching. Then integrated algorithm [7] for represent the curve by using extracting the border of each fragment [8]. The potential alignment between adjacent fragments can be suggested by matches contour segment [6]. Color and geometry can be done by clusters such a curve contour into a multiple segment.The result of pairwise matching algorithm is in a set of possible matching between identified pairs of fragments, which are some correct or not.

1. Group wise matching

When the couple of image in pairwise matching is form then in that add one fragment of image and form a group.[10] The Smith waterman algorithm is used for group wise matching in which color matching for contour of fragments. The redundant matches can be produces by pairwise matching which are intentionally generate in order to tolerant erroneous adjacency identification due to noise local minima, so it can be better filter out this false matches can be done global group wise matchingFalse matches are better filter in group wisematching. This is a combinatorial optimization problem and NP hard in extensive examination. Best first search strategies with back tracking to solve the problems are used in many previous work. A novel graph based searching problem can formulated by global composition in our work,when we can solve a multiple fragments will get more reliable global reassembly.

2. Graph based optimization

The fragment can compose by groupwise matching globally.so this result dependent upon composition of the sequence, the alignment errors will be accumulated which may even cause a failure in the reassembly of one fragment relative to its adjacent one. The purpose of this step is to findgeometricaltransformation. The Iterative Closed Point (ICP) algorithm is used in graph based optimization.To reduce the global matching error between the adjacent fragment can done graph optimization algorithm.

This work can contribute is as follows:

a) Pairwise matching integrate both geometry and color information are more reliable alignment between adjacent fragments.

b) A graph based algorithm efficiently handles the errors results which are given by pairwise alignment and also get correct adjacency information of all the fragments.

c) Graph optimization can develop the variation a graph optimization at an end to reduce a error to refine the reassembly and achieve the optimal result.

4.Overall image reassembly

The final step is called the overall reassembly which aims to reassemble the fragmented image. Once the matching contour segment of couple of input image fragments are identified and properly aligned, remaining step is to reassembly of the overall image.Overall reassembly in which the collection of fragmented image is to form a reassemble image as output.

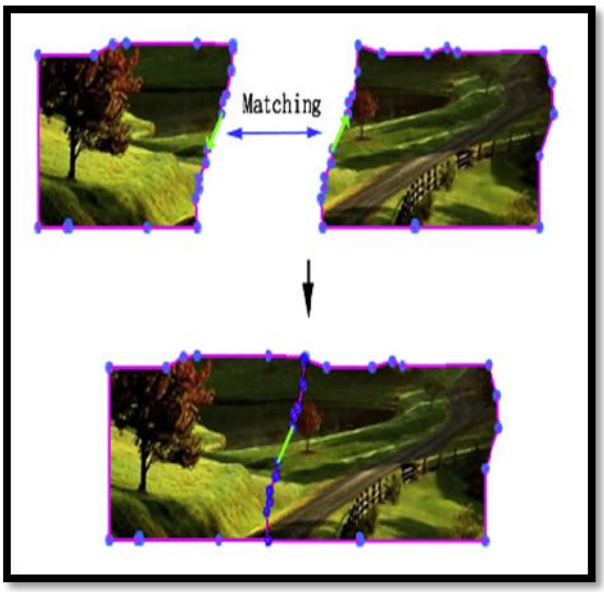

Figure 1 :- Pairwise matching

Figure 2 :- Grouwise matching

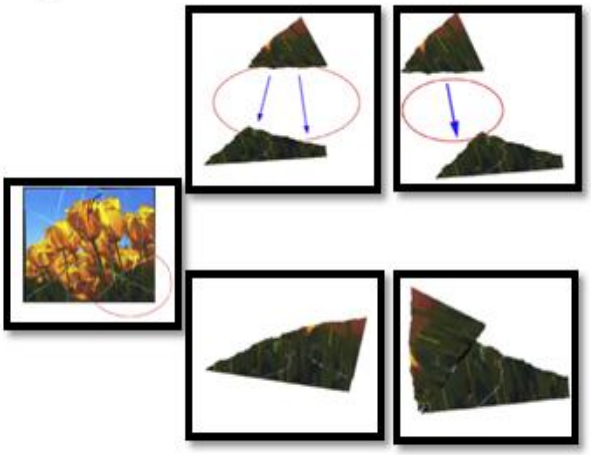

Figure 3:- Graph based optimization

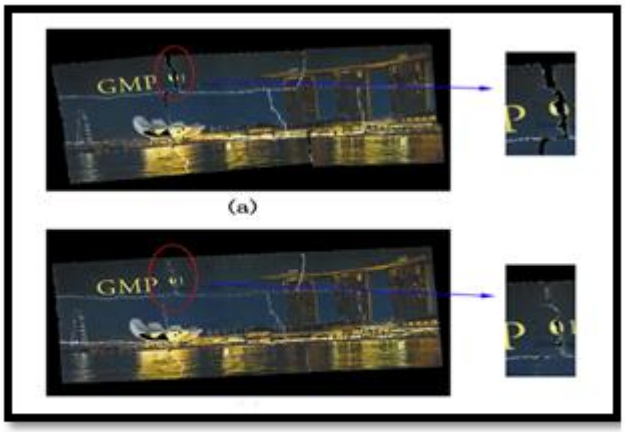

Figure 4:- Overall reassembly of image

III.BACKGROUND AND COMPARATIVE ANALYSIS

Many algorithms & techniques have been proposed up till now for reassembly of fragmented images.Some of them have focused on to improve the accuracy.

In paper [1], The curve matching framework for planar open curves under similarity transform1 based on a new scale invariant signature. The signature is derived from the concept of integral of unsigned curvatures. If one input curve as a whole can be aligned with some part in the second curve then the algorithm will find the requisite starting and end positions and will estimate the similarity transform in time. We extend our frame work to a more general case where some part of the first input curve can be aligned with some part of the second input curve. This is a more difficult problem that we solve in ON3 time. The contributions of the paper are the new signature as well as faster algorithms for matching open 2D curves. We present examples from diverse application set to show that our algorithm can work across several domains.

In paper [2], Reconstruction of archaeological monuments and potteries from fragments found at archaeological sites is a tedious task that requires many hours of work from archaeologists and restoration personnel. Excavations from famous archaeological sites in Jordan such as Petra, Jerash, Um Qeis, Ajlun etc. indicated civilization throughout centuries, from prehistoric periods, up to present. The restoration process is tedious and lengthy due to the mass of fragile fragments which consists of thousands of sherds found at excavation sites. An approach is the use of shadow moire experimental technique to obtain the 3D model of pots from 3D measurements of the surface profile using the photos captured. This method is a non-destructive optical technique used for visual surface inspection, and surface profile measurements. The approach is simple, requires minimal mathematical calculations and reduces the risk of frequent handling of the fragile sherds, because the photos can be captured using a simple experimental setup in the site. Matching of fragments and aligning them geometrically is based on matching the profiles and edges of the broken parts virtually. This virtual assembly technique may assist the archaeologists as much as possible in solving their task with minimum time and minimum damages to fragments. The technique, of course, does not completely replace the archaeologist, but provides a useful estimation of valid fragment combinations, and accurately measures fragment matches. It also simplifies modeling the pots virtually using 3D-MAX modeling software to obtain the missing pieces.

In paper [3], Digital images may be considered as collection of pixels. If a single image is divided into more than one part, then these subparts are treated as fragments for an image. Joining of 2D fragments of an in image means we have to reassemble these images fragments. The joining of fragments to reconstruct images and objects is a problem associated in several applications, like archeology, medicine, art restoration, and forensics .We mainly focused on 2D Image Reconstruction by joining two 2D fragments. This approach is based on the information generated from the boundary. Local
curvature is calculated to obtain the lines in order to find the angle between them to rotate the second fragment. Based on the information of the boundary comparison is done to obtain maximum matching parts among fragments. Finally longest matching parts can be joined to obtain single image. The techniques illustrated in this paper constitute the core of a more general method for reassembling n fragments we are developing.

Sr. No	Technique (or) algorithm	Disadvantages
1	Jigsaw's Method	Requires preliminary knowledge on the shapes of puzzle
2	Kimia's Method	3 pieces are merged at a time, based on assumption
3	2D recognition	Difficult to find starting and ending point of alignment
4	Moire surface technique	Accuracy is less
5	PRS2 Method	Reassemble only even fragments

Table 1. Literature survey

Parameter	Existing System	Proposed System
Accuracy	Less	More
Number of fragments	Even	Even and Odd
Performance	Less	More
Complexity	More	Less

Table 2. Comparition between Existing system and proposed system

IV. PROPOSED SYSTEM

The problem of reassembling image fragments arises in many scientific fields, such as forensics and archaeology. In the field of archaeology, the pictorial excavation findings are almost always in the form of painting fragments. For example, they can be fragments of painted pottery, murals, or mosaics,
which must be assembled to form the original painting. Improvements can be done in each step ofproposed method.Interchanging steps used in proposed method.Can work on more than 6fragments. In proposed system we work on both even and odd fragments.

- **Mathematical model**

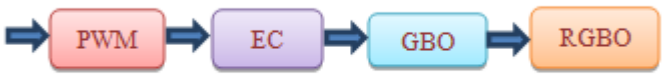

Figure 5:- Mathematical model

Sys = {Fragments, PWM,EC,GBO,RGBO }

Fragments = { f1 , f2 , f3 , … ,fn }
PWM = FPWM { f1 , f2 , f3 ,…,fn }

EC = FEC { PWM }
GBO = FGBO {EC}
RBGO = F { GBO }
Store = RBGO

PWM = FPWM { f1,f2,f3, … , fn }

PWM = (w1 + α + w3) / w2

Where,

w1= Σ [l(Sik) + l (Sjh)] /2
w2 = Σw1 * d[c(Sik),c(Sjh)]
w3 = No.of pairs of clusters (Sik) & (Sjh)
α = Weights the importance of w3

EC = FEC { PWM }

T(eij) * T(vj) = T(eik) * T(vk)

Where,

eij &eik , two different edges
vj & vk , node from most one selected edges

GBO = FGBO {EC}

$$F(x)=\sum_{eij \in E}(xi,xj,zij)^T \Omega ij\ f(xi,xj,zij)$$

Where,
xi & xj represent each edge of graph
zij represents constraint
Ωij weight matrix related parameter
f(xi,xj,zij) vector error function

RBGO = F { GBO }

$$f(x)=\sum_{eij \in E} \| T(eij)-T(vi)*T(vj)^{-1}\|^2*W(eij)$$

Where,
T(eij) relative transformation of edge
T(vi) transformation matrix on each vi
T(vj) transformation matrix on each vj
W(eij) associated matching score

V. SYSTEM WORKFLOW

First login to the system and then connects to system. Browse the image and take images. Process on that images, join two pairs of contour by checking adjacent contour, alignment of contour. Then add third contour by checking the geometric transformation. In this way reassemble all fragmented images.

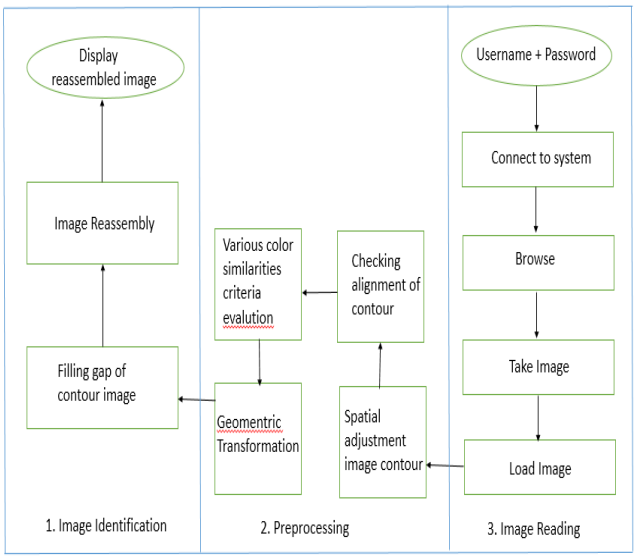

Figure 6:-System Architecture

VI. RESULTS

In the proposed system, reassembled the even as well as odd fragmented images and accuracy is improved. In the result comparison between existing system and proposed system is shown in the figure.

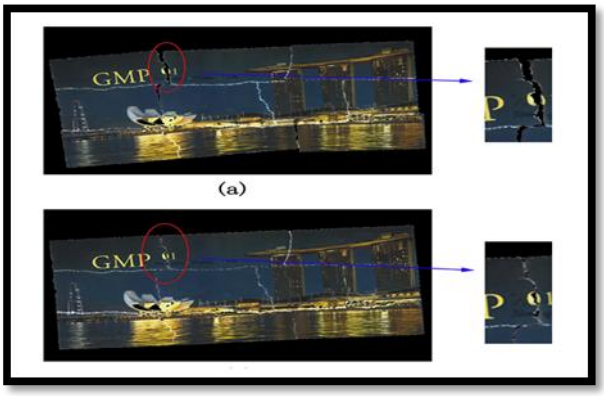

Figure 7:- Comparison between existing system and proposed system

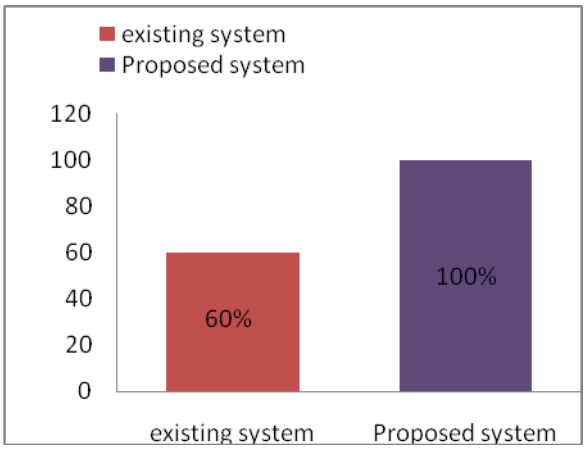

Figure 8:- Accuracy graph

VII. CONCLUSION

We present a novel computational method for the automatic reassembly of fragmented images. It consists of three main steps: pair wise matching between two image fragments, graph-based global fragment reassembly, and refinement of the reassembly via graph optimization. In Step 1, we present a better curve-matching algorithm: each pair of image fragments are aligned via a pair wise matching integrating both geometry and color. In step 2, we present a reliable graph-based global search algorithm, which reassembles multiple pieces together to reach the overall composition; In step3, we develop a novel graph optimization strategy on the previous reassembly result, which can effectively refine the position of the fragments globally.We evaluate our algorithm using various real world images and demonstrate that it is effective and robust.

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