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RESEARCH ARTICLE

An Approach to Reassemble Forensics and Archaeological Image Fragments into Equivalent Original Image

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ABSTRACT

Reassembling of Image fragment problems arises in many scientific field like archeology, forensics and many other. To solve such a problem of reassembling of image fragments by human intervention takes a lot time. And sometimes it might be costlier. To overcome this problem, we are working on a system which will automatically reassemble those image fragments to form original image. With the help of 2D image fragment and contour detection algorithms we can make an efficient use of this system. Reassembling technique is divided into four types. Initially content based image retrieval system is use to identify spatially adjacent fragment. The second step is dynamic programming technique to identify matching contour segment. Third step is to identify optimal transformation to align matching contour segment and last step is overall image reassembling. With the help of these algorithms an optimal transformation in contour can be detected. Doing automation in such work will certainly help in faster, more efficient and patiently reassembling this image fragments

Keywords: Archeology, Contour, Dynamic Programming, Spatially Adjacent, Optimal Transformation.

INTRODUCTION

As stated earlier the problem of reassembling of image fragments in scientific fields like archeology and forensic arises frequently. In excavation findings archeologist mostly finds image or painting fragments. Also in forensic study, forensic experts come across various image, painting or some evidence which are split into various fragments and assembling such destroyed image or painting is a complicated task. It will also take a lot of time to reassemble fragmented image. Thus Automation of in this field is very important and can lead faster and more efficient reassembling of images and painting. To solve this problem, we have studied 2D image fragments and contour detection algorithms. The challenge of how to recover original image from fragments along with noisy information is executed using 2D image restoration technique. In this paper, we are using four step models. First step is to identify spatially adjacent Fragment in order to reduce the computational burden of subsequent steps (Efthymia and Ioannis, 2009; Cui et al., 2008)).

In this step several color-based techniques are employed which is implemented using content based image retrieval system (CBIR) technique. Then Second step is identification of matching contour segments. This step employs a neural network based color quantization approach to identify image contour which is implemented by dynamic programming technique, which use smith-waterman algorithm to identify matching image contour (Mishra et al., 2012).

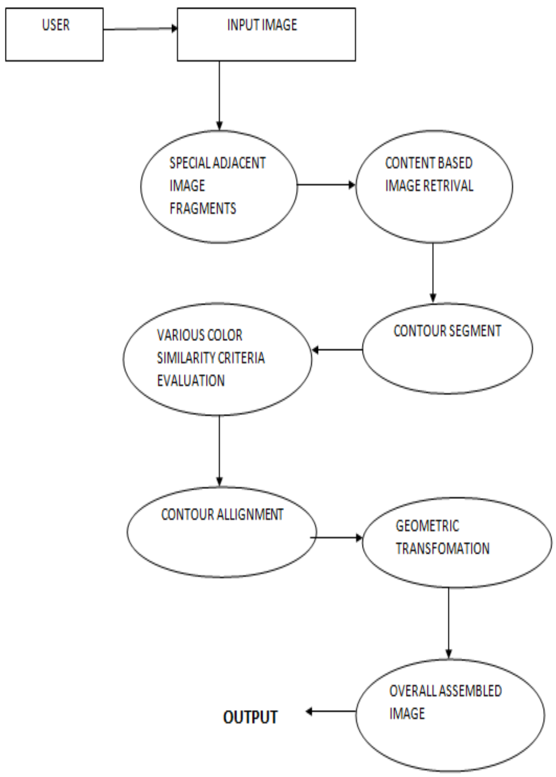


Fig. 1. Overall image reassembly approach

Once matching contour segments are identified, then third step came into action. In this step, the geometrical transformation takes place. In which best align two fragment contour are matched. This step is implemented using popular technique known as *Iterative Closest Point* (ICP) method. It reduces the effect of noise on the registration performance. The last step of reassembling problem is overall image reassembly of image fragments. This operation is performed by a novel algorithm. It employs both the contour matching results and the alignment angels of the fragments, achieved during second and third step respectively. As each step of algorithm depends on its previous step. Hence error in any step will affect reassembling of image at greater extent or may even fail completely. Our goal is to build most robust techniques in order to produce accurate results at each intermediate step. Main steps proposed in paper are summarize as shown in Fig.1

RELATED WORK

A. Fast, Robust and Efficient 2D Pattern Recognition for Reassembling Fragmented Images

In Fast, robust and efficient 2D pattern recognition for reassembling fragmented image paper, an important Italian art, split into thousand of fragments by allied bombing in second world war, was reassemble as original image implementing discrete Circular Harmonic expansion based on sampling theory. Because of rotation invariance properties and successful optical implementation, Circular Harmonic decomposition is used in pattern matching. The moments constructed by correlation of image with circular harmonic system is overall information, used for a complete comparison with another signal. They provided good results on small scale and local registration problem but still difficult to implement algorithms where feasible and reasonable compromise among robustness and location-rotation resolution can be realized on large scales (Massimo and Domenico, 2005; Rajput and Kang, 2013).

B. Reconstruction of 2D Image Fragments

In this paper, Image is divided into various fragments and this fragmented images are reassemble considering two cases: 1) when the fragments are aligned. 2) When the fragments are non-aligne (Mishra et al., 2012.).

This is achieved using following steps: 1) Finding the boundary of fragments. 2) Finding boundary array using chain code.3) find longest subsequence using fragment matching algorithm and last step. 4) Join the two fragments according to these longest common sub sequences (Mishra et al., 2012).

B. Curve Matching for Open 2D

It present a curve matching framework for planar open curves under similarity transform based on a new scale invariant signature. Signature is concept of integral of unsigned curves. Given two curves as input, it seek to find what part of the first matches the best with a part or the whole of the second curve by finding requisite starting and ending positions and will estimate the similarity transform.This type of query is useful in many applications involving shape comparison. Example applications areas are geospatial analysis and registration of images, computer aided geometric design, computer vision, manufacturing, etc.

Fig. 2: Comparisons with existing methods.
(a) Reassembly results computed by existing method, (b) the results computed by our method.

CONTENT BASED IMAGE RETRIEVAL ALGORITHM

In early days because of very large image collections the approach was more difficult. In order to overcome these difficulties Content Based Image Retrieval (CBIR) was introduced. Content-based image retrieval (CBIR) is the application of computer vision to the image retrieval problem. In this approach instead of being manually annotated by textual keywords, images would be indexed using their own visual contents .The visual contents may be color, texture and shape. This approach is said to be a general framework of image retrieval .There are three fundamental bases for Content Based Image Retrieval which are retrieval system design ,visual feature extraction, multidimensional indexing. The color aspect is implemented by the techniques like averaging and histograms. The texture aspect can be implemented by using transforms or vector quantization .The shape aspect can be implemented by using gradient operators or morphological operators (Michael, 2010).

The retrieval is mainly based on four important techniques

i. Retrieval based on color
ii. Retrieval based on structure
iii. Retrieval based on Shape
iv. Retrieval based on features

In initial step, we are required to find spatial adjacent image fragment by using their probable high color similarity. Hence we are using retrieval based on color technique achieved using histograms. Spatial Chromatic Histogram provides information both of color presence and color spatial distribution. Let Spatial Chromatic Histogram S_I of image I having Cquantized colors given by

$S_I(i)= [h(i),b(i),\sigma(i)]$, $i=\{1,\ldots,C\}$ (Michael, 2010).

Where,

h =Normalized color histogram
h(i) =Number of pixel having color i divided by total number of pixels.
b (i) =2D vector expressing the center of mass
σ (i) =Standard deviation of the i^{th} color label

In following equations h1 and h2 denote the normalized color histograms extracted from images I_1 and I_2.

1) Scaled L_1 norm[1]
   Store the L1 differentiation in the normal form derivation.
2) Scaled L_2 norm[1]
   Store the L2 differentiation in the normal form derivation.
3) Scaled Histogram Intersection[1]
   Scale the histogram based on the above calculated value.
4) Spatial Chromatic Distance
   Find out the spatial Chromatic distance based on the main and max value.

Inputs
F: set of N image fragments.
L:the size most chromatically similar fragments per input image fragments.

Output
Σ: set of image fragments couples.
1.S ◄ Φ; {S is a list of spatial chromatic histograms}
2. for all f € F do
3. quantize f using Greadag Macbeth color checker,
4.estimate the spatial chromatic histogram of image fragments
5.appendSf to S;
6.end for
7.Σ ◄Φ;
8. for i= to N-1 do
9. for j=i+1 to N do
10. m[j-i-1] = d(Sfi,Sfj);
11. end for
12. sort m in descending order; thr= m[L];
13. Σ = Σ U {(fi,fj)d (Sfi,Sfj)>= thr};
14.end for.

Fig.3: First step of the proposed 2-D image reassembly approach.

MATCHING CONTOUR SEGMENT OF ADJACENT IMAGE

After completion of CBIR implementation i.e. Step 1, we have set of image fragment pairs. Now to identify matching contour segment of pair of input fragment, we will use some novel algorithms. Instead of comparing contour pixels directly, we will perform color quantization preprocessing step, which takes pixel samples from contour of all image fragments (Michael, 2010).

We employ Kohonen Neural Networks (KNNs) for color quantization purposes. It belongs to class of unsupervised neural networks .KNN include two node layers: Input and Output layer. Each node in input layer S_i has a connection $W_{ik}$with every node $c_k$in output layer. Vector w_j= [w_{1k}, w_{2k} ...wnk] ending at an output node c_k, is the center of cluster.

First, a random number of $N_p$pixels are sampled from input image and mapped to La*b* color space. Sampled $N_p$pixels are minimal portion of the total image fragment pixel. Let X=[x1, x2, x3] be one of the N_p sampled pixels, after mapping to La*b* color space. Given below is iterative learning procedure (Michael, 2010).

1) A winning node $C_j$is selected i.e., output node whose weight vector $w_j$has the highest similarity with input vector x, than output node Ck

|| X-Wj ||= min {|| k – Wk ||}

2) A neighborhood estimate the weight vector updates[1].

DEL of wk = γ ΩCj(ck) (|| x – Wk ||)

Where,

ΩCj(ck) = e rase to (|| pk – pj || 2)/ 26

Γ=Learning parameter

σ=Spread of the "neighborhood" around winning node

P_k=place inside lattice of an output node C_k

P_j=place inside lattice of winning node C_j

Let U and V be two pixels sequences and their label list $[a_i]^n_{i=1}$ and $[b_j]^m_{j=1,}$ Mapping function ϕ search for contour pixel , such that:

- For every $\phi[u_i]=v_k$and $\phi[u_{i+1}]=v_{1,}k<=l<=m$;

It means more than one contour pixels in U can be mapped to same contour pixel in V.

- $\Phi[u_i]!=\Theta$.

It ensure that every contour pixel in U is mapped to a contour pixel in V.

Algorithm used to map this function is called as Smith Waterman dynamic programming algorithm, which is local sequence matching algorithm. A similarity n*m matrix **H** is set up, where row matrix corresponds to u_i. and column to v_j. The algorithm gradually fills matrix H and forms the mapping function **ϕ**. Each matrix cell is assigned with the highest possible value, In order to maximize the mapping score S. The solution to an instance of the problem is given in terms of solution to its smaller sub instances.

H i j ={Hi-1, j-1 + F ui,uj [ai,bj]}

H i j ={Hi, j-1 + g}

H i j ={Hi-1, j+ g}

Where g < 0.

The Smith Waterman algorithm steps are shown in below:

Inputs
U=Contour pixel sequences of fragments Fp.
V= Contour pixel sequences of fragments Fr.
Ai= color cluster label sequence of U.
Bj= color cluster label sequence of V.
Parameter of the Smith Waterman Algorithm e, d, g: e>0,
D<0, g<0.

Output
Φ : a mapping function between Ui and Vj.
Spr : the mapping score of ϕ
1.{initialize H}
2. for i= 1 to n do
3. for j= 1 to n do
4. Hij = F ui,uj (ai,bj);
5. end for
6. end for
7. for i = 1 to n do
8. for j = 1 to n do
9. Hij =max {Hi-1, j-1 + Fui,uj(ai,bj), Hi-1, j+9,
Hi, j-1+9,0}
10. end for
11. end for
12. select an area in matrix H. Let H e1, e2 and Hs1, s2 be the lowestright and highest left border of this area
13. Spr = H e1, e2
14. i=e1; j= e2
15. while {i>=S1 , j>=S2} do
16.index = max {Hi-1, j-1, Hi-1, Hi, j-1};
17. if index = 1 then
18. Φ[ui] = vj; i=i-1 : j=j-1;
19. else if index = 2 then
20. Φ[ui-1] = vj-1 ; j=j-1
21.end id
22.end while

Fig. 4: Second step of the proposed reassembly approach

CONTOUR ALIGNMENT OF IMAGE FRAGMENTS

In this section, we aligns fragment contour along their matching segments in order to find best geometrical transformation. Thus before reassembling of overall image all matching contour segment should be align properly. For implementation of this algorithm we use most popular registration technique method i.e. Iterative Closest Point (ICP).

ICP algorithm generally starts with two point sets and an initial guess of their relative rigid body geometrical transformation. After that transformation parameter are refines, by iteratively generating pairs and by minimizing an error metrics (Memon and Pal, 2006).

Given two curves $p = \{p_1,\ldots,p_{Np}\}$ and $M=\{m_1,\ldots,m_{Nm}\}$

1) Compute the subset of pairs of closest points

$Y=\{(p_i, m_j)|p_i \in p, m_j \in M\}$

M_j is closest point to p_i.

2) Compute a Least Square estimate mapping p onto M

$$(R,t)= \arg\min \Sigma\ I \text{ to } p\ ||\ mi - Rpi - t\ ||2$$

3) Apply the transformation to the p data points

$p=R\,p+t$

4) If stopping criterion is satisfied exit; else, go to step 1

But this form of ICP does not provide robust to outliers, as it does not trim noisy data. Hence if it is not handle properly than it will create a serious problem. This can be overcome by many ICP variant. One of them is Trimmed ICP and Picky ICP

A. *Trimmed ICP and Picky ICP*

The main steps of both trimmed ICP and picky ICP algorithm[1] are as follows.

1) For each point of p, find closest point in M and compute the individual distances d_i^2.

2) Sort d_i^2 in ascending order, select the N_{po}least values and calculate their sum S'_{LTS}.

3) If stopping conditions is satisfied, exit: otherwise, set $S_{LTS}=S'_{LTS}$ and continue.

4) For the N_{po}selected pairs, compute the optimal geometrical transformation (R, t) that minimizes S_{LTS}.

5) Transform p according to (R, t) and go to step 1.

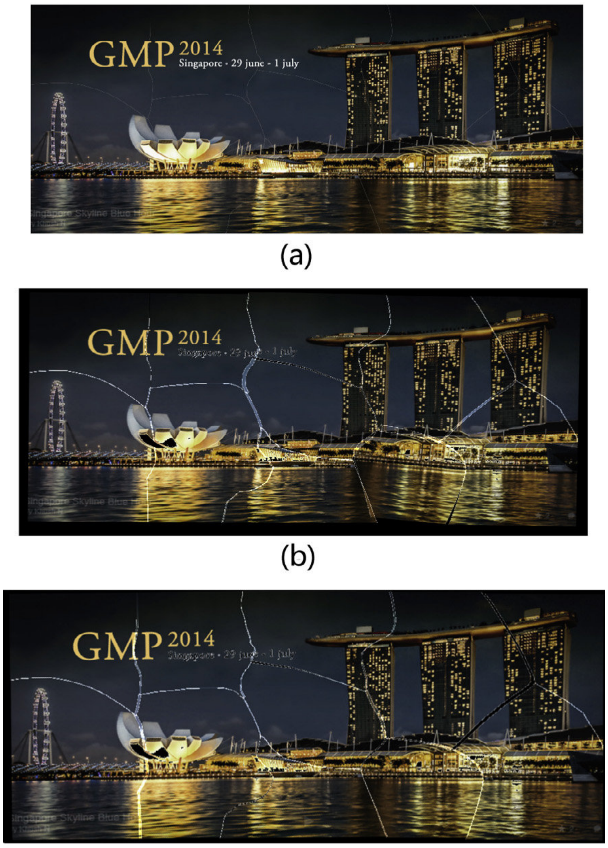
If the trimmed mean squared error $e=S_{LTS}/N_{op}$ is less than user defined threshold or relative change of trimmed mean squared error |e-e'| or the maximum number of iterations is reachedthen Algorithm terminates

OVERALL IMAGE REASSEMBLY

Once we have done with all three steps of matching contour and proper alignment is done, then we are remaining with last step i.e. Reassembly of overall image. Consider three image fragments f_i, f_j and f_k each one matches contour with rest one. Let Θ_i be rotation angle of fragment f_i. And alignment angle of f_i by which it can be rotated in order to fit with fragment $f_j$is Θ_{ij}. Following step must occur in order to align f_i and f_j with respect to each other.

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

2) Rotate fragment f_i by $\Theta_{ij}+\Theta_j$ to correctly align its matching contour segment with corresponding matching contour segment.



(a)

(b)

(c)

Fig. 6: The error estimation of our algorithm.

(a) The ground truth image, (b) the initial reassembly result before graph optimization, and dG ¼ 0:25%, (c) final reassembly result, and dG ¼ 0:19%. We can see that the error is reduced about 20%.

This is implemented using following algorithm.

Inputs
F: set of N image fragments
Σ : set of retained image fragments couples (fi,fj)

Output
I: set of reaseembled image
1.I ◄0;
2.p =(fi-fj)€ Σ: Sij is one of the M highest
3. for each (fi,fj) in y do
4. reassemble a new image I from fi and fj
5. I = I U {1};
6. end for
7. repeat until no image will be found for reassemble

Fig:-5. Overall image reassembly step.

CONCLUSION AND FUTURE WORK

In this paper, We have introduce various distinct novel algorithm. There drawbacks, limitation and deficiencies and also get to know about alternatives that will overcome those drawback. So that there can be efficient and time consuming execution of program. We plan further to improve the performance of proposed method. Finally, the evaluation of proposed system in archeological studies and any other practical implementation is worth exploring.

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