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Automatic Reassembly of Fragmented Images

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ABSTRACT

In many scientific field Such as archeology, forensics and many other, there arises a problem of Reassembling of Image fragment. The solution of such problem by human intervention takes a lot of time and sometimes it might be costlier. So to overcome this problem, we are working on a system which will automatically reassemble those image fragments to form original image. Thus we can make an efficient use of this system with the help of 2D image fragment and contour detection algorithms. Reassembling is divided into four types of techniques. 1) Content based image retrieval system is use to identify spatially adjacent fragment. 2) Dynamic programming technique to identify matching contour segment. 3) Identify optimal transformation to align matching contour segment and 4) overall image reassembling. Thus with the help of these algorithms an optimal transformation in contour can be detected. Doing automation in such work will certainly help in faster, efficient and patiently reassembling this image fragments.

Keywords—Archeology, Contour, Spatially Adjacent, Dynamic Programming , Optimal Transformation

I. 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[1]. First step is to identify spatially adjacent fragment in order to reduce the computational burden of subsequent steps. 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.

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. 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

II. 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[4] 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.

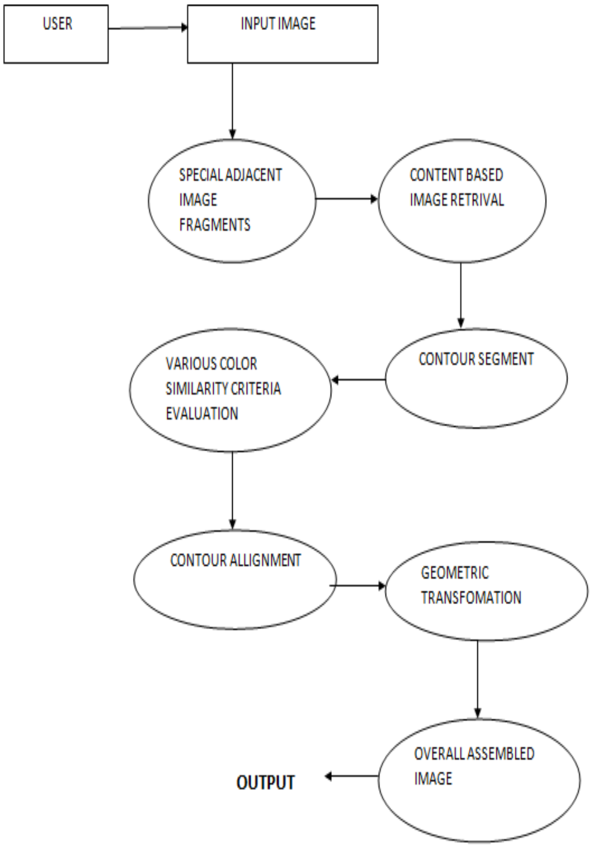

Fig. 1. Overall image reassembly approach

B. Reconstruction of 2D Image Fragments

In this paper[3], 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-aligned.

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.

C. *Curve Matching for Open 2D*[2]

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, manufacturing, computer vision etc.

III. CONTENT BASED IMAGE RETRIEVAL ALGORITHM

In early days because of very large image collections the manual annotation 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 images are indexed using their own visual contents .The visual contents may be color, shape texture. 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.

The Image 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[1] S_I of image I having C quantized colors given by $S_I(i)=(h(i),b(i),\sigma(i))$, i={1,…,C}.

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 are the normalized color histograms extracted from images I_1 and I_2.

1) Scaled L_1 norm[1]

$$d_{L_1}(h_1,h_2) = 1 - 0.5\sum_{i=1}^{C}|h_1(i) - h_2(i)|\,.$$

2) Scaled L_2 norm[1]

$$d_{L_2}(h_1,h_2) = 1 - \frac{1}{\sqrt{2}}\sum_{i=1}^{C}(h_1(i) - h_2(i))^2\,.$$

3) Scaled Histogram Intersection[1]

$$d_{HI}(h_1,h_2) = \sum_{i=1}^{C}\min\left(h_1(i),h_2(i)\right)\left(1 - |h_1(i) - h_2(i)|\right).$$

4) Spatial Chromatic Distance

$$d_{SC}(I_1,I_2)=\sum_{i=1}^{C}\min\left(h_1(i),h_2(i)\right) \times \left(\frac{\sqrt{2}-\|b_1(i)-b_2(i)\|^2}{\sqrt{2}}+\frac{\min\left(\sigma_1(i),\sigma_2(i)\right)}{\max\left(\sigma_1(i),\sigma_2(i)\right)}\right).$$

Inputs

$\mathcal{F}$: set of N image fragments

L: the size of most chromatically similar fragments per input image fragment.

Outputs

$\mathcal{E}$: set of image fragments couples.

$\mathcal{S} \leftarrow \emptyset$;{$\mathcal{S}$ is a list of spatial chromatic histograms.}
for all $f \in \mathcal{F}$ **do**
  quantize f using Gretag Macbeth Color Checker ;
  estimate the spatial chromatic histogram of image fragment f, S_f, according to [27];
  append S_f to $\mathcal{S}$;
end for
$\mathcal{E} \leftarrow \emptyset$;
for $i = 1$ to $N-1$ **do**
  for $j = i+1$ to N **do**
    $m[j-i-1] = d(S_{f_i}, S_{f_j})$; {m is a one dimensional real matrix. d is one from (1) to (4).}
  end for
  sort m in descending order ; $thr = m[L]$;
  $\mathcal{E} = \mathcal{E} \cup \{(f_i, f_j) | d(S_{f_i}, S_{f_j}) \geq thr\}$;
end for

Fig. 2. First step of the proposed 2-D image reassembly approach[1]

IV. 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.

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 i.e 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.

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

$$\|\mathbf{x}-\mathbf{w}_j\| = \min_{\forall c_k}\{\|\mathbf{x}-\mathbf{w}_k\|\}.$$

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

$$\Delta_{\mathbf{w}_k} = \gamma\Omega_{c_j}(c_k)\left(\|\mathbf{x}-\mathbf{w}_k\|\right)$$

Where

$$\Omega_{c_j}(c_k) = e^{(-\|\mathbf{p}_k-\mathbf{p}_j\|^2)/2\sigma^2},$$

Γ=Learning parameter

σ=Spread of the “neighborhood” around winning node

P_k=place inside lattice of output node C_k

P_j=place inside lattice of an 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 $\phi[u_{i+1}]=v_1$, $k<=l<=m$;
  i.e more than one contour pixels in U can be mapped to same contour pixel in V.
- $\Phi[u_i]!=\Theta$.
  This 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.

$$H_{i,j} = \begin{cases} H_{i-1,j-1} + F_{u_i,v_j}[a_i,b_j] \\ H_{i,j-1} + g \\ H_{i-1,j} + g \end{cases}$$

Where g<0.

The Smith Waterman algorithm steps are shown in Fig. 3

Inputs

$U = [u_i]_{i=1}^{n}$: contour pixel sequences of fragment f_p

$V = [v_j]_{j=1}^{m}$: contour pixel sequences of fragment f_r

$[a_i]_{i=1}^{n}$: color cluster label sequences of U

$[b_j]_{j=1}^{m}$: color cluster label sequences of V

parameters of the Smith-Waterman algorithm e, d, g: $e > 0$, $d < 0, g < 0$

Output

$\mathbf{\Phi}$: a mapping function between $[u_i]_{i=1}^{n}$ and $[v_j]_{j=1}^{m}$.

S_{pr}: the mapping score of $\mathbf{\Phi}$.

{Initialize $\mathbf{H}$ }

for $i = 1$ to n **do**

  for $j = 1$ to m **do**

    $H_{i,j} = F_{u_i,v_j}(a_i, b_j)$;

  end for

end for

for $i = 1$ to n **do**

  for $j = 1$ to m **do**

    $H_{i,j} = \max\{H_{i-1,j-1} + F_{u_i,v_j}(a_i, b_j), H_{i-1,j} + g, H_{i,j-1} + g, 0\}$

    {The zero value in is used in order to prevent $\mathbf{H}$ entries from taking negative values.}

  end for

end for

Select an area in matrix $\mathbf{H}$. Let H_{e_1,e_2} and H_{s_1,s_2} be the lowest right and highest left borders of this area;

$S_{pr} = H_{e_1,e_2}$;

$i = e_1$; $j = e_2$;

while $\{i \geq s_1 \wedge j \geq s_2\}$ **do**

  $index = \max\{H_{i-1,j-1}, H_{i-1,j}, H_{i,j-1}\}$;

  {$index$ corresponds to the place of the maximum element in $\{H_{i-1,j-1}, H_{i-1,j}, H_{i,j-1}\}$, i.e. $index \in \{1, 2, 3\}$}

  if $index = 1$ **then**

    $\Phi[u_i] = v_j$; $i = i - 1$; $j = j - 1$;

  else if $index = 2$ **then**

    $\Phi[u_{i-1}] = v_j$; $i = i - 1$;

  else

    $\Phi[u_i] = v_{j-1}$; $j = j - 1$;

  end if

end while

Fig. 3. Second step of proposed reassembly approach[1]

V. 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.

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

1) Compute 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 Least Square estimate mapping p onto M

$$(\mathbf{R}, \mathbf{t}) = \arg\min_{\mathbf{R},\mathbf{t}} \sum_{i=1}^{|\mathcal{Y}|} \|\mathbf{m}_i - \mathbf{R}\mathbf{p}_i - \mathbf{t}\|^2$$

3) Apply the transformation to p data points

p=R p+t

4) If stopping criterion is satisfied then 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*

Following are the main steps of both trimmed ICP and picky ICP algorithm[1]

1) Find closest point in M for each point of p, 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) Exit: If stopping conditions is satisfied, 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 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 reached then Algorithm terminates

VI. 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.

This is implemented by following algorithm.

Inputs

$\mathcal{F}$: set of N image fragments.

$\mathcal{E}'$: set of retained image fragments couples (f_i, f_j), (see section III). The following information must be supplied along with each couple (f_i, f_j):

θ_{ij}: the alignment angle by which fragment f_i must be rotated in order to be aligned with the matching contour segment of f_j.

S_{ij}: the mapping score of the couple.

M: amount of image fragments couples taken from $\mathcal{E}'$ used to initialize this algorithm.

Output

$\mathcal{I}$: set of reassembled images.

$\mathcal{I} \leftarrow \emptyset$;

$\mathcal{T} = \{(f_i, f_j) \in \mathcal{E}' : S_{ij}$ is one of the M highest similarity scores$\}$;

for each (f_i, f_j) *in* $\mathcal{T}$ **do**

  rotate f_i under θ_{ij} and align it with the matching contour segment of f_j ;

  reassemble a new image I from f_i and f_j ;

  $\mathcal{I} = \mathcal{I} \cup \{I\}$;

end for

repeat

  Take one partially reassembled image I from $\mathcal{I}$; $\{$Let $I = \{f_1, f_2, \ldots, f_m\}\}$

  Find an image fragment $f_i \notin I$ such that $(f_i, f_j) \in \mathcal{E}'$, and $S_{ij} = \{\max_{i|f_i \notin I}\{\max_{j|f_j \in I}\{S_{ij}\}\}\}$;

  $I' = \{f_j | f_j \in I \wedge (f_i, f_j) \in \mathcal{E}'\}$; $\{I'$ is the set of image fragments that belong in the partially reconstructed image I and have a matching segment with fragment f_i. $\}$

  Estimate $\phi^j_i, \forall f_j \in I'$;

  Let r be the cardinality of the estimated relative alignment angles, i.e. $\phi^l_i, l = \{1, \ldots, r\}$;

  Form sets $\mathcal{T}_l = \{f_j \in I' : \phi^{j_1}_i = \phi^{j_2}_i = \ldots = \phi^{j_n}_i\} \cup (I - I')$,

  where $l = \{1, \ldots, r\}$ and n is the size of each $\mathcal{T}_l$; $\{$Each set $\mathcal{T}_l$ contains image fragments, for which fragment f_i has the same relative alignment angle, plus the rest fragments in I for which f_i has no matching contour segment with. $\}$

  for all $\mathcal{T}_l, l = \{1, \ldots, r\}$ **do**

    Form a new image NI after rotating f_i under ϕ^l_i and aligning it with the corresponding matching contour segments of fragments in $\mathcal{T}_l$;

    $\mathcal{I} = \mathcal{I} \cup \{NI\}$;

  end for

  $\mathcal{I} = \mathcal{I} - \{I\}$; $\{$remove old image I.$\}$

until no fragment can be added in any reassembled image $I \in \mathcal{I}$

Fig.4. Overall Reassembly of Image[1]

Fig 5. Scanned Image Fragments[1]

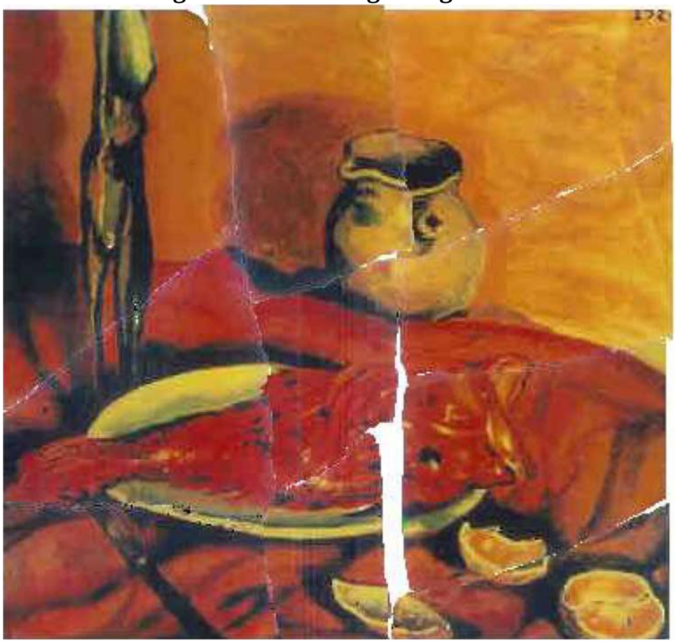

Fig 6. Automated Reassemble Image[1]

VII. 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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