

A Conceptual Study on Image Matching Techniques

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Abstract-Matching Is The Technique To Find Existence Of A Pattern Within A Given Description. Image Matching Is An Important Application Required In The Field Of Image Processing. Images Are Represented As N-Dimensional Feature Vectors. Objects Of Same Class Possess Same Features And Those Objects Which Are From Different Class Possess Different Features. In The Image Matching Process, Features Are Used To Detect Whether Images Are Similar Or Not. Even We Can Find Whether Pattern Image Is A Subset Of Original Image Or Not. To Find Similarity Among Various Images Their Feature Vectors Are Matched. An Efficient Matching Technique Should Find Similarity Or Dissimilarity In Lesser Time Period. A Lot Of Matching Techniques Have Been Developed Till Today And Still Research For Developing An Optimized Matching Technique Is Going On. Most Commonly Used Matching Technique Is Nearest Neighborhood Technique. It Is An Important Technique Used In Applications Where Objects To Be Matched Are Represented As N-Dimensional Vectors. Other Matching Techniques Used Are Least Square Method, Coefficient Of Correlation Technique, Relational Graph Isomorphism Technique, Approximate Nearest Neighbor Technique And Matching Using Simulated Annealing Etc. All Of These Matching Techniques Have Their Own Advantages And Disadvantages. The Matching Technique Should Be Chosen Depending Upon The Application Area In Which It Is To Be Applied.

Keywords-Coefficient of Correlation, HSD, Image matching, K-NN, Nearest Neighborhood, Simulated Annealing, Sub Block Coding.

I. INTRODUCTION

Pattern matching is the technique to find existence of a pattern within an image. To localize a given pattern 'w' in the image 'f', concept of mask is used. An image matrix of pattern 'w' is the mask. This mask is placed over all possible pixel locations in the image 'f' and contents of image mask and image 'f' are compared. As a result of this comparison, a factor matching score is computed. If this matching score is greater than a predefined threshold value, the pattern 'w' is said to be matched with some portion of

$$d^2(x, y) = \sum_{i=1}^M \sum_{j=1}^N \{f(X_i - x, Y_j - y) - w(X_i, Y_j)\}^2 \quad (2)$$

image 'f'. For the comparison of pattern 'w' and image 'f' various techniques have been proposed. the pattern 'w' is said to be matched with some portion of image 'f'. For the comparison of pattern 'w' and image 'f' various techniques have been proposed.

II. MATCHING TECHNIQUES

Image matching techniques are the techniques used to find existence of a pattern within a source image. Matching methods can be classified in two categories i.e. Area based matching techniques and feature based matching techniques. In Area based matching techniques, images are matched by numeric comparison of digital information in small sub arrays from each of the image. It includes methods such as Cross Correlation based matching technique, Least Square Region based technique and Simulated Annealing based matching techniques etc. In Feature based matching methods features of the image like edges, texture at different scales are extracted. Matching is performed with comparison based on characteristics of such extracted features. It includes methods such as Edge String based matching technique, Corner based matching technique and Texture region based matching technique etc [1].

1. Coefficient of Correlation technique

Yang, Y., et al. [2] used least square method for matching process. In this technique, location (x_0, y_0) is pointed out find out in the image that minimizes the least square distance between original image $f(X, Y)$ and pattern image $w(X, Y)$. The distance is calculated using equation

$$d^2(x, y) = \sum_{i=1}^M \sum_{j=1}^N \{f(X_i - x, Y_j - y) - w(X_i, Y_j)\}^2 \quad (1)$$

where $M \times N$ is the size of pattern 'w'.

In cross correlation technique, derivative of least square is taken and pattern is matched by maximizing the second term of equation

But both Cross Correlation and Least Square methods get failed, if there is large variation in image intensity function. To remove this problem, M.S. Sussman and G.A. Wright proposed Correlation Coefficient technique for pattern matching. In Coefficient of Correlation technique, distance function is minimized in equation

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$$d^2(x, y) = \sum_j (x_j - y_j) - w'(X_i, Y_j)\}^2 \quad (3)$$

where $f'(X, Y) = [f(X, Y) - \bar{f} / \sigma(f)]$

and $w'(X, Y) = [h(X, Y) - \bar{h} - \sigma(h)]$

2. Nearest neighborhood technique

To implement Nearest Neighborhood technique, objects are first represented in the form of n-dimensional vectors. For such vectors, Euclidean distance is calculated to find similarity among various objects. Vectors having lesser distance have larger similarity. Euclidean distance in n-dimensional feature vector is distance between two vectors 'a' and 'b_i'.

Consider $a = (a_1, a_2, \dots, a_n)$ and $b_i = (b_1, b_2, b_3, \dots, b_n)$ then Euclidean distance is given as:

$$D_e(a, b_{ij}) = \sqrt{\sum_{j=0}^{n-1} (a_j - b_{ij})^2} \quad (4)$$

Although Euclidean distance is commonly used measure of similarity, it is not the best method. More moderate approach that can be used to find similarity among vectors is to use the sum of absolute differences in feature vectors. It will save computational time and distance in such cases will be:

$$D(a, b_i) = \sum_{j=0}^{n-1} (a_j - b_{ij}) \quad (5)$$

Euclidean distance method is translation, rotation and scaling invariant. Similar to Euclidean distance weighted and Mahalanobis distance methods are also used. In weighted Euclidean distance method weights w_j are assigned as weighted factor to show the importance of jth feature of vector [3]. Weighted Euclidean distance is defined as:

$$D(a_i, b_i) = \sqrt{\sum_{j=0}^{n-1} w_j (a_j - b_{ij})^2} \quad (6)$$

In Mahalanobis distance method, statistical divergence properties of feature vector are used as weights. Distance in this method is given as:

$$D(a, b_i) = (a - b_i)^T \sum_i^{-1} (a - b_i) \quad (7)$$

where summation over 'i' is variance-covariance matrix. Object having minimum Euclidean distance from 'a' is considered as nearest most similar object to 'a'.

3. K-nearest neighbor technique

The general version of nearest neighbor method is k-nearest neighbor method. In this method, nearest k neighbors are searched out rather than only one nearest neighbor. A query in k-NN technique is defined as

Consider a vector 'a', and an integer 'k'. k-NN searches for k neighbors of vector 'a' according to distance between 'a' and kth neighbor. The result of k-NN query consists of k vectors such that:

$$\|a - p\| \leq \|a - q\| \quad (8)$$

where $p \in R$

and $q \in DB-R$

R is result set of 'k' neighbors.

DB-R is the set of remaining points which are not among 'k' neighbors.

The drawback of k-NN method is its response time which is very large. The indexing matching methods have been proposed to overcome the problems of k-NN method.

To improve speed of K-NN image matching technique various approaches have been developed. For multidimensional feature space MIM technique has been proposed.

4. MIM image matching method

In MIM, feature space is partitioned into clusters and with the help of those partitions search is pruned. It has been observed that MIM works well for low dimensional feature space, even it works satisfactorily for high dimensions up to a threshold value [4][5][6][7][8].

To overcome dimensionality problem of MIM, a few other approaches have been developed.

- The Dimensionality Reduction Technique
- Approximate Nearest Neighbor Technique
- Multiple Space Filling Curve Technique
- Filter Based Technique

In Dimensionality Reduction technique *G.Strang*[9] has suggested to condense most of the information into a few dimensions by applying SVD (singular value decomposition) technique. It will save time for indexing. According to *K.V.R. Kanth, D.Aggarwal and A. Singh* although Dimensionality Reduction approach has solved dimensionality problem, but many other drawbacks have been observed. They are:-

- Accuracy of query has been lost.
- DR works well only if feature vectors are correlated.[9]

S.Arya[10] has discussed ANN technique to find 'k' approximate nearest neighbors in very short response time within an error bound 'e'.

Given a query vector 'q' and a distance error 'e' > 0 then, 'p' will be an ANN of 'q' such that for any other point 'p' in feature space

$$\|q - p\| \leq (1+e)\|q - p'\| \quad (9)$$

N.Megiddo and *U. Shaft* have discussed an approach in which n-dimensional space is reduced to 1-n space and gives linear ordering of all the points in the feature space. In multiple spaces filling curve approach n-dimensional space is arranged in 1-dimensional space according to mapping $R^d \rightarrow R^1$.

In this linear arrangement, nearer points on space-filling curve corresponds to nearer points in n-dimensional space. But the problem with this approach is that some nearest neighbors may be ignored in it [11] [12]. In filter based approach, *R.Weber, H.J. Schek and S.Blott* have reduced the range of vectors to be searched for pattern matching. In this technique only a few vectors are scanned during search of matching process. It returns exact K-NN of an object. Selected vectors with which object will be matched is extracted by filtering method. VA-file filtering approach has been discussed by *R.Weber, H.J. Schek and S.Blott*. VA-file divides feature space into 2^b rectangular cells. It allocate a unique b length bit string to each cell and approximate data points that fall in to cell by that bit string. K-NN queries are processed by scanning all approximations and by excluding majority of vectors from search based on these approximations. The problem with VA- file is that its performance converges to sequential scan and get worse as number of bits used for approximation get increased. To remove this problem *Guang-Ho, Xiaoming Zhu*[13] has proposed an *efficient indexing method for NN searches in high-Dimensional image database*. In LPC-file some additional information is stored which is independent of dimensionality.

5. LPC-File indexing method

An indexing matching method has been proposed by *Guang-Ho, Xiaoming Zhu*[13] to reduce the response time of k-NN technique. Indexing method proposed by them was named as LPC-file. LPC is for local polar coordinate file. LPC-file improves search speed even in high dimensional feature space [13]. LPC-file is a filter based approach for image matching. LPC-file approach is similar to VA-file, but it adds polar coordinates information of vector to the approximation. It is sufficient to use 3 bytes for polar coordinates, 2 bytes for radius and 1 byte for angle. Unlike MIM, where cells are organized in hierarchical manner, in LPC vector space is partitioned into rectangular cells and then these cells are approximated by their polar coordinates. In LPC-file for each vector ' p_i ', where $i \in \{1, 2, 3, \dots, N\}$, an approximation ' a_i ' is found out. In next step vector ' P ' is represented using polar coordinates (r, θ) in the cell in which ' P ' lies.

Thus ' P ' is represented as triplet $a = (c, r, \theta)$

Where c is approximation cell, ' r ' is radius and ' θ ' is angle of ' P '.

Complete LPC-file is an array of approximations of all the vectors. To find out K-NN only filtered vectors are stored in LPC- file are scanned.

On the basis of approximations of vector, bound on the distance between query point and vector is derived to restrict the search space between k-NN searches.

$$d_{min} = |p|^2 + |q|^2 - 2|p||q|\cos|\theta_1 - \theta_2| \quad (10)$$

and

$$d_{max} = |p|^2 + |q|^2 - 2|p||q|\cos(\theta_1 - \theta_2) \quad (11)$$

In filtering process, vectors are collected to form candidate set. For this collection, each vector's d_{min} and d_{max} is computed. If a vector is found where d_{min} exceeds the distance $k\text{-NN}^{\text{distance}}(q)$ of kth NN encountered so far, then corresponding vector can be eliminated since k better candidates have already been found.

Consider a 5-dimensional vector space $V = \{\text{orientation, x, y, scale, intensity}\}$. In 5 dimensional vector 3 bits will be used for assigning bit string to each dimension.

According to LPC, we also store ' r ' and ' θ '. On the basis of value of ' r ' and ' θ ' vectors are filtered.

6. Image Matching By Simulated Annealing

A number of matching techniques have been developed but the problem with such matching techniques is that they have very high response time for matching process. An optimized image matching technique has been developed by *Laurent Herault, Radu Horaud*[14]. This technique was based on simulated annealing, where firstly image is represented in the form of relational graph. Then a cost function is derived for the graph of the image. This cost function is optimized with the method of simulated annealing. To use simulated annealing method for image matching, description of image is represented in the form of relational graph. In this graph nodes represent features and arcs represent relation among these features. This relational graph is casted into optimization problem and such problem is solved using simulated annealing technique. For simulated annealing cost function is represented as quadratic function. It will help to calculate energy variation in annealing process. In physical annealing process, in order to reach at a low energy state, metal is heated up to high temperature and then is cooled down slowly. To apply simulated annealing for image graph, states, state transition, random generation of state transition and change in energy associated with state transition is explicitly defined [14]. Let ' a ' and ' b ' be the two graphs where ' b ' should be isomorphic to ' a '. To optimize the matching process, isomorphism among ' a ' and ' b ' must minimize the equation

$$E = \sum_{s=1}^S \lambda_s E^s \quad (12)$$

where ' E ' is cost function and ' S ' is the number of possible relationships in graph ' a ' and ' b ' and

$$E^s = \sum_{k=1}^N \sum_{l=1}^N (1 - 2a_{kl}) \cdot b_{\pi(k)\pi(l)} \quad (13)$$

Where N = number of nodes in graph,

λ_s = weight assigned to each of relationship

Π = one-one correspondence between vertex of ' a ' and vertex of ' b ' which minimize the distance between two graphs.

7. HSD (Histogram Based Similar Distance) based Matching Technique

Boaming Shah, Fengying cui[15] presented HSD (Histogram Based Similar Distance) technique combined with ARPIH(Angular Radial Partitioning Intensity Histogram) matching technique to find number of matching points between source and target image. HSD provides high performance for geometric attacks like rotation and shearing. It gives better performance even in case of illumination change.

Using ARPIH technique, a strength histogram is constructed and considered as an image. In ARPIH descriptor, image is partitioned into 18 sub regions according to angle θ which are $(\pi/3, 2\pi/3, \pi, 4\pi/3, 5\pi/3, 2\pi)$ and the ratio of radius 'r'.

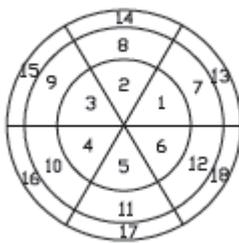


Fig 1: ARPIH image subregions

In ARPIH descriptor a two-dimension histogram is constructed which represents the pixel grayscale distribution in the image region and the geometry relationship between the sub regions. The x-axis of histogram is the serial number of sub region, and y axis is grayscale (0-255) which is evenly divided into 18 gray ranges. Then the pixels in every sub region are distributed into every gray range by its own grayscale.

HSD is based on MAD(Mean Absolute Difference Algorithm) and MLD technique. In these techniques rather than calculating all point's distance from one aggregate to another, distance between two corresponding points is taken as main similarity measure. Therefore, the similarity between every pair of corresponding points is calculated and then similarity is accumulated according to minimum difference to get distance between two images.

To explain it consider the template image as $S(m, n)$, its size is $M \times N$, the target image as $I(u, v)$, its size is $U \times V$. The position of template image in the target image is (i, j) , suppose $S'(m, n) = I(i+m, j+n)$, $d(i, j)$ denotes the distance function between the same size image windows, (i^*, j^*) denotes the optimal matching position, 'P' is the matching range, 'P' is defined as follows:

$$P = \{(i, j), 0 \leq i \leq U - M, 0 \leq j \leq V - N\} \tag{14}$$

The distance measurement function based on traditional mean absolute difference algorithm (MAD) is defined as follows:

$$d(i, j) = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N R_{MAD}(S(m, n), S'(m, n)) \tag{15}$$

where

$$R_{MAD}(S(m, n), S'(m, n)) = |S(m, n) - S'(m, n)| \tag{16}$$

The optimal matching position is

$$d(i^*, j^*) = \min\{d(i, j) | (i, j) \in P\} \tag{17}$$

MLD is defined as follows [16]:

$$d(i, j) = \sum_{m=1}^M \sum_{n=1}^N R_{MAD}(S(m, n), S'(m, n)) \tag{18}$$

where

$$R_{MAD}(S(m, n), S'(m, n)) = \begin{cases} 1, & |S(m, n) - S'(m, n)| \leq T \\ 0, & \text{else} \end{cases} \tag{19}$$

where $d(i, j)$ means similarity, so the optimal matching position is

$$d(i^*, j^*) = \max\{d(i, j) | (i, j) \in P\} \tag{20}$$

The difference between the two algorithms is that the former computes the sum of the entire pixel's grayscale absolute difference, while latter one only computes the number of the similar points. To perform matching only the similar number of points are considered between the template image and target image, to measure the similarity degree, and at the same time it discards those points that have more differences with the template. In HSD matching technique, histograms for both images template and target are drawn and two images are considered similar if they satisfy following conditions:

$$D_{HSD} \geq T_1 \tag{21}$$

$$D_{HSD} = \sum_{m=1}^M \sum_{n=1}^N R_{HSD}(H(m, n), H'(m, n)) \tag{22}$$

$$R_{HSD}(H(m, n), H'(m, n)) = \begin{cases} 1, & |H(m, n) - H'(m, n)| \leq T_2 \\ 0, & \text{else} \end{cases} \tag{22}$$

where, T_1 and T_2 are the threshold values which are predefined.

Steps followed during HSD are as:

- 1) Find ARPIH of the template image.
- 2) Select the sub-region from the top left corner of the target image in the same size with the template image, and find its ARPIH.
- 3) Match the two histogram according to HSD technique
- 4) Glide the template image on the target one, and search the sub-region with the same size as template image, then get its ARPIH.

- 5) Repeat above until to finish a whole scan for target image, the matching position is the area which has the maximal DHS D value.

8. Sub Block coding based matching technique

A template based matching method is discussed by *Yuping FENG, Shi LI, and Ming DI* [17]. This method combines local gray value encoding matching technique and phase correlation technique. Here matching is divided into two parts: rough matching and fine matching. In Rough matching image is divided into certain blocks called R-blocks, and sum of gray value of each R-block pixel is calculated. After that R-blocks are encoded according to gray value distribution of R-block with neighboring R-blocks and matching is performed between template and each search sub image. The detailed description of this method is as:

A. Rough matching

An image of size $N \times N$ is divided into some $k \times k$ size non overlapping blocks called R-block. Each R-block has eight neighborhoods and four D neighborhoods, and they have the following relations:

$$D1 = R1 \cup R2 \cup R4 \cup R5$$

$$D2 = R2 \cup R3 \cup R5 \cup R6$$

$$D3 = R4 \cup R5 \cup R7 \cup R8$$

$$D4 = R5 \cup R6 \cup R8 \cup R9$$

D Neighborhoods are sorted on the basis of sum of their pixel's gray value. There are 24 (4!) kinds of possibility for sorting the gray value sum of each R block pixel in every D-neighborhood. Every possible sorting result can be represented by five bits binary code, that is P (Dj) belongs to {00000, 00001... 10111}. Each R-block has four D-neighborhood, each D-neighborhood has one five bits binary code. The Ri block coding is to connect the adjacent D-neighborhood code, and obtain twenty bits binary code, which is:

$$F(Ri) = P(D1)P(D2)P(D3)P(D4) \quad (24)$$

where F (Ri) is called R-block's code. Coding features of an image are made up of all R-block's codes. Through encoding, the content of the image is present as R-block's codes which indicate the different spatial gray value distribution of the image. Similarity among images is found as: more same feature codes images have, more similar they will be. It reduces the complexity and computation of matching. The more sub-blocks are divided, the better the content of image is described deviously, but it increases the encoding and matching computation. To improve searching speed scanning point by point is replaced with scanning of pixels at certain steps. This search strategy greatly saved calculation time.

The R-block's code set is expressed with (N/ k) orders square matrix $A \square T$ and $A \square S \ i \ j \square$ that is called characteristic coding matrix, 'k' is the size of R-block and $N \times N$ is the size of 'T'. Matching takes the number of the

same feature code as similarity measure. The more same feature codes they have, the more similar regions they have. In Rough matching process the template and search image are divided into some non overlapping R-blocks, then characteristic coding matrix of the template and all R-block's code of the search image is calculated; after that search image is scanned by step, the coding matrix of template and each search sub-image is compared with to get the number of the same element recorded, say 'w'. Last, the location of the largest 'w', 0(io, jo) is the final coarse matching result. During the process of scanning, if the value of 'w' is greater than a certain threshold, the matching is interrupted.

B. Fine Matching Using Phase Correlation

In rough matching, the scanning process is performed by a certain step, where the template and search sub-image may be not completely overlapped. Therefore, rough matching result may not represent the correct matching. Due to this, precision matching amendment using phase correlation is adopted after rough matching. In Fine matching temporary matrix from image is taken on the basis of result of rough matching. After that phase correlation between temporary matrix and template is calculated. Based on cutting position and the matching result translation factor is obtained for matched template. On the basis of this phase correlation factor final matching is performed. Phase correlation method [18] based on Fourier transform is used for estimating the translation by phase relationship; it is not impacted by the different image content. The linear transformation of pixel grey value and image noise mainly effect amplitude in frequency domain but not its phase. Phase correlation has higher matching accuracy because of sharp correlation peak, and also has the stability of small-angle rotation. Assuming that the following translation relations between 'g1' and 'g2' images are given:

$$g_1(x, y) = g_2(x - x_o, y - y_o) \quad (25)$$

The Fourier transform for above equation is as:

$$G_1(u, v) = G_2(u, v)e^{-j2\pi(ux_o + vy_o)} \quad (26)$$

The cross-power spectrum for g1 and g2 is as:

$$\frac{G_1(u, v)G_2^*(u, v)}{|G_1(u, v)G_2^*(u, v)|} = e^{-j2\pi(ux_o + vy_o)} \quad (27)$$

The phase correlation function is that:

$$corr(x, y) = F^{-1}(e^{-j2\pi(ux_o + vy_o)}) = \delta(x - x_o, y - y_o) \quad (28)$$

where $\delta(x - x_o, y - y_o)$ is a pulse peak function. The biggest peak position is the translation(x0, y0). The temporary matrix whose size is the same as template size is cut from search image according to rough matching point (i0, j0). The phase correlation translation (x0, y0) between temporary matrix and T is used to modify the rough match, as following:

$$(x, y) = (i_o + x_o, j_o + y_o) \quad (29)$$

Here (x, y) are the finally matched coordinates.

III. CONCLUSION

In Image Processing applications matching is very important phase. For the application having vectors of low or medium dimensions, MIM, R* tree and SR tree etc. are perfectly affordable. As dimensions increases filtered based approaches should be used to shorten the response time of matching process. LPC- file and VA- file are filtered based matching methods. LPC-file outperforms VA-File and K-NN matching methods. Its response time and disk space consumption is very less as compared to other matching techniques. It works well for both random and skewed distributed vector space. To optimize matching process of images simulated annealing technique can also be preferred. A combination of local gray value encoding matching and phase correlation matching technique gives two times better performance than existing sub block coding based matching techniques. HSD is technique used for matching images affected by geometric attacks like rotation etc.

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