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Finger- image Segmentation using K-means clustering and a comparative analysis with L*A*B* method and detection of the segment using Correlation and Fourier-Series

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Abstract- *Image segmentation is an important component in many image analysis and computer vision tasks. Finger-print recognition security systems deploy dormant, contact based scanners that rob the system of its viable flexibility. In this paper, foundation for a contactless finger-image recognition system is laid. Using K-means clustering method, finger images, captured using smart-phones, are segmented to extract the finger region. The same is accomplished using L*A*B* image segmentation algorithm, and a comparative analysis is framed. Basically a computer based application, Contactless security system demands an automated tool dedicated for identifying the desired finger-segment from the complete image. For this purpose, two independent algorithms, namely- correlation and FFT are practiced. The earlier segmentation results, obtained from both the methods, are employed in these algorithms and the results are scrutinized.*

Keywords- *K-means, L*A*B*, Correlation, Fourier -Series, Finger.*

1. Introduction

Digital images are one of the most key medium of conveying information. Extracting the information from images and understanding them such that it can be used in several other applications is its important characteristic. Image segmentation is a vital operation performed on images to extract necessary information from them. Color image segmentation was useful in many applications. From the segmentation results, it was possible to identify regions of interest and objects in the scene, which was very beneficial to the subsequent image analysis or annotation. Recent work includes a variety of techniques. Criterion for Segmentation was at first, colors in the image are coarsely quantized without significantly degrading the color quality. The purpose was to extract a few representing colors that can be used to differentiate neighboring regions in the image. Typically, 10-20 colors are needed in the images of natural scenes. A good color quantization was important to the segmentation process. After quantization, the quantized colors are assigned labels. A color class was the set of image pixels quantized to the same color. The image pixel colors are replaced by their corresponding color class labels. The new constructed image of labels was called a class-map.
During a cholera outbreak in London in 1854, John Snow used a special map to plot the cases of the disease that were reported. A key observation, after the creation of the map, was the close association between the density of disease cases and a single well located at a central street. After this, the well pump was removed putting an end to the epidemic. Associations between phenomena are usually harder to detect, but the above was a very simple, and for many researchers, the first known application of cluster analysis. Since then, cluster analysis has been widely used in several disciplines, such as statistics, software engineering, biology, psychology and other social sciences, in order to identify natural groups in large amounts of data[2].

Clustering methods can be divided into two basic types: hierarchical and partitional clustering. Within each of the types there exists a wealth of subtypes and different algorithms for finding the clusters. Hierarchical clustering proceeds successively by either merging smaller clusters into larger ones, or by splitting larger clusters. The clustering methods differ in the rule by which it was decided which two small clusters are merged or which large cluster was split. The end result of the algorithm was a tree of clusters called a dendrogram, which shows how the clusters are related. By cutting the dendrogram at a desired level a clustering of the data items into disjoint groups was obtained.

Partitional clustering, on the other hand, attempts to directly decompose the data set into a set of disjoint clusters. The criterion function that the clustering algorithm tries to minimize may emphasize the local structure of the data, as by assigning clusters to peaks in the probability density function, or the global structure. Typically the global criteria involve minimizing some measure of dissimilarity in the samples within each cluster, while maximizing the dissimilarity of different clusters. A commonly used partitional clustering method is K-means clustering.

1.1 K-means Clustering:

There are many approaches of clustering designed for a wide variety of purposes. K-means is a typical clustering algorithm (MacQueen, 1967). K-means is generally used to determine the natural groupings of pixels present in an image[3]. The function k-means partitions data into k mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data. In k-means clustering method, each observation in your data is treated as an object having a location in space.

Mathematically, in K-means clustering the criterion function was the average squared distance of the data items X_k from their nearest cluster centroids,

$$E_K = \sum_k \|\mathbf{x}_k - \mathbf{m}_{c(\mathbf{x}_k)}\|^2$$

Where, $C(X_k)$ was the index of the centroid that was closest to X_k . One possible algorithm for minimizing the cost function begins by initializing a set of Kcluster centroids denoted by m_i ; i=1,….k .

A partition is found in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. It can be chosen from five different distance measures, depending on the kind of data being clustering.

Each cluster in the partition is defined by its member objects and by its centroid, or center. The centroid for each cluster is the point to which the sum of distances from all objects in that cluster is minimized. K-means computes cluster centroids differently for each distance measure, to minimize the sum with respect to the measure that you specify.

K-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. The positions of the m_i are then adjusted iteratively by first assigning the data samples to the nearest clusters and then re-computing the centroids. The iteration was stopped when *E* does not change markedly any more. This algorithm moves objects between clusters until the sum cannot be decreased further. The result is a set of clusters that are as compact and well-separated as possible. You can control the details of the minimization using several optional input parameters to k-means, including ones for the initial values of the cluster centroids, and for the maximum number of iterations.

On summarizing the above explanation, it is understood that this method decomposes the image into clusters of similar pixels, depending on their data content. By using different values of ‘k’, different clusters can be obtained individually, thus making the analysis flexible. But this is suitable for manual inspection of segmented images, where the user can view the individual segments and chose the desired. For a complete automated application, it becomes essential to devise a method to identify the cluster occupying maximum region. For example in a Finger print analyzing software, wherein the finger prints are taken using a normal mobile camera. In this case, first step is to segment the image into various regions depending on their color in order to extract the finger portion from the overall image. The next step is to select the segment spanning over majority of the region. This is done with the help of an algorithm that converts the segments into a mathematical value, which can be used as to identify the desired segment. Two such methods are described below.

1.2 Correlation:

Correlation is a method for establishing the degree of probability that a linear relationship exists between two measured quantities. In 1895, Karl Pearson defined the Pearson product-moment correlation coefficient ‘r’. Pearson’s correlation coefficient ‘r’, was the first formal correlation measure and is widely used in statistical analysis, pattern recognition and image processing[4]. The Pearson's method is widely used in statistical analysis and in applications involving comparing multiple images for image registration purposes, disparity measurement, etc.

For monochrome digital images, the Pearson’s correlation coefficient is defined as,

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}}$$

where, x_i and y_i are intensity values of i^{th} pixel in 1^{st} and 2^{nd} image respectively. Also, x_m and y_m are mean intensity values of 1^{st} and 2^{nd} image respectively. The correlation coefficient has the value r = 1, if the two images are absolutely identical; r = 0, if they are completely un-correlated ; r = -1, if they are completely anti-correlated[5].

In order to apply this algorithm to multi-color segments, they need to be converted first into a grayscale image. By applying the correlation algorithm to these segments obtained using k-means clustering technique, individual PCC are obtained. The highest PCC of all would be the cluster occupying majority area in the original image. By analyzing the PCC's, desired segment is chosen and used for further processing.

Advantages of this algorithm are that it condenses the comparison of two 2-D images down to a single scalar value 'r'. Also it is completely invariant to linear transformations of x and y. So, r is insensitive (within limits) to uniform variations in brightness or contrast across an image.

1.3 Fast Fourier Transform:

In order to identify the desired cluster for further processing, without manual assistance, another computational method makes use of Fast Fourier Transform (FFT).

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components[6]. The Discrete Fourier Transform (DFT) is a specific form of Fourier analysis to convert one function (often in the time or spatial domain) into another (frequency domain). DFT is widely employed in signal processing and related fields to analyze frequencies contained in a sample signal, to solve partial differential equations, and to perform other operations such as convolutions. The practical implementation of the DFT on a computer nearly always uses the Fast Fourier transform (FFT). FFT is simply an algorithm (i.e., a particular method of performing a series of computations) that can compute the discrete Fourier transform much more rapidly than other available algorithms. Fast Fourier Transform is applied to convert an image from the image (spatial) domain to the frequency domain. Applying filters to images in frequency domain is computationally faster than to do the same in the image domain. FFT is surely the most widely used signal processing algorithm and is the basic building block for a large percentage of algorithms in current usage[9].

Fourier Transform decomposes an image into its real and imaginary components which is a representation of the image in the frequency domain. If the input signal is an image then the number of frequencies in the frequency domain is equal to the number of pixels in the image or spatial domain. The inverse transform re-transforms the frequencies to the image in the spatial domain.

The 2D transform can be done as 2 1D transforms as shown below (shown only in the horizontal direction) - one in the horizontal direction followed by the other in the vertical direction on the result of the horizontal transform. The end result is equivalent to performing the 2D transform in the frequency space.

$$F(x,y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(m,n) e^{-j2\pi\left(x\frac{m}{M}+y\frac{n}{N}\right)}$$

$$f(m,n) = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} F(x,y) e^{j2\pi\left(x\frac{m}{M}+y\frac{n}{N}\right)}$$

The output of the Fourier Transform is a complex number and has a much greater range than the image in the spatial domain. Therefore to accurately represent these values, they are stored as floats. Furthermore, the dynamic range of the Fourier coefficients are too large to be displayed on the screen, and hence, these values are scaled (usually by dividing by Height*Width of the image) to bring them within the range of values that can be displayed. In this algorithm, the segmented image is converted into a matrix first. FFT is computed on individual pixel of the segmented image. For generating feature vector we divide the color image into its R, G, B components, and then transformation is applied to obtain transform coefficients. The value of transform at the origin of frequency domain [i.e.F(0,0)] is called the DC component of the transform. The first coefficient (DC component) represents the energy information. The first coefficient (DC component) of each transformed color component i.e. R, G & B is used for feature vector generation, so in this method for each color component we obtain one feature value. The feature vector of one RGB image consist of three feature values one feature corresponding to each color component. Once the feature vectors are generated for all images in the database, they are stored in a feature database. Where $F_q[i]$ is the i^{th} query image feature and $F_{db}[i]$ is the corresponding feature in the feature vector database.Feature vector database is a matrix is formed, that consists of the feature vectors of individual pixel.These elements are added and a coefficient is obtained. This applies to a single image. Similarly, for every segmented image such coefficients are obtained. The highest coefficient corresponds to the segment occupying maximum area in the original image. The image is then selected for further processing.

The advantage of representing an image in the frequency space is that performing some operations on the frequencies is much more efficient than doing the same in the image space. Convolution in the spatial domain corresponds to multiplication in the frequency domain. This enables efficient implementations of very large convolutions in image processing and other algorithms/operations in many fields.

2. Methodology

I)The first part of methodology follows two different paths using different segmentation methods. The first path uses L*a*b* color space based segmentation. This gives three segmented images for the original image in captured by Smartphone camera.

II)The second path uses K-Cluster based segmentation. This gives segmented images for the original image captured by Smartphone camera as shown in fig. 2a below:

Fig. 1a - Original Image

III)In the next step, we detect the finger that may be present in any of these segmented images. For this algorithm fuses decision from the results obtained from two different metrics namely:

(1) Pearson Correlation coefficient [PCC]
(2)Magnitude of the Fourier spectrum [Fs]

2.1. Pearson Correlation Coefficient [PCC]

Pearson Correlation coefficient provides quantitative measures between two variables to indicate how well they are correlated or not correlated.

Flowchart variables are assigned for different parameters like original captured image, segmented images and array variable for storing correlation coefficients. The "i" here acts as count which runs correlation loop three times to perform correlation of three segmented images. The three segmented images are all results of same segmentation method. Either L*a*b* color space segmentation or K-means based segmentation. The function 'corr2( )' performs two dimensional correlation to find correlation coefficient. It is given by:

$$Pcc_i = \frac{\sum_{mn}(Omn - |O|)(Rimn - |Ri|)}{\sqrt{(\sum_{mn}[Omn - |O|]^2)(\sum_{mn}[Rimn - |Ri|]^2)}}$$

Where m and n are matrix dimensions of the images.

The two dimensional correlation is performed since images which are comprised of pixels are two-dimensional function. The original image (O) is correlated with each of the segmented images (Ri) using 'corr2( )' function and the correlation coefficients (Ci) are obtained. It is found that segmented image containing finger is maximally correlated with the original image. Also it has maximum magnitude for correlation coefficient than the rest of the two. The Pearson correlation coefficients are found for segmented images obtained by both segmentation methods one at a time[1][8].

2.2 Magnitude of Fourier Spectrum

In this step for the given segmented image we find its Fourier transform. Similar to PCC the two dimensional Fourier function 'fft2()' is used here. This function finds the Fourier transform of each elements of the image matrix. The resultant matrix obtained represents the magnitude of the Fourier spectrum. After taking Fourier transform all elements in the image matrix are summed up to get Fourier coefficient for the image. The Fourier transform is obtained by formula:

$$Ci(\omega 1, \omega 2) = \sum_{m}\sum_{n} ci(m,n)e^{-j\omega 1m}e^{-j\omega 2n}$$

Where $\omega 1$ and $\omega 2$ represents frequency variable, represents frequency domain coefficients of which is one of the segmented image. The Fourier transformed elements of the image matrix are summed up using Parseval's theorem that can be computed as follows:

$$Mi = \sum_{\omega 1}\sum_{\omega 2}|Ci(\omega 1, \omega 2)|$$

It was found that the coefficient obtained for each segmented image is maximum for the one which contains the finger. This is because the Fourier Spectrum indicates the large magnitude centered at origin or near to the origin. Since images are captured such a way that the location of the finger is at the centre of the image i.e. at the origin, the coefficient for segment containing the finger will be maximum. Similar to the PCC, the coefficients are found for segmented images obtained by both segmentation methods one at a time[1].

3. Experiment

The experiment was performed on finger images in different backgrounds and on ordinary image. Initially K-means clustering was applied to one image and samples are obtained. Correlation and Fourier Spectrum is applied on the samples and respective results are obtained and categorized. Segmentation is now performed using L*A*B* method on the same original image taken above and segments were obtained and like the previous step, correlation and Fourier Spectrum is performed on the obtained segments. These results are categorized and compared with those obtained using K-means clustering. Similar procedure is followed for two other images and the result are obtained and analyzed.

The results obtained after executing the above experimental procedure are placed below. The left column shows K-Clustered segments while the right column shows L*a*b* segments along with their Pearson

Correlation co-efficient (PCC) and Fourier spectrum magnitude (Fs) respectively. The third segment is the high index segment for both of the segmentation methods.

4. Output

Finally we fuse the decision from the results obtained from metrics viz. PCC and magnitude coefficient of Fourier spectrum to select any one of the segmented image on basis of majority in both metrics. This segment containing finger is thus detected from the captured image which can be further use for verification purpose. This procedure was performed on 50 different images and the outcomes were analyzed. One of the result obtained by using both segmentation methods (L*a*b* color space and K-Cluster) are shown below in fig. 2a and fig. 2b respectively.

Fig. 2a

Fig. 2b

5. Conclusion & Future Scope

In this paper image segmentation has been performed using K-means cluster and comparatively analyzed the two segmentation methods viz. L*a*b* color space segmentation and K-cluster segmentation. Based on the experimental outcomes of the above made comparative analysis, it was concluded that K-means Clustering provides efficient segmentation results than l*a*b* method thus providing distinct, recognizable and utilitarian image segments. Whereas, l*a*b* method results in a satisfactory, yet low quality segmentation of the image encompassing distortions. Further, it fails to efficiently segment the images in which color segments are scattered. Thus K-means clustering proves to be a superior to l*a*b* method and serviceable in the contact less finger-based security system.

The analysis reckons Fourier-Series a better option compared to correlation coefficient because of its accuracy in assigning discrete values to each segment based on their occupancy in the image. Thus, a necessary condition observed from the experimental results, is the finger must occupy majority of the image field in order to be detected by these detection algorithms, in the contact-less finger-based security system application that it is supposed to be used in. The experiment confirms K-means clustering for segmentation fused with Fourier-Series method for segment detection as the best combination among those deployed in the study.

Hence, with this analysis the first task of finger segmentation is accomplished. Now this image can further be used for fingerprint verification and other processes that lie in its path towards achieving the ultimate goal of developing an efficient contact-less finger based security system.

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