

Image Matching with Edge Detection

Somi R. Kevin

B.E, M.Tech. in Computer Science
somi_ab@yahoo.co.in

Abstract - Image matching, which measures the degree of similarity between two image sets that are superposed upon one another, plays a key role in many areas such as pattern recognition, image analysis and computer vision. Matching two images requires the images to be matched go through a number of operations before the similarity is determined. This paper presents a method in which the edges of the given images are matched with the new entries using different algorithms and it determines its validity with the available pictures. In many areas of business, these systems are entrusted to verify identities of personnel before allowing access to restricted information or facilities. In the area of criminal investigation, these same systems are entrusted to find, match and identify criminals. In order to enhance important features accurately in the image matching, methods in edge detection are applied.

Keywords - Edge, Edge detection, image matching, feature extraction

INTRODUCTION

Image Matching

Image matching, measures the degree of similarity between two image sets that are superposed upon one another. It is applied to various fields such as pattern recognition, image analysis and computer vision. Matching two images requires the images to be matched go through a number of operations before the similarity is determined. These operations include feature extraction, distance transformation, matching measurement and searching for the best match. Image thresholding is a technique for converting a grayscale or color image to a binary image based upon a threshold value. If a pixel in the image has intensity less than the threshold value, the corresponding pixel in the resultant image is set to white otherwise, if the pixel is greater than or equal to the threshold intensity the resulting pixel is set to black.

Edge detection

Edge Detection is a scheme to locate positions in the image where intensity changes abruptly. Edge Detection is used to identify boundaries that segment an image into regions. But images do not have edges; objects do. Therefore this paper provides a method of solving the problem of edge detection. It has been shown that much of the essential information about a scene is contained in the edge map of the image, and that edge structures have an apparent relevance in biological vision systems. In addition, the edge information in an image tends to be robust under changes in illumination or related camera parameters. For these reasons, edge structure has been used extensively in computational vision.

The purposes of edge detection in image matching are to significantly reduce the amount of data found in matching two images and leave only the most significant information. Edge detection works by finding points on an

image where the gray scale value changes greatly between pixels. If we consider edge detection in a one-dimensional array of gray scale values where an edge is present, it might look like figure 1. This illustrates an obvious contrast in gray scale intensity. The darker pixels have low gray values while the lighter have high gray values.



Fig.1. Example of One-dimensional Gray-scale Image to illustrate an Edge

One method of performing edge detection is based on convolution. Convolution is mathematical ways of blending one function with another to produce a result expressing the amount of overlap the function have on one another. Two of the most common edge detection filters are the Laplacian and the Canny operators. The Laplacian operator is a method of edge detection based on taking the second derivatives of the gray intensity (in the Cartesian coordinate system) while the Canny operator uses the first derivative of the intensity. The Canny operator is the most commonly used method for edge detection in image matching since there are no significant advantages in other systems. The Laplacian function is shown in equation 1.

$$L(x, y) = \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2}$$

Equation 1. The Laplacian, which expresses the second derivative of a function.

There are some problems with using the Laplacian, since it is especially prone to picking up features, which are not actually edges in the image. The Laplacian operator results in incorrect readings where the gray value changes in small amounts consistently over part of the image. To reduce this noise in an image, a gaussian blur is often applied before the Laplacian operator

After a second derivative is found, a threshold must be applied to determine actual edges. More noise is produced with a lower threshold while a high threshold may miss some edges. A simple example of the image matching system has been displayed in figure 2.

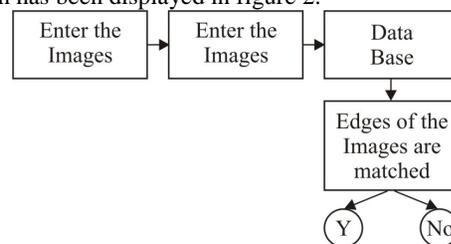


Fig.2. A simple Image matching system based on their edges

CANNY-DERICHE OPERATOR

The Canny-Deriche operator initially identifies candidate edge pixels through a set of edge-detection criteria; the image is convolved with two square masks, producing estimates of the horizontal h and vertical v components of the brightness gradient at every pixel. The intensity gradient at each pixel location can then be estimated by taking the linear combination of these directional values, providing an estimated magnitude m and direction θ (Eqn 1).

$$m = \sqrt{h^2 + v^2}$$

$$\theta = \tan^{-1} \frac{v}{h} \quad \text{Equation.1}$$

For all pixels, "non-maximum suppression" based on the gradient magnitude is performed by exploring in the direction of steepest gradient. A pixel is kept as a possible edge point only if it has a larger gradient than its neighbours located in the direction closest to that of the gradient, and than its neighbours located in the opposite direction. The remaining local maxima belong to one-pixel-wide edge segments. Thresholding based on gradient magnitude is then performed on these points. A point above a high threshold is kept, as well as any segment connected to it which consists of points above a lower threshold, reducing the probability of subdividing a segment whose magnitude fluctuates near the high threshold. Canny proves this approach to be optimal solution for image edge-detection under certain conditions. The Canny operator when applied to images get transformed into images which is displayed in the following figure 3.



Fig.3. Example of the image transformed into edges by Canny operator

Edge Detection in grey-scale images

In practice, edge detection is performed on grey-scale images. We are focusing on the 2d case and define a 2d-image:

Definition 1 A 2d-image is a discrete scalar function p on a rectangular grid having

N_1 grid points in x -direction, N_2 in y -direction with distances $_{x,y}$ and value set $W \subset C$:

$$p : \{0,1_{x}, \dots, (N_1 - 1)_{x}\} \times \{0,1_{y}, \dots, (N_2 - 1)_{y}\} \rightarrow W.$$

For pixels p_{ij} the following notation is used:

$$r_{ij} = _i_x$$

$$j_y_p_{ij} = p(r_{ij}).$$

A 2d-image is defined by the collection $P = (N_1, N_2, _x, _y, W, \{p_{ij}\})$.

Each grey-scale value is assigned to a scalar number $w \in W$.

Filter Operations

There exist many different possibilities for filters for image processing. We concentrate on the class of linear-and-shift-invariant (LSI) filters as their impulse response can be described as a neighborhood representation. For application of LSI filters the performed operation can be either convolution or correlation. While the correlation operator directly performs a pattern matching to a given filter on the given signal, the convolution uses a mirrored version of the filter. As the neighborhood representation of a filter can also be regarded as an image.

Definition 2 Let g be a 2d image, h be a 2d filter. The discrete convolution $g _ h$ is defined as

$$(g + h)_{m,n} = \sum_{i=0}^{N_1-N_2-1} \sum_{j=0}^{N_2-N_2-1} h_{i,j} g_{m-i,n-j}.$$

Convolution is a computationally expensive operation. It is in practice simplified by transferring image and filter into frequency domain, where the convolution operation reduces to a multiplication. The result is then transformed back into spatial domain. As transformation between spatial and frequency domain the fast Fourier transform (FFT) can be used. Through the application of filters different goals can be achieved. One special class of filters is used to smooth images to reduce various types of noise in an image. Examples for smoothing filters are box filters, binomial filters, and Gauss filters. Another class of filters was especially designed for edge detection. Those filters basically focus on gradients in an image. Examples for filters are the simple gradient filters (first order) and Laplace filter (second order). An optimized version of the gradient filter is the Sobel operator. The Marr-Hildreth operator is an enhancement of the Laplace operator. It combines a noise-reducing Gauss filter with a Sobel edge detection filter.

NEURAL NETWORKS

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between

elements. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

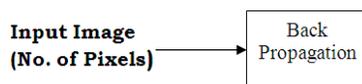
Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network.

Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems.

Neural networks are generally used for high-level processing or decision making [15]. However, even in low level processing decisions, as threshold value evaluation, they can be efficiently used [16]. For some tasks, like edge detection, the threshold value should be evaluated according to the image features. Therefore the automatic generation of a neural network for the purpose of implementing these functions is very useful. In fact, the decisions that are highly dependent on the image features can be performed easily by changing their weights after training.

Image processing by neural networks

One simple way to implement a system that perform image processing tasks is to present an input image and a desired output image. The natural choice to develop an architecture that can learn the task to be executed in this way is to use an artificial neural network. The network chosen in this work is the multiplayer perceptron (MLP). A neural network was trained in software using as inputs a 3×3 neighborhood of the output pixel. A dataset consisting of an input image and the desired output images was built. Using the back propagation method performs network training. An input image and a desired output image are used to train the network. Different weight sets are obtained for each task. The weights of the synapses are then converted to a chosen precision, and the ideal activation function is substituted by the function available in the developed circuit (piecewise-linear). The system is then evaluated to verify if the original requirements are still reached. The whole system may be depicted as follows:



RESULT ANALYSIS

Initially we work on static mode and apply the algorithm on few numbers of images. There are 10 images in our database. By applying the algorithm (canny or log) on an input image first of all we find the edges of the image. On the basis of edge we find the similarity or recognize the image by using Back propagation method. It is found that there is less number of comparisons of pixels as compared to the color or gray scale images. Due to the presence of

edges, pixels could be in black or white color. Image work as binary image. We compare only white color edge to the database image. Accuracy could be more as compared to the simple image recognition methods. Execution time is also less and requires less amount of information for recognition. For recognition it does not require color or gray scale values, so this algorithm is independent of color or gray images.

CONCLUSION

It is concluded that accuracy could be more when less number of edges are present in the images. Size should be same for input image and database image. It is independent of colors and gray values. For recognition it requires less number of pixels. Due to less number of pixels, execution time is less and number of pixel comparisons is also less.

To overcome the drawbacks of this algorithm, find the edges having large length and compare only those edges whether they are present in the image or not. For adding more number of images in the database, the size of the image should be less.

To decrease the size of the image use some compression techniques like wavelet etc. Categorize the image on the basis of content of image like flowers, human beings, animals etc.

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AUTHOR'S PROFILE



Mrs. Somi R Kevin

Date of Birth:-26/07/1979, Qualification: B.E. in Computer Science in the year 1998-2002 from Christian college, Bhilai (Chattisgarh) INDIA.
M.Tech. in Computer Science (Part Time) in the year 2005-2009 from Barkatullah University, Bhopal (M.P), INDIA.
Specialization: Image Processing, Designation - Assistant Professor