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Hand shape recognition

Yun Long Lay*

Department of Electronic Engineering, National Chin-Yi Institute of Technology, Sec 1, Chung-Shan Road, Taiping, Taichung 411, Taiwan

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Abstract

Automated hand shape recognition has been studied over the past decade and some commercial systems have been developed. Despite these advances, there is not much open public literature discussing the hand shape verification research. This study proposes a method by using quadtree techniques, which are able to recognize the hand shape image within an extremely short time. The geometrical shape of a hand is a biometric characteristic of human beings, although it is different even for a twin sibling. This study uses a parallel grating to project onto the backside of a hand. The parallel grating will be distorted by the curvature shape of the hand and processed by image processing techniques for recognition. This study also presents our recognition results of 100 students captured over a period of time. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

The input devices of a computer system have been changed from keyboard, mouse to light pen, bar code, and touch screen etc. Due to the improvement of computer technology, a lot of biometric input devices have been manufactured for security checking. Up to now, the human identification devices for information systems can be divided into two major kinds on the market: (i) the card or person identification number (PIN); and (ii) the biometrics identification system. In this article, we use a quadtree algorithm to do the feature extraction and recognition process of a human hand. The feature extraction of traditional pattern recognition must process the original image file back and forth many times. It takes a long time to process due to such things as thinning, edge enhancement, and noise filtering [1–6], otherwise, the feature weighting is difficult to define and the accuracy of recognition rate is worse. The process of texture pattern recognition of human beings can easily and accurately be done even

if the image possesses some noise. We can accurately and directly identify the image and do not need to filter the noise first. The binary form of the origin image can remove most unnecessary pixels and the linear quadtree can code a binary form image to be a very short feature file.

We use a parallel grating to project onto the backside of a hand. The curvature shape of the hand will distort the parallel grating. The distorted grating image will be grabbed by a CCD camera and processed by image processing techniques for recognition. The image is coded by quadtree for attaining the features, which are one-dimensional binary vectors. Our software calculates the variance of the standard sample feature coefficients and the testing sample feature coefficients. A threshold value will determine the recognition result.

2. The shadow of the distorted grating

A periodic grating is illuminated with a collimated beam of light, casting a shadow of the grating onto the object. The shadow is easily represented mathematically if the grating transmittance is sinusoidal [7–9] of

^{*} Tel.: +886-4-3924505 ext. 7332; fax: +886-4-3926610.

E-mail address: layyl@chinyi.ncit.edu.tw (Y.L. Lay).

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the form:

$$T(x, y) = \frac{1}{2} + \frac{1}{2}\sin\left(\frac{2\pi}{p}x\right)$$
(1)

where *p* is the period of the grating. Behind the grating is a generalized surface, and the distance *z* from the grating to the object is a function of *x* and *y*. If the illuminating beam occurs on the grating at an angle α , the intensity at point *P*₁ with coordinates *x*₁, *y*₁, *z*(*x*₁, *y*₁) can be expressed by:

$$I_{p1}(X_1, Y_1) = \frac{I_0}{2} \left(1 + \sin\left(\frac{2\pi}{P}x_1 - z(x_1, y_1) \tan \alpha\right) \right)$$
(2)

3. Linear quadtree

A "tree" is such that a data structure can be accessed beginning at the root node. Each node is either a leaf or it is a parent which refers to child. More formally, a connected forest. Contrary to a physical tree, the root is usually located at the top of the structure, and the leaves are located at the bottom. A quadtree is a means of encoding an image as a tree structure. Each node of the tree has up to four children. The root node represents the entire image; its children represent the four quadrants of the entire image; their children represent the sixteen subquadrants; the children of those represent the sixty-four sub-subquadrants, and so on. A leaf node corresponds to a single pixel or a small block area pixels, and is marked with a black or white pixel only. If an entire quadrant of the image is white or black, that information can be stored in a single quadtree node, and no children are generated by the node.

In a linear quadtree [10], each leaf node can be assigned a unique location number corresponding to a sequence of directional quadrants that locate the leaf node along a path starting at the root of the tree. If a black node of a $(2^N \times 2^N)$ dimensional binary image is

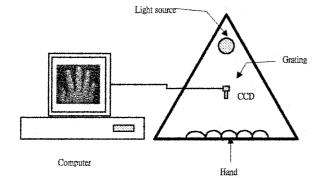


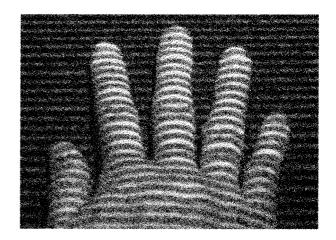
Fig. 1. The optical testing set up.

encoded as $A = (A_0A_1 \cdots A_{N-1})$ with quaternary digits 1, 2, 3, 4 for A_i , where each digit in the sequence represents the quadrant subdivision from which it originates, then the linear quadtree is defined as the collection of all black node descriptions and is usually represented as a list whose elements appear in increasing order of location numbers.

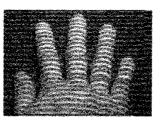
4. Feature extraction and coding

The optical testing set up is shown in Fig. 1. A periodic grating (0.5-cm pitch) is placed above the palm with 45° slant, and the hand is projected by a fluorescent lamp through the grating. The hand is then observed to have the same grating of parallel lines between the source and the CCD camera. The shadow of the grating is deformed by the curvature of the hand to be a set of distorted gratings as shown in Fig. 2. This hand fringe image has 512×512 pixels and is sampled twice to be a 128×128 pixels file. For simplicity of manipulation, the hand image has been set to an appropriate thresholding level and converted to be a binarized image as shown in Fig. 3.

Most hand shape recognition systems fix the testing hand by some small stakes to get the precision image.



512x512



128x128

Fig. 2. Distorted grating of a testing hand.

Even so, the grabbed image does not ensure the precision of placement. We designed an image overlapping method to solve the problem. The user must log in his PID into the system and then the system shows the mapping image of the database on the monitor. When a user inserts his hand into the image grabbing system, the system converts the hand image to be a transparent type. The transparent image is as a template to overlap with the database image and is adjusted by the user for best matching conditions.

A normal image is easy to convert to a transparent image using the following steps. The testing image is binarized and leaves the necessary pattern to be black pixels and converts all background to be white pixels. Using OR operator to merge the database image and the test image, the moving hand is like a transparent image. That is why a user can do the pattern adjustment from the monitor and ensure the image grabbing precision as shown in Fig. 4.

We use quadtree to code and get the features. Since the image has been sampled as a 128×128 -image file. From the top root to the bottom leaves, the file can be coded into seven levels. The rank of the first level has the linear code number 1, 2, 3, 4. The second level will be 5, 6, 7, 8; 9, 10, 11, 12; 13, 14, 15, 16; 17, 18, 19, 20. A simple node mapping equation can be described as Eq. (3). The first three levels will be shown as Fig. 5.

$$Node = (Node_{l-1} * 4) + i;$$
 (3)

where i = 1, 2, 3, 4; *l* is a level.

All the features are converted to short curves with no black area to occur from the first level to the forth level, so the image starts as coded by quadtree algorithm from the fifth level of the tree to yield enormous

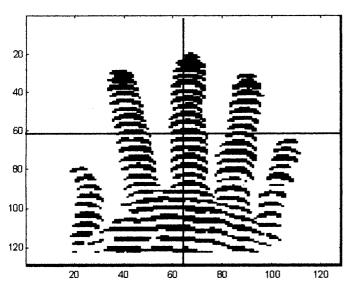


Fig. 3. Binarized image of a hand.

savings in storage size. Here is the coding algorithm of the quadtree.

Initialize quadtree number

Define two link lists LIST1, LIST2, and the coding result file

(The structure of the node include quadtree number, block-length, start point)

Set the root as the only element of LIST1

Loop from the root to the bottom level Traverse LIST1

Get a node of LIST1 and divide the node into four quadrants

If a quandrant is gray (not white or black) then put the quadrant into LIST2, write the number of the black quadrant to the result file

End traverse Copy LIST2 to LIST1

End loop

From the output data, it is obvious that if the features of two images are similar, their RMS (root mean square) error is smaller than 0.6. If not, the RMS error is larger than 1.5. The palm features are shown in Fig. 5, which can be plotted as a one-dimensional waveform.

The index method

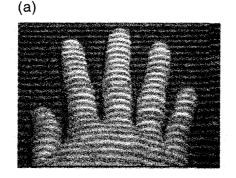
The major recognition error of this system is caused by the tiny shift of the hand before grabbing. To improve the recognition rate, a user's hand image must be grabbed five times for getting a different shift image and stored in the database. If each testing image has to compare with the five-database images, the processing time will be long. To solve the compare-time problem, each raw feature image must be extracted from the center 32×32 area and coded by quadtree again as the index portion. Thus, the five quadtree feature files of a certain person are mapped to the indexes of five small quadtree codes, which have been linked by a link-list structure. Any test image only uses the $32 \times$ 32-center image to traverse the link-list and find the best matching index. From the index, the final recognition procedure, as mentioned in the last section, will be done.

6. Experiment

We have tested the system described in the previous sections using images of 100 hands from our database. The system performance is then tested on 100 test hands. The output unit over the entire population is good since 99.04% of the 100 hands were evaluated correctly and the matching pairs yield a RMS error output below the setting threshold. The average error rate is about 0.96% with roughly half the errors due to false rejections and half to false acceptances. If we change our decision threshold, and enforce a 0% rate of false acceptances, the rate of false rejection increases to 3.5%. This error rate needs to be reduced, but even so it could be acceptable for certain applications.

7. Conclusion

From the experimental results, we find that the parallel grating pattern is very sensitive for tiny distance change or angle rotation. We can easily use distorted grating to obtain the features of a palm. We succeed using quadtree to find the optimal or the most appropriate membership block for the input pattern and to recognize small differences of two images. The fault tolerance of a binary image does not interfere with the

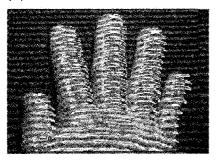


Database image

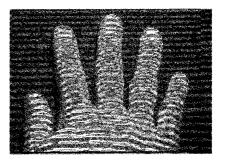


CCD grabbed image (transparent)

(b)



Unmatched images



Well matched images

Fig. 4. The position adjustment of a testing hand.

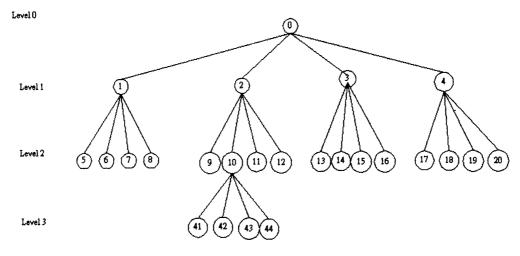


Fig. 5. Quadtree map.

noise in a static environment. In summary, this present work has proven a quadtree scheme, which can effectively be applied in the feature extraction for pattern recognition to yield satisfactory performance. On the other hand, the index techniques are good for minimizing the image search of a best matching pattern. The small pieces of quadtree file of the feature curves are easy to store and recognize.

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