Iris Image Real-Time Pre-estimation Using Compound BP Neural Network

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Abstract. A practical iris identification application system faces different types of bad iris images resulted from many reasons. Because previous image quality evaluation methods estimate an iris image whether bad or else by the resolution and the definition of the iris part, they just can deal with few types among them. For saving the time occupied by the localization in images real-time estimation, improving friendly interaction of an iris identification system, decreasing the localization failure on account of importing the bad-image, this paper proposes a method of real-time pre-estimation using the compound BP neural network. Multiple independent BP neural networks are used to extract both the overall contour feature and the local of an iris image and to calculate the pre-estimation output by different training weights. The experimental result is shown that the method can detects most types of the bad-image with comparatively low error rate and the pre-estimation network has fairly large throughput. It should satisfy the pre-estimation requirement of a real-time iris identification system.

1 Introduction

Biometrics technology using intrinsic physiological or behavioral characteristics of human beings to authenticate identities, so far, is the most prospective candidate displacing the traditional identification method (e.g., token-based or knowledge-based methods). Many different biometric methods, including fingerprint, iris, hand geometry, face, signature, and so on, have successfully deployed to provide useful value in practical applications. For distinctive abundant texture and good stability, under the precondition of having captured normal iris images, the iris identifier shows excellent performance (i.e., fairly low false acceptance rate, FAR, false reject rate, FRR, and friendly interaction). At one time, it also has relatively high failure to enrollment because it requires rigid sampling condition [1]. Users often feel uncomfortable at the time of failure to enrollment again and again specially in a real-time application system, which hampers the research community to broaden the iris identification to a large scale real application [2].

As shown in figure 1, there are many types of the bad-image (e.g., no iris part in an image, half-baked iris, excess distortion of iris, low definition for incorrect focus, losing much texture information for few pixels of iris part, eyes moving at the instant of capturing image.) because of different reasons, and therefore several factors

possibly result in which an iris sampler can not capture images according to the demand of identification process (i.e., appearing bad images).

Generally, the iris identification technology disposes the challenge of the bad-image with a strategy of feedback which can divide into three categories: 1) It evaluates each image captured by a camera, and then decides whether an image is bad or not by the output of the evaluation [3]. 2) From the hardware perspective, for instance, it use a peculiar mirror, so called the mono-direction-mirror, by which an user can directly see the approximate size and location of his iris in the mirror [4]. 3) A person controls the iris identifier and decides whether an input image satisfies the requirement of identification [4]. Apparently, the third category will be discarded gradually, because it is opposite to the trend of the automatic identification which is expected as little human supervision as possible.

Fig. 1. Bad images possibly captured by iris identification system, (a): Iris absence in an image, (b): Incorrect view angle owing to head motion, (c): Errors of sampler-self

As shown in figure 1, these images are difficulties towards no matter the first category or the second. If iris image samples are pre-estimated automatically by a virtual watcher, and its output will decide whether an identifier continues the next step or captures images again, most types of the bad-image will be eliminated before the process of localization. This paper proposes a new idea of the pre-estimation accomplished by a compound BP neural network. That is, input samples are estimated in real time by the pre-estimation network before the localization step.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the pre-estimation method using the compound BP neural network including three subsections. Section 3 illuminates experimental items and their results. Analysis and discussion are reported in section 4.

2 Compound BP Neural Network

The pre-estimation of image samples is belonged to the forefront of the iris identification preprocess. In a real-time iris identification application system, it disposes an image or sequence images kept in the memory and exports an outcome parameter, by which the system decides to go to the next processing or back to the previous step again. This paper proposes a new compound BP neural network to pre-estimate iris image samples, in which it uses the back propagation algorithm with moment factors and expects to depress the adverse effect resulting from the BP neural network inextricable faults recurring to its novel network topology and training modes [5]. The whole network comprises three parts (as shown in figure 2).

Fig. 2. Compound BP neural network for the pre-estimation of real-time images

2.1 Reconstruction of Image Data

Firstly, an iris image I is resized to be the image $I_{n \times m}$ and keep the same proportion of n to m of $I_{n \times m}$ as I (n and m is the number of rows and columns of the image $I_{n \times m}$, respectively) to ensure $I_{n \times m}$ not to be distorted. After converting the image $I_{n \times m}$ to the binary image by a threshold, the elements of this binary image is assembled to the input matrix $P2_{n \times m}$. Finally, $P1_{n \times 2}$ and $P3_{2 \times m}$ are built by $P2_{n \times m}$ as shown in formulas (1) ~ (6). The matrix T is the training target of these BP neural networks and its size is equal to the number of input training samples. If an input training sample is a bad image, the corresponding element of T is -1; and if a normal image, it is 1.

$$I_{n \times m} = \text{resize}(I), \quad (n, m \in N), \quad P2_{n \times m} = \text{binary}(I_{n \times m}). \quad (1)$$

$$P1_{n \times 2}(i, 1) = \mu_{i1} = \frac{1}{m} \sum_{j=1}^m P2_{n \times m}(i, j), \quad i \in (1, \dots, n), j \in (1, \dots, m). \quad (2)$$

$$P1_{n \times 2}(i, 2) = \sigma_{i2} = \frac{1}{m} \sum_{j=1}^m [P2_{n \times m}(i, j) - \mu_{i1}]^2. \quad (3)$$

$$P3_{2 \times m}(1, j) = \mu_{1j} = \frac{1}{n} \sum_{i=1}^n P2_{n \times m}(i, j). \quad (4)$$

$$P3_{2 \times m}(2, j) = \sigma_{2j} = \frac{1}{n} \sum_{i=1}^n [P2_{n \times m}(i, j) - \mu_{1j}]^2. \quad (5)$$

$$P1_{n \times 2} = \begin{pmatrix} \mu_{11} & \sigma_{12} \\ \vdots & \vdots \\ \mu_{n1} & \sigma_{n2} \end{pmatrix}, \quad P2_{n \times m} = \begin{pmatrix} a_{11} & \dots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nm} \end{pmatrix}, \quad P3_{2 \times m} = \begin{pmatrix} \mu_{11} & \dots & \mu_{1m} \\ \sigma_{21} & \dots & \sigma_{2m} \end{pmatrix}. \quad (6)$$

2.2 Part I of the Network

The network part I consists of three independent BP neural sub-networks nn_{BP1} , nn_{BP2} and nn_{BP3} . As shown in figure 2, they all include one input layer, two hidden layers and one output layer, but the corresponding layer node number of various networks are different except their output layers that are composed of single node and severally confirmed by the experience and the experimental effect [6][7][8]. Weight matrices of nn_{BP1} , nn_{BP2} and nn_{BP3} are respectively defined as $(W_{BP1}^1, W_{BP1}^2, W_{BP1}^3)$, $(W_{BP2}^1, W_{BP2}^2, W_{BP2}^3)$ and $(W_{BP3}^1, W_{BP3}^2, W_{BP3}^3)$, and their bias matrices are $(b_{BP1}^1, b_{BP1}^2, b_{BP1}^3)$, $(b_{BP2}^1, b_{BP2}^2, b_{BP2}^3)$ and $(b_{BP3}^1, b_{BP3}^2, b_{BP3}^3)$ as well. Their active functions select the consecutive derivative *Sigmoid* function. $p1_{n \times 2}$, $p2_{n \times m}$ and $p3_{2 \times m}$ shown in the formula (6) form input vectors of those sub-networks, and then their outputs o_{BP1} , o_{BP2} and o_{BP3} respectively according to nn_{BP1} , nn_{BP2} and nn_{BP3} construct the matrix $p4_{3 \times 1}$, as shown in formulas (7) ~ (10), regarded as the input vector of the network II (nn_{BP4}). The calculation ‘ $\square$ ’ in formulas means that $\sum_{i=1, j=1}^k X_{(i,j)} \times Y_{(j,i)}$ (X as a weight matrix and Y as an input matrix), and k is the dimension number of an input vector.

$$O_{BP1} = f_{Sigmoid}^3(W_{BP1}^3 \square f_{Sigmoid}^2(W_{BP1}^2 \square f_{Sigmoid}^1(W_{BP1}^1 \square p1_{n \times 2} + b_{BP1}^1) + b_{BP1}^2) + b_{BP1}^3). \quad (7)$$

$$O_{BP2} = f_{Sigmoid}^3(W_{BP2}^3 \square f_{Sigmoid}^2(W_{BP2}^2 \square f_{Sigmoid}^1(W_{BP2}^1 \square p2_{n \times m} + b_{BP2}^1) + b_{BP2}^2) + b_{BP2}^3). \quad (8)$$

$$O_{BP3} = f_{Sigmoid}^3(W_{BP3}^3 \square f_{Sigmoid}^2(W_{BP3}^2 \square f_{Sigmoid}^1(W_{BP3}^1 \square p3_{2 \times m} + b_{BP3}^1) + b_{BP3}^2) + b_{BP3}^3). \quad (9)$$

$$P4_{3 \times 1} = \begin{pmatrix} o_{BP1} \\ o_{BP2} \\ o_{BP3} \end{pmatrix}, \quad (O_{BP1}, O_{BP2}, O_{BP3} \in [-1, 1]) \quad (10)$$

$$O_{BP4} = f_{Sigmoid}^4(W_{BP4}^2 \square f_{Sigmoid}^1(W_{BP4}^1 \square P4_{3 \times 1} + b_{BP4}^1) + b_{BP4}^2), \quad (O_{BP4} \in [-1, 1]). \quad (11)$$

2.3 Part II of the Network

The network II also is a independent BP neural network nn_{BP4} . The connection between the network II and the network I is switched off at the time of training network I. After having accomplished the training of the network I, the output $p4_{3 \times 1}$ of the network I is regarded as the training input data of the network II. According to the same training target matrix T , the network nn_{BP4} is trained. Finally, three parts of the compound BP neural network are connected to pre-estimate input samples and the

pre-estimation final result is the network output (i.e. o_{BP4} shown in the formula 11). The sub-network nn_{BP4} consists of one hidden layer (including two nodes), one output layer (including one node) and one input layer $p4_{3 \times 1}$. In the training process of nn_{BP4} , the error back-propagation just take place in the bound of the network Π , refreshing its weight matrices (W_{BP4}^1, W_{BP4}^2) and bias matrices (b_{BP4}^1, b_{BP4}^2) .

3 Experimental Results

Because the pre-estimation of image samples is in front of the previous processing of image quality evaluation, fast detecting whether an image sample includes the ingrate iris part is the unique task of the pre-estimation network. The whole experimental image samples are from the local iris database (Self-Databases), the bad-image database, CASIA-Open iris database [9] (CASIA-open) and the training iris database provide by the first contest of biometrics of China [10] (CASIA-contest-iris-DB1&DB2). Examples shown in figure 1 and figure 3 are selected from these databases.

There are 64 images demonstrated in figure 3 which include some typical image samples captured under different conditions, such as different sampling instruments, different illuminations, different imaging distances, different poses and different people.

There are sizeable discriminations between images captured by different instruments, as shown in figure 3. And, therefore, above four databases are not mixed at most of experiments. Finally, for proofing the robust of the pre-estimation network, mixed databases are done. As shown in Table 1, these classified experiments appear hortative result: Their false rates are lower than 1% and the throughput of the pre-estimation network mostly is 18000 samples per second. It should satisfy the requirement of a real-time iris identification application system.

Fig. 4a, 4b, 4c and 4d severally describe the output distribution of the pre-estimation network to four databases, corresponding the table 1, and fig. 4e and 4f demonstrate two types of mixing databases. In these figures, the horizon coordinate denotes the number of the testing sample and the vertical coordinate denotes the network output value to the input sample.

Fig. 3. Normal images accepted by pre-estimation network

Table 1. The experimental result

Databases	Training Samples		Testing Samples		Gross testing time (s)	False Rate (%)
	Normal samples	Bad-image samples	Normal samples	Badimage samples		
Self-Databases	540	244	1310	1104	0.125	0.042
CASIA-open	256	244	500	1104	0.094	0.37
Contest-DB1	400	244	800	1104	0.109	0.58
Contest-DB2	400	244	800	1104	0.110	0.58
DB1&DB2	800	244	1600	1104	0.156	0.41
DB1,DB2&open	1056	244	2100	1104	0.172	0.41

Fig. 4. The output distribution of the pre-estimation network to different databases

4 Analysis and Discussion

Addressing the purpose of the pre-estimation of iris images, It is easy to note on the experimental result that the pre-estimation method based on the compound BP neural network represents approving performances both the throughput and the false rate of the pre-estimation and can preferably satisfy the real-time estimation requirement of an iris identification system. By the novel network topology, the data-reconstruction, the independent training and associated testing tricks, sub-BP-neural-networks have been trained with lesser epochs. That is, depressing the possibility of the over-training, and meantime, leading the whole pre-estimation network to possess better generalization than an ordinary BP neural network. And that, three independent data channels of the network I can extract both overall and local features of the iris image geometric contour. Moreover,

according to the figure 4, though the false rate of estimation is non-zero toward every database, the output of the pre-estimation to the bad-image belongs to the diminutive domain of -1 (i.e. the false acceptance rate of the pre-estimation network is zero).

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