A NON Reference Fingerprint Image Validity via Statistical Weight Calculation

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ABSTRACT: Clarity of fingerprint image structure is crucial for many fingerprint applications, as well as the performance of built systems which relies on the validity and quality of captured images. Validity check will eliminate invalid images before starting the life cycle of fingerprint metadata enrolling for system processing cycle; therefore the overall benchmarking system accuracy will not be affected by rejecting an invalid image before getting in the system cycle. In this paper we propose a validity check algorithm (VCA). The VCA is applied to the base image element statistical weight calculation because the image element (pixel) describes an image object with the contrast, brightness, clarity and noising attributes. Our algorithm depends on fingerprint object segmentation, background subtraction, total image thresholding and pixel weight calculation. A VTC2000DB1_B, TIMA databases was used to evaluate the VCA and it has been compared with NIST fingerprint image quality results. Correlation results indicate that the proposed algorithm is feasible in detecting low quality as well as non-fingerprint images.

Categories and Subject Descriptors

I.4 [Image processing and computer vision]; I.3.3[Image and Picture generation]; G.3 [Probability and statistics] General Terms

Finger Print images, Statistical measurements

Keywords: Fingerprint, Segmentation, Image subtraction, Otsu threshold, Image quality.

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1. Introduction

Due to its permanence, uniqueness and distinctiveness, fingerprints are widely used in identification, authentication, security, and crypto generation systems on implanting scenarios, offline as well as online [1]. Most available systems use global and/or local fingerprint features for matching based systems, therefore feature extraction is very sensitive to validity, integrity, and quality of source images. For instance, false features extracted may appear due to poor and invalid fingerprint factors such as: physiological, i.e. dry fingers, worm, and finer ridge structure, behavioural factor, e.g. uncooperative or nervous subject, environmental factor, e.g. humidity, temperature and ambient light, operational and technological factor, e.g high throughput, reduced capture time and unclean scanner platen and interaction usage, this is shown in the quality image illustration, Figure1, [2]. Settling and enrolling invalid and missed image features degrades the performance and accuracy benchmarking of system production. A rejection of invalid examined images will reduce system processing time, and increase system reliability. It is therefore essential to design an automatic pre-enrollment step that examines and checks the validity of captured images. There are previous fingerprint image quality assessments but none of them tackle the validity factors and total image information within visual quality. We propose an objective validity check approach that correlates with perceived quality measurement. Previous literature concentrated on quality computation methods based on features and classifiers. Lim et al [3] proposed a method using local feature ratio values of gradient vectors to estimate local orientation certainty and used the orientation flow to determine the orientation quality. The ratio values can indicate the confidence level of orientation estimation only if the noise is not directional.

However, some capturing sensors produce images with some vertical lines and directional independent noise prevent the orientation assurance level from accurately reflecting the image quality. Ratha et al [4] proposed image quality estimation in the wavelet domain; their method is suitable only for Wavelet Scalar Quantization compressed images. But it is not attractive for uncompressed images such as Tagged Image File Format (TIFF), since the wavelet transform is highly computational. Shen et al [5] applied a Gabor feature filter to sub-block images; they concluded that a good quality block with clear replication of local features (ridge and valley pattern) can be recognized by the output of a Gabor filter bank. Their method used orientation information of fingerprint image. However, as the gray level local features structure of fingerprint image contains much more information than the orientation alone and a source image shows a global smooth ridge flow, the local direction strength is not sufficient to measure the quality assessment of finger images



Dry Finger Light Print Moist Finger Dark Print Worm Ridge Structure Poor Finger Placement None Object Structure

Figure 1. Sample images, with different validity and quality

Hong et al [6] modeled fingerprint ridge and valley patterns as a sine wave, and computed the amplitude, as well as the variance of the sine wave to decide the quality of the given image. Chen et al [7] analyzed fingerprint Global structure by computing the 2D Discrete Fourier Transform (DFT). For a fingerprint image, the ridge frequency value lies within a certain range. A region of interest (ROI) of the spectrum is defined as an annular region with radius ranging between the minimum and maximum typical ridge frequency values. As fingerprint image quality increases, the energy will be more concentrated in ring patterns within the ROI. The global quality was measured by the energy concentration in ringshaped regions of the ROI therefore a set of constructed bandpass filters to compute the amount of energy in ringshaped bands. Good quality images will have the energy concentrated in few bands. However these methods as well as reviewed schemes [8] cannot distinguish some invalid images from the valid ones. This work could act as a prequality step to eliminate invalid images before applying any of quality assessment schemes.

2. Proposed Method

The major novelties of our proposed approach consist of blind validity check and simple computational models. Our

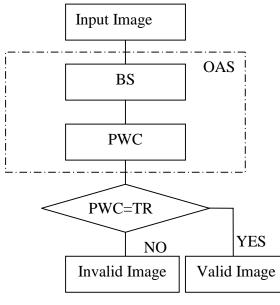


Figure2. VCA flowchart

approach is consisting of two processing blocks, Figure 2. Firstly the Object Area Segmentation (OAS) which performs

Dry Finger Light Print Moist Finger Dark Print Worm Ridge Structure Figure 3. (a) objects segmented areas

a background subtraction (BS), and Pixels Weight Calculations (PWC). Secondly the Image Validity judged by threshold ratio (TR) which experimentally obtains the base of good fingerprint images. TR is defined to be judging values between 0.5 and 1; therefore the values out of this range indicate invalidity of tested images. TR is used to train our approach for validity check to achieve a computational performance as well as principle core of image quality measures. A none reference VCA signifies that the statistical weight calculation is relative to absolute pixel value after object background subtraction. It is working on a fact that no knowledge of the original image, and don't make any assumptions on the type of invalidity factors. VCA found to be able to assign indicating quality predictor.

2.1 Objective Area Segmentation

This block will segment the object region from the background figure based on morphological operations of global image threshold using Otsu method implementation Figure 3, [9]. Otsu method was chosen for its computational efficiency, where the image is a 2D grayscale intensity function and contains N pixels with gray levels from 1 to L. The pixels are classified into two classes based on a comparison of their intensity values with the threshold T º [0.255], class C1 with gray levels [1,..., t] and C2 with gray levels [t+1,..., L]. Then, the gray level probability distribution for two classes.

Then, the gray level probability distribution for two classes

$$\begin{array}{l} c_1 : p_1 / \omega_1(t), \dots p_t / \omega_t(t) \\ \text{and} \\ c_2 : p_{t+1} / \omega_2(t), p_{t+2} / \omega_2(t), \dots, p_L / \omega_2(t) \\ \text{where} \end{array}$$

Also, the means for classes $\,C_{_1}\,$ and $\,C_{_2}\,$ are

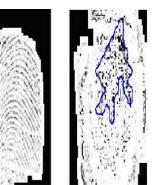
$$\mu_1 = \sum_{i=1}^{t} i p_i / \omega_1(t)$$
$$\mu_2 = \sum_{i=1+1}^{L} i p_i / \omega_2(t)$$

The mean intensity for the whole image

 μ_{T}

$$\omega_1 \,\mu_1 \,+ \omega_2 \,\mu_2 =$$





Poor Finger Placement None Object Structure

will be



Dry Finger Light Print Moist Finger Dark Print Worm Ridge Structure Poor Finger Placement None Object Structure Figure 3. (b) object weighted areas

The between-class variance of the thresholded image was defined using discriminant analysis [9].

$$\sigma_{B}^{2} = \omega_{1}(\mu_{1} - \mu_{T})^{2} + \omega_{2}(\mu_{2} - \mu_{T})^{2}$$

The optimal threshold (*ot*) is chosen so that the between class variance σ_B^2 is maximized:

$$ot = MAx\{\sigma_{B}(t)\}$$

The object region segment from the background morphologically is defined by:

$$\begin{split} & \text{if } I(x, \, y) > T, \\ & I(x, \, y) \; \varepsilon \; \text{object} \\ & \text{if } I(x, \, y) \; d \leq \; T, \\ & I(x, \, y) \; \varepsilon \; \text{background} \end{split}$$

The background is subtracted to work over pure segmented, threshold image, binorized based on threshold level black and white image for the next block usage.

2.2 Pixels Weight Calculation

In this block, pixels will be counted into two groups, black group which is supposed to have a ridge structure of our fingerprint tested images, and a white group which belongs to the valley structure, ratio of black and white counts will indicate the validity contrast as well as hints of validity check of the whole image as result of image validity which is judged by threshold ratio. The valid result must be in the range between 0.5 and 1; therefore the values out of this range indicate invalidity of tested images.

3. Experimental Analyses

The proposed algorithm is extensively tested on DB1, FVC2000, FVC2004 databases, and TIMA MSN database [10]. Fingerprint images (TIFF, WSQ, JPG, BMP, format, different sizes, and resolutions). Our approach was compared with the results of subjective quality survey as well as with results of NFIQ, NIST Fingerprint Image Quality [11].

3.1 Subjective Test

The subjective experiment was done as an image quality survey (IQS) based on visual assessment (subjective measurement). It was conducted on different image qualities, and validity taken from the previous databases. The validity factors were taken as image contrast, ridge clarity, valley clarity, image noise, and image content quality [informative of image object, percentage of finger image]. The validity factors are selected between [0 and 100], 0 for none factor satisfaction, 100 for excellent presence of factor. For more refined assessments of image validity IQS was passed to 15 subjects working in the field of image processing and biometrics, since they are familiar with images and their directions. The 15 scores of each image were averaged to a final validity Mean Opinion Score (MOS), Table 1.

3.2 NIST Fingerprint Image Quality Test

Same images were converted to WSQ format and tested under NFIQ software which generate image quality map by MINDTCT to measure quality of localized regions in the image

Image	Validity MOS	NFIQ	VCA
Image 1	0.5025	0.49	0.52
Image 2	0.363	0.34	0.32
Image3	0.524	0.47	0.52
Image 4	0.297	0.3	0.26
Image 5	0.3095	0.31	0.25
Image 6	0.348	0.36	0.26
Image 8	0.307	0.33	0.21

Table 1. Part of validity IQS, NFIQ and VCA results

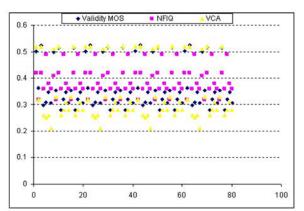


Figure 4. Approaches scatting relation

	correlation relation			
	Validity MOS	NFIQ	VCA	
Validity MOS	1	0.977984	0.981753	
NFIQ	0.977984372	1	0.948127	
VCA	0.981752833	0.948127	1	

Table 2. Correlation relation results of image validity measures

including determining the directional flow of ridges and detecting regions of low contrast, low ridge flow, and high curvature. The information in these maps is integrated into one general map, and contains 5 levels of quality (4 being the highest quality and 0 being the lowest). The background has a score of 0, a score of 4 means a very good region of fingerprint. The quality assigned to a specific block is determined based on its proximity to blocks flagged in the above-mentioned maps. The result in table 1 for NFIQ was the activation score of quality of images.

3.3 VCA Test

VCA was implemented in matlab, and applied extensively on the same test source images as well as on the whole databases with the respect of human visual eye trace. This is because the human visual perception has a remarkable ability to detect invalid object in visual image. Figure.4 shows the scatter relation between three tested approaches, where VCA is more close to human visual perception survey. Table 1 demonstrates how much each measurement approach coincides with human visual measure, while table 2 shows the correlation relationship among tested approaches. All tests show that VCA can be added to the NFIQ factors to enhance its validity result. Also it could be part of a blind quality assessment for fingerprint images as a function of monitoring and controlling of image enrollment for the sake of increasing the efficiency of whole dependent system, i.e. verification, identification and over above crypto key generation systems.

4. Conclusion

In this paper, we have presented a novel approach for image validity check, which is computationally efficient. Since no complicated processes are computed and it is using previous system processing blocks such as segmentation and subtraction. We show that the proposed approach is competitive with the state of the art method NFIQ and it could be a complementary factor in the image quality assessment process. Studying the characteristics structure of other biometric objects such as IRIS, FACE, implemented approach could be used. We believe, with the development of acquiring devices, and combination of NFIQ and VCA algorithms the acquiring devices such as scanners will lead to smart detection and checking of capturing sources.



Mokhled Sulaiman Al-Tarawneh is a PhD candidate at the Newcastle University, UK. Earlier he worked at Mutah University. His research interests include computer vision, pattern recognition, image processing, image quality assessment, and biometrics.

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