ORIGINAL ARTICLE

Examining Barrel Distortion, Super-resolution on Single-view-based Ear Biometrics Rotated in Depth

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Abstract: Numerical simulations were performed using super-resolution images and barrel-distorted images to improve the viability of the authors' previous work regarding single-view-based ear biometrics. Empirical demonstrations show that, using barrel-distorted images and super-resolution images, accuracy decreases. However, our present proposed method for model normal vector creation applied to these images compensated for losses in accuracy. Furthermore, an experimental investigation of the influence of earrings on results is included. The difference between the averaged rank between images of subjects with and without earrings at each input angle was found to be statistically insignificant.

Keywords: *ear biometrics, single-view-based, barrel distortion, super-resolution, earrings*

1. INTRODUCTION

1.1 Background

Ear shape can be sufficiently unique to identify individuals and has been used in forensic science over the past 40 years [1]. Whereas masks and sunglasses are often purposely used to obscure facial features, ear shape can be all that is required to identify a criminal in surveillance images [2,3]. Ear shape from surveillance-camera images has been used as legal evidence in criminal justice courts with some criminals sent to jail on the basis of this evidence. However, the quality of surveillance-camera images using wide-angle lenses is not always good and suffers from barrel distortions and low resolutions. Further, differences in angle of a shot between suspect and criminal also degrade the quality of the evidence. Therefore, concerning the admissibility of evidence of surveillance camera images, resolution, barrel distortion [4], and the differences in the angle of shot [2,3] present problems and challenges. Hence, resolving these problems is necessary if computer-based biometric systems are to be accepted by the forensic community. Further, the influence of earrings worn by subjects on the accuracy of such a system is desirable for better understanding by the forensic community.

1.2 Related studies

A broad survey of automatic ear recognition systems is available in [5-8], where databases, algorithms, experimental conditions, and accuracies are detailed. However, reports on resolution, barrel distortion, off-angle pose variation and earrings in the context of ear biometrics are scant.

Regarding the resolution, the authors have previously reported the accuracy of their ear biometric system on low-resolution images [9]. Using 70×100 pixel images of ears, accuracy trends were found to be similar, i.e., up to 20% (14×20 pixel ear images), although these worsened at 10% (7×10 pixels ear images) at angles where scaphae are visible.

In actual scenarios, a super-resolution technique is often used in up-conversion of the images. Although up-conversion clarifies the images, such images may not represent the clearly captured subject and admissibility of this evidence is often questioned. Hence, a quantitative accuracy using super-resolution images is necessary, but such accuracy has not been reported in the biometrics literature [5-8].

In barrel distortion, straight lines bulge outwards at the center, as in a barrel. These distortions are common to fish-eye and wide-angle lenses used in surveillance cameras.

In these images, magnification decreases with distance from the optical axis, and subject size depends on the distance from the optical axis. Hence, accounting for this effect is necessary before photometric evidence can be admissible. Concerning barrel distortions in surveillance images, Biwasaka [4] has reported its effect on face images. However, a similar study for ears has not been reported in the biometrics literature. Furthermore, the influence of earrings appearing in images has not been reported in this literature.

With regard to angle of shot, Moriyoshi [2,3] has thoroughly investigated the effect of differences in angle of shot in the context of forensic science. As far as image processing and computer vision are concerned, a few

studies have treated variations in the angle of shot [10, 11]. However, these are limited to in-plane rotation. The authors improved the robustness of the method for off-angle rotation in single-view-based ear recognition [9, 12]. Nevertheless, the applicability of the above single-view-based ear biometrics system using super-resolution images, images with barrel distortion, and images with earrings has not been reported.

1.3 Aim of this study

To improve on our earlier work of single-view-based ear biometrics [9, 12], the applicability of the above single-view-based ear biometrics system using super-resolution images and images with barrel distortion was examined through numerical simulations. Counter measures are proposed to compensate for losses in accuracy using these images. Further, the influence of earrings on assessments is experimentally investigated.

1.4 Remark

This paper expands on a contribution to the special issue of the ICBAKE 2013 (International Conference on Biometrics and Kansei (affective) Engineering). A preliminary and condensed version of this manuscript can be found in the conference proceedings of ICBAKE2013.

2. METHOD USED FOR EXPERIMENT

2.1 Outline

For completeness, the method we used for this experiment is summarized briefly in subsections 2.2–2.4 and 2.6. Countermeasures against barrel distortions and up-converted super-resolution images are proposed in subsection 2.5.

2.2 Gabor features of ear minutiae

Let $\mathbf{x}=(x,y)$ be a point in a plane. A 2D plane wave defined by wavevector $\mathbf{k}=(k_x, k_y)$ and modified by a Gaussian function is called a Gabor function (a Morlet wavelet):

$$\psi(\mathbf{x}) = \frac{|\mathbf{k}|^2}{\sigma^2} \exp\left(-\frac{|\mathbf{k}|^2 |\mathbf{x}|^2}{2\sigma^2}\right) \left[\exp(i\mathbf{k} \cdot \mathbf{x}) - \exp\left(-\frac{\sigma^2}{2}\right) \right] \quad (1)$$

Here σ denotes the width as determined by the Gaussian function. The factor $\exp(-\sigma^2/2)$ is a compensation term that eliminates averages; this condition is required from wavelet theory, but if σ is large enough, this term can be neglected.

Gabor functions are characterized as localized wavy shapes in various directions determined by the plane waves. Gabor filters, i.e., convolutions with these Gabor functions, extract direction and wavelength of these localized wavy shapes of an image near the point under consideration.

Figure 1: Feature points of an ear

Wavy shapes in various directions also characterize the outer ear. Thus, endpoints, junctions, and protuberances of the ridges of the outer ear are selected as feature points (Fig. 1). Wavy shapes near these feature points are measured and coded using Gabor filters.

Five wavelengths, 4, $4\sqrt{2}$, 8, $8\sqrt{2}$, 16, are adopted for the Gabor filters, to cover the various widths of ridges along the ear that appear in the experimental data. Furthermore, to cover all directions evenly, eight directions corresponding to $\pi/4$ turns are employed. We implemented this Gabor filter using a mask, 101×101 pixels in extent, for the convolution window, and this convolution is performed using fast Fourier transform.

2.3 Estimation of Gabor features after off-angle rotation

Pose variations within a camera plane can be estimated by rotating the image. Such reproductions are unavoidably inaccurate, because changes in shading induced by pose variation are not taken into account. However, if shading is relatively light, as a result of using sufficient lighting, this becomes a relatively minor issue compared with the difficulty in reproducing images rotated in depth.

This difficulty stems from the depth of a subject in an image. Clearly, plane objects without depth are easier to process. Reasonable image reproductions rotated in depth can be obtained using affine transformations.

Locally, near the feature points, the subject is approximated by a tangent plane. The tangent plane does not have a depth. Hence, the image of this plane rotated in depth can be estimated (Fig. 2). This estimated image reflects local features under pose variations near the feature points.

Figure 2: Tangent plane approximation of subject rotated in depth

Similar to the tangent plane, Gabor jets only represent local features. Motivated by the above, we explore the benefits of Gabor jets of subjects rotated in depth. The following outlines the reproduction method, estimating Gabor jets of subjects with different poses [9, 12]. Suppose that a subject plane, initially placed parallel to the camera plane, is rotated by ϕ around its x -axis and then θ around its y -axis. By observing the transformations of unit vectors, a point on the subject plane initially at $\mathbf{u} = (x, y)$ is transformed to $\mathbf{x}$ given by

$$\mathbf{x} = \mathbf{A}\mathbf{u}, \quad \mathbf{A} = \begin{pmatrix} \cos \phi & \sin \theta \sin \phi \\ 0 & \cos \theta \end{pmatrix}.$$

If this plane is initially placed at (ϕ_1, θ_1) and not parallel to the camera plane, the above transformation is

$$\mathbf{x} = \mathbf{A}(\phi_2, \theta_2)\mathbf{A}(\phi_1, \theta_1)^{-1}\mathbf{u}.$$

Here, $(\phi_2, \theta_2) = (\phi_1 + \Delta\phi, \theta_1 + \Delta\theta)$ is the pose of the plane after rotation; $\Delta\phi, \Delta\theta$ are the changes in the roll and yaw angles, respectively. Under this transformation, the transformation of the Gabor jets corresponding to the pose change can then be estimated. In what follows, $\mathbf{A}(\phi_2, \theta_2)\mathbf{A}(\phi_1, \theta_1)^{-1}$ is denoted as $\mathbf{A}$ for simplicity. Components of the transformed Gabor jets are obtained by convoluting the Gabor function with the transformed image $I(\mathbf{A}^{-1}\mathbf{x})$. Using $\mathbf{x} = \mathbf{A}\mathbf{u}$, $\mathbf{x}' = \mathbf{A}\mathbf{u}'$, this is

$$\begin{aligned} j'_k(\mathbf{x}) &= \int I(\mathbf{A}^{-1}\mathbf{x}')\Psi_k(\mathbf{x} - \mathbf{x}')d\mathbf{x}' \\ &= \int I(\mathbf{u} - \mathbf{u}')\Psi_k(\mathbf{A}\mathbf{u}')|\mathbf{A}|d\mathbf{u}'. \end{aligned}$$

Assuming the following approximation

$$\Psi_k(\mathbf{A}\mathbf{u}')|\mathbf{A}| \approx \sum_{k'} c_{kk'}(\mathbf{A})\Psi_{k'}(\mathbf{u}') \quad (2)$$

the Gabor jet transformation is written simply as

$$j'_k(\mathbf{x}) \approx \sum_{k'} c_{kk'}(\mathbf{A})j_{k'}(\mathbf{u}).$$

Once $\mathbf{C}^{(\mathbf{A})} = (C_{kk'}(\mathbf{A}))$ is obtained, the transformation of the Gabor jets can be estimated using

$$\mathbf{j}'(\mathbf{x}) \approx \mathbf{C}^{(\mathbf{A})}\mathbf{j}(\mathbf{u}). \quad (3)$$

Matrix $\mathbf{C}$ is obtained by multiplying both sides of Eq. (2) by $\overline{\Psi_{k'}(\mathbf{u})}$ and integrating both sides.

2.4 Normal vector models

There are two pairs of variables that are difficult to determine. One is (ϕ_2, θ_2) , which depends on the pose of the input image. This is unknown in real scenarios. In [9, 12], we solved this issue, by producing the Gabor feature of many other poses in advance. The other unknown variable pair is (ϕ_1, θ_1) , which represents the

normal vector of the tangent plane at each feature point. Because it is difficult to determine this variable pair from a single-view image, some kind of modeling is necessary. In [9, 12], this model is produced using exhaustive search of the smaller equal error rate in the variable ϕ and θ using a five-fold cross-validation.

2.5 Countermeasure for barrel distortions and up-converted images using super-resolution

When creating the normal vector model in [5, 8], images without degradation or distortion were used. In this experiment, images with barrel distortion, degraded images with low resolution and noise, and super-resolution images are created and used to build the normal vector model. Using these normal vector models, feature vectors for other poses were estimated subject to linear discriminant analysis that will be described below.

2.6 Training using estimated Gabor features

In addition to real registration data, the estimated Gabor jets for other poses obtained following the above outline are used as training data, and combined into class information for each individual. Using this class information, we try to improve the robustness of our method against pose variations.

For the training algorithm, multiple discriminant analysis [13] is employed. This algorithm provides coordinate transformations to coordinates where class separations are easier. The matrix $\mathbf{W}$ performing this coordinate change is obtained by maximizing the following function defined by

$$J(\mathbf{W}) = \frac{|\mathbf{W}'\mathbf{S}_b\mathbf{W}|}{|\mathbf{W}'\mathbf{S}_w\mathbf{W}|}, \quad (4)$$

where $\mathbf{S}_b$ is the inter-class scatter and $\mathbf{S}_w$ is the intra-class scatter. The column vectors $\mathbf{w}_i$ of the matrix $\mathbf{W}$ are obtained by solving the following generalized eigenvalue problem

$$\mathbf{S}_b\mathbf{w}_i = \lambda_i \mathbf{S}_w\mathbf{w}_i. \quad (5)$$

If the number of samples is not large enough compared with the dimensions of the data (in our setting the dimension of the Gabor jets), the intra-class scatter $\mathbf{S}_w$ is degenerate, and not all vectors $\mathbf{w}_i$ are necessarily obtained accurately.

3. DATA USED FOR EXPERIMENTS

3.1 Images database for the experiments

To examine robustness against pose variations, experiments were performed using the human and object interaction processing (HOIP) database [14],

Figure 3: Ear images taken at various yaw angles

which is a database of 300 subjects photographed from 504 (72 yaw angles every 5° and 7 roll angles every 15°) directions. In these facial images, the size of the ear approximately fits within a 70×90 pixel window. The feature points of the ear are located using jet space similarities.

Ear images of a single subject taken at various yaw angles are given in Fig. 3.

By convention, yaw angles 0° and 90° correspond to the frontal-view and true-left profiles respectively. Thus, compared with the 60° image, the 40° image is closer to a frontal view whereas the 80° image is closer to a true left profile.

3.2 Images with barrel distortions

Fisheye lenses, which take hemispherical views, have barrel distortion to map an infinitely wide object plane into a finite image area. Here, we consider stereographic projection where a point $\mathbf{X} = (X, Y)$ on the image without distortion corresponds to point $\mathbf{x} = (x, y)$ on the fish-eye image subject to barrel distortion under the following map

$$\mathbf{x} = \frac{r}{\sqrt{(rR)^2 + |\mathbf{X}|^2}} \mathbf{X}.$$

Here, R is the magnification near the center of the distortion and r the radius of the hemisphere. Using this map, we imprinted various barrel distortions on the images using a magnification factor $R = 1$ so that ear size is normalized appropriately (Fig. 4).

Figure 4: Examples of images with barrel distortion

Original image

Degraded image
(25% image size)

Super-resolution image

Figure 5: Example of degraded images and an up-converted image using super-resolution

3.3 Degraded images and its super-resolution image

The original images were rescaled to 25% of their size and random noises were added (Fig. 5, middle). Sixteen images were created similarly. Using the super-resolution method of Farsiu [15] in OpenCV, up-converted images were created.

3.4 Experiments using images with barrel distortions and super-resolution images

Recognition experiments were performed with images of potential suspects (registration images) taken from a yaw angle of 65°, and surveillance images (input images) of the suspect with one of the yaw angles between 40° and 80°. Again, for input, registration, and training data, subjects with more than four (resp. seven) visible feature points at all yaw angles were selected from a hundred and sixty-four (resp. ninety-six) subjects. Gabor features for these yaw angles estimated using images with various distortions (resp. up-converted super-resolution images) are prepared in advance and subjected to LDA training.

3.5 Validity metrics for the experiments using barrel-distorted and super-resolution images

The performance metrics are the equal error rates (EERs) obtained from the receiver operator characteristics (ROC). There are two types of error rates; false positive rates and false negative rates, which depend on decision thresholds. Equal error rates are the error rates where both false

Figure 6: Ear images with earrings. *r stand for reversed ear images

positive rates and negative rates are equal. Hence with lower EERs, the biometrics systems are more accurate.

For computing these metrics, we have used the algorithm as recommended in Annex. F.1 of [16].

3.6 Experiments on the effect of earrings

To increase the number of subject with earrings, not only left ear images, but also flipped images of the right ear, i.e., pseudo-left ear images were used, thus increasing the number of biometric samples. Within the 329 subjects (including reversed ears) that exhibited more than four visible feature points, there were nine left ears with earrings (Fig. 6).

3.7 Validity metrics for the experiments on the influence of earrings

As a validation metric, we used the rank of the input images as defined in [16]; specifically, the similarity scores between an input biometrics sample and registered biometrics sample are computed. Within these scores, the ranking of the similarity score between the input biometric sample and the registered biometric sample from the same person is obtained. Thus, the input biometric samples with lower ranking numbers are easily identified using the biometric system. For computing these metrics, we have used the algorithm as recommended in Annex. F.2 of [16].

4. RESULTS AND DISCUSSION

Empirical results using images with barrel distortions are presented in Fig. 7(a)–(c). In this graph, the abscissa represents the yaw angles of the input biometric samples

Figure 7: Equal error rates (EERs) at various angles for barrel-distorted input images

and the ordinate signifies equal error rates (EERs). Lower EERs indicate the biometrics system is more accurate. As the registered biometric samples have a yaw angle of 65° in all experiments, accordingly, as the difference in angle between input and registration images becomes larger, the accuracy decreases (graph goes up). By comparing EERs from various methods at each input angle, it was found that our proposed method, using distorted images for model normal vector creation, improves the accuracy further than that of [9,12] (Fig. 7(a) and (b)). When the distortion is relatively small, our method is as accurate as if there is no distortion (Fig. 7(a)).

The experimental result (Fig. 8) obtained using super-resolution on degraded images shows that the recovered images are to a high degree of accuracy near registration pose images without degradation. Aside from registration posed images, differences become larger and accuracy declines. This difference becomes smaller using our previous result [9,12] or our proposed method using super-resolution images to create normal vectors for our model.

Figure 8: Equal error rates (EERs) at various angles using super-resolution images

The experimental results regarding the influence of earrings in evaluations are given in Tables 1 and 2.

In Table 1, the ranks of selected input images *with earrings* are listed. The numbers in each row determine the rankings of the input biometric samples of a subject indicated in the first column, associated with a pose (angle of a shoot) given in the first row. The last two rows list the averaged ranks and standard deviations for the nine biometric image samples for each of the poses. As the yaw angle is 60° for the registered biometric samples in all experiments, the difference in angle between input and registration increases accordingly, and hence the averaged accuracy decreases (i.e., ranks go up).

In Table 2, the averaged ranks and standard deviations of input image samples *without earrings* are listed for the various pose angles in a similar manner to Table 1. Again, as the difference in angle between input and registration increases, the averaged accuracy decreases (ranks go up).

The difference between the averaged ranks between subjects with earrings and subjects without earrings at each input angle was found to be statistically insignificant ($p < .05$). The result is reasonable given that our proposed method does not directly use ear lobe shape. Instead, our algorithm uses the local shape near seven points as indicated in Fig. 1.

Table 1: Ranks of input images *with earrings* at various input angles

angle(°) subject	30°	40°	50°	70°	80°	90°
a	1	1	1	1	1	1
b	80	3	1	1	1	1
c	1	1	1	1	1	1
d	1	1	1	1	1	1
er	2	2	1	1	1	49
ar	1	1	1	1	1	1
br	20	5	1	1	1	55
cr	1	1	1	1	1	2
dr	1	1	1	1	1	1
average	12.0	1.8	1.0	1.0	1.0	12.4
st. dev.	26.3	1.4	0.0	0.0	0.0	22.5

Table 2: Average and standard deviation of *ranks* of input images *without earrings* at various input angles

angle(°)	30°	40°	50°	70°	80°	90°
average	13.2	2.3	1.0	1.0	1.9	3.1
st. dev.	35.0	10.1	0.1	0.1	10.9	7.5

5. CONCLUSION

To improve the viability of the authors' previous work regarding single-view-based ear biometrics [9,17], empirical evaluations were performed using images with barrel distortion and super-resolution images. A decrease in accuracy was empirically demonstrated when using barrel-distorted images and super-resolution images. However, using the same images, our present proposed method for model normal vector creation compensated for losses in accuracy. Further, experimental investigation on the influence of earrings is included. The difference between the averaged ranks at each pose angle for images of subjects with and without earrings was found to be statistically insignificant.

We hope to establish a multi-view ear database with barrel distortions and super resolution up-conversion using captured images through wide-angle lenses that would mimic surveillance images taken in actual settings. Analysis using these images is left for future study.

We concur with Dr. Khalid Saeed, one of the conference chairs of ICBAKE 2013, the conference for which this special issue by paraphrasing his remarks [18]: Biometrics and affective engineering are both based on the 'technology for understanding humans'. By bringing together researchers from both sides, new interdisciplinary areas of research are expected. We believe such an area may include the development of a system that understands who are present in a car (driver and passengers) and provide an atmosphere in the cabin that is attuned to their preferences based on prior analysis. Assessing the applicability of ear biometrics to such systems and similar scenarios is left for future study.

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