Feature-domain super-resolution framework for Gabor-based face and iris recognition

K. Nguyen, S. Sridharan, S. Denman, C. Fookes
Image and Video Research Lab, Queensland University of Technology
2 George Street, GPO Box 2434, Brisbane, QLD 4001, Australia
kien.nguyenthanh@student.qut.edu.au, {s.sridharan,s.denman,c.fookes}@qut.edu.au

Abstract

The low resolution of images has been one of the major limitations in recognising humans from a distance using their biometric traits, such as face and iris. Super-resolution has been employed to improve the resolution and the recognition performance simultaneously, however the majority of techniques employed operate in the pixel domain, such that the biometric feature vectors are extracted from a super-resolved input image. Feature-domain super-resolution has been proposed for face and iris, and is shown to further improve recognition performance by capitalising on direct super-resolving the features which are used for recognition. However, current feature-domain super-resolution approaches are limited to simple linear features such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), which are not the most discriminant features for biometrics. Gabor-based features have been shown to be one of the most discriminant features for biometrics including face and iris. This paper proposes a framework to conduct super-resolution in the non-linear Gabor feature domain to further improve the recognition performance of biometric systems. Experiments have confirmed the validity of the proposed approach, demonstrating superior performance to existing linear approaches for both face and iris biometrics.

1. Introduction

Super-resolution (SR) techniques have previously been employed to address the low resolution problems of imaging systems. There are two differing SR approaches: reconstruction-based and learning-based [18]. Reconstruction-based approaches fuse the sub-pixel shifts among multiple low resolution images to obtain a higher resolution image. Alternatively, learning-based approaches model the relationship between low-resolution and high-resolution training images and learn prior knowledge to constrain the SR process [18].

Recently, SR techniques have been applied to biometric systems. A number of SR techniques have been successfully developed for face [2, 11, 13, 8, 22] and iris [6, 23, 9, 17]. However, one main concern raised by both Gunturk *et al.* [7] and Nguyen *et al.* [16] is how to apply SR for a specific biometric modality effectively to improve recognition performance, rather than visual clarity. Two issues have been raised:

- The aim of applying SR to biometrics is not for visual enhancement, but to improve recognition performance. Most existing SR approaches are designed to produce visual enhancement. *If recognition improvement is desired, why do we not focus on super-resolving only items essential for recognition?*
- Each biometric modality has its own characteristics. Most existing SR approaches for biometrics are general-scene SR approaches. *Can any specific information from biometric models be exploited to improve SR performance?*

Based on these concerns, feature-domain SR techniques have been proposed for face [7, 10] and iris [16, 1] to improve recognition performance. These approaches no longer super-resolve images in the pixel-domain, but super-resolve the extracted features that are used for classification in the feature-domain, and the SR output (a super-resolved feature vector) is directly employed for recognition. Different linear features including Principle Component Analysis (PCA) [7, 16], Linear Discriminant Analysis (LDA) [1], and Tensor Face [10] have been investigated to improve biometric performance. These features are super-resolved using a maximum a posteriori estimation approach. Specific knowledge of face and iris models is incorporated in the form of prior probabilities to constrain the SR process, improving robustness to noise and segmentation errors. These approaches have been shown to outperform the equivilent pixel-domain SR approaches for face and iris recognition.

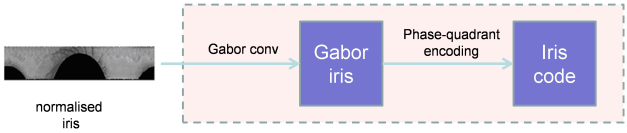


Figure 1. A conventional iris encoding procedure [4]. The iris image is segmented, then normalised to a fixed-size rectangle. This normalised rectangle is then encoded using the phase-quadrant 2D Gabor wavelet encoding technique to create an IrisCode. The IrisCode is the representation of an iris.

However, the linear features such as PCA and LDA are not optimum for recognition, and nonlinear Gabor-based features have been shown to be one of the most discriminant features for face [21] and iris [5]. The challenge of using these nonlinear features in super-resolution is the difficulty in formulating the relationship between the low-resolution features and the high-resolution features in the feature domain. To further improve the recognition performance, we seek to conduct feature-domain SR using these nonlinear Gabor-based features.

The remainder of this paper is organised as follows: Gabor-based encoding techniques for face and iris are analysed in Section 2; a framework for applying feature-domain SR with these nonlinear Gabor-based features is proposed in Sections 3 and 4; experiments applying the proposed framework to face and iris recognition are presented in Section 5, and the paper is concluded in Section 6.

2. Gabor-based encoding techniques for face and iris recognition

Gabor-based features have been shown to effectively extract discriminant information for both iris [5] and face [21] since they achieve the best trade-off in both spatial and spectral resolution when mimicking the human brain cortex [3]. For Gabor-based iris recognition, a typical recognition approach is illustrated in Figure 1. The iris region is segmented from the eye image, then normalised to a fixed-size rectangle before being encoded using the phase-quadrant Gabor wavelet encoding technique to create an IrisCode [4].

For Gabor-based face recognition, there are two types of techniques applicable: analytical approaches and holistic approaches, as illustrated in Figure 2. While the analytical approaches compute the response of an image to a Gabor wavelet in a set of discrete locations, the holistic approaches employ a global response, which is subsequently processed with other encoding techniques [21]. In this research, we choose to work with the holistic approaches as they are closely aligned with the iris techniques, making the proposed framework more practical.

Despite of the superior recognition performance when compared to linear techniques such as PCA and LDA [5, 21], these Gabor-based features have not been exploited

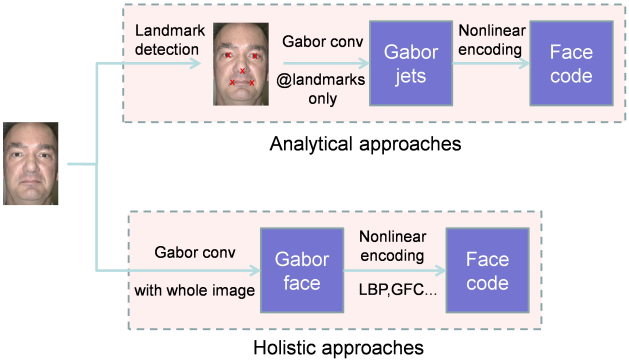


Figure 2. There are two types of encoding techniques based on Gabor features for face recognition: analytical approaches and holistic approaches. While the analytical approaches compute the response of an image to a Gabor wavelet in a set of discrete locations, the holistic approaches employ a global response, which is subsequently processed with another encoding techniques [21].

for feature-domain SR. The major challenge that prevents feature-domain SR from being successfully applied to the Gabor-based encoding techniques is the non-linear nature of the encoding technique (e.g. phase-quadrant [4] for iris; and Local Gabor Binary Pattern Histogram Sequence (LGBPHS) [24], Gabor Fisher Classifier (GFC) [15], Kernel PCA [14] for face). The existing feature domain SR frameworks of [7, 16, 10, 1] are unable to super-resolve nonlinear features such as Gabor-based features. In this paper, to further improve the recognition performance of feature-domain SR approaches when applying to biometrics, we propose a framework to enable feature-domain SR in nonlinear features such as Gabor phase-quadrant for iris and LGBPHS for face. The framework is introduced in the next section.

3. Feature-domain SR framework for Gabor-based face and iris recognition

3.1. General framework

When investigating Gabor-based face and iris recognition processes, we observe that at a high level there is a common framework for Gabor-based iris approaches and holistic Gabor-based face approaches, as illustrated in Figure 3. Both approaches compute the global response of the normalised image with a Gabor wavelet before further encoding with other nonlinear techniques (e.g. phase-quadrant for iris, and LGBPHS for face).

Importantly, we note that the global Gabor response is linear, whilst the nonlinearity of the overall encoding techniques results from the secondary encoding steps (e.g. phase-quadrant for iris, and LGBPHS for face). Hence, if feature-domain SR is conducted on the global Gabor response, rather than the final features; we can take advantage

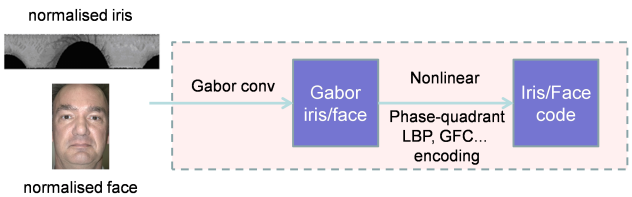


Figure 3. The common encoding flow in iris and face recognition systems using Gabor-based features. Both face and iris systems calculate the global response by convolving the whole image with the Gabor filter. After that, the Gabor images are further encoded with nonlinear steps such as phase-quadrant, LGBPHS.

of the linear property of the global Gabor response. This global Gabor response is in the form of complex-valued 2D Gabor features. From this observation regarding the origins of the non-linearity, we propose a framework to apply feature-domain SR using nonlinear Gabor-based features as presented in Figure 4.

3.2. Feature-domain SR approach

Stage 1: Observation model in the spatial domain

Let x be the original HR iris/face image, and $y^{(i)}$ be the ith observed LR iris/face image after being degraded by downsampling, $D^{(i)}$; blurring, $B^{(i)}$; and warping, $W^{(i)}$. The relation between $x, y^{(i)}$ is described as follows,

$$y^{(i)} = D^{(i)} B^{(i)} W^{(i)} x + n^{(i)}, \tag{1}$$

where $n^{(i)}$ is the observation noise.

Stage 2: Observation model in the feature domain

We seek to transform the observation model from the spatial domain to the feature domain. The nonlinear 2D Gabor-based features (phase-quandrant 2D Gabor features for iris and LGBPHS for face) of HR irises/faces, H, and LR irises/faces, $h^{(i)}$, are represented as follows,

$$\begin{aligned} H_{Re,Im} &= sign_{Re,Im}(G), \\ h^{(i)}_{Re,Im} &= sign_{Re,Im}(g^{(i)}), \end{aligned} \tag{2}$$

for iris, and

$$\begin{aligned} H_{Re,Im} &= LBPHS(G), \\ h^{(i)}_{Re,Im} &= LBPHS(g^{(i)}), \end{aligned} \tag{3}$$

for face, where G and $g^{(i)}$ are the complex-valued 2D Gabor features of HR irises/faces and LR irises/faces given by,

$$G = \int_\rho \int_\phi x e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi, \tag{4}$$

$$g^{(i)} = \int_\rho \int_\phi y^{(i)} e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi. \tag{5}$$

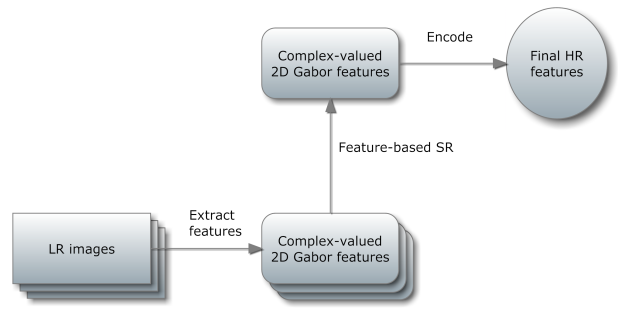


Figure 4. Feature-domain super-resolution framework for Gabor-based face and iris recognition.

Substituting the spatial observation model of Equation (1) into the HR feature representation of Equations (5), we have,

$$\begin{aligned} g^{(i)} &= \int_\rho \int_\phi (D^{(i)} B^{(i)} W^{(i)} x + n^{(i)}) \times \\ & e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi \\ = & \int_\rho \int_\phi D^{(i)} B^{(i)} W^{(i)} x e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} \times \\ & e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi \\ + & \int_\rho \int_\phi n^{(i)} e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi \\ = & \; G1 + G2 \end{aligned} \tag{6}$$

We make the following assumptions:

1. For each iris/face image, blurring and warping factors, which degrade the quality of the iris/face image, are changing along the image. This explicitly means the blurring and warping level varies due to the location of the pixel in the image. In this case, $B^{(i)}$ and $W^{(i)}$ are a function of ρ and ϕ. However, we can make an approximation and assume that $B^{(i)}$ and $W^{(i)}$ are uniform over the normalised iris/face image. With this assumption, the first component of Equation (6) can be represented as,

$$\begin{aligned} G1 &= \int_\rho \int_\phi D^{(i)} B^{(i)} W^{(i)} x e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} \times \\ & e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi \\ &= D^{(i)} B^{(i)} W^{(i)} \int_\rho \int_\phi x e^{-((r_0-\rho)^2/\alpha^2 + (\theta_0-\phi)^2/\beta^2)} \times \\ & e^{-i\omega(\theta_0-\phi)} \rho d\rho d\phi \\ &= D^{(i)} B^{(i)} W^{(i)} G \end{aligned} \tag{7}$$

2. Noise $n^{(i)}$ is properly assumed to be an Independently Identical Distributed (IID) Gaussian signal. The 2D Gabor wavelet transform can be considered as a local Fourier transform. Moreover, the 2D Fourier transform of an Gaussian signal has a Gaussian form. Hence, the 2D Gabor

wavelet transform of the noise, which is the second component in Equation (6), can be approximated as an IID Gaussian signal.

$$G2 = v^{(i)} \tag{8}$$

With these two assumptions, Equation (6) can be rewritten as,

$$g^{(i)} = D^{(i)}B^{(i)}W^{(i)}G + v^{(i)}. \tag{9}$$

Equation (9) shows the relationship between the HR and observed LR features. The following sections will discuss a solution to estimate the HR features from this equation.

Stage 3: Estimating HR features

In Bayes statistics, a maximum a posteriori probability estimate can be used to estimate an unobserved quantity on the basis of empirical data. Using Bayes maximum a posteriori probability estimation, a HR feature can be estimated as,

$$\widetilde{G} = argmax_g p(g^{(1)}, \ldots, g^{(M)}|G)p(G). \tag{10}$$

The estimated HR feature, $\widetilde{G}$, is the value that maximises the product of the conditional probability $p(g^{(1)}, \ldots, g^{(M)}|G)$ and the priori probability $p(G)$.

Stage 4: Incorporating iris/face model information

To solve the above estimation problem, specific information relating to iris/face models can be incorporated in the form of prior knowledge of the prior probability and noise. We proposed to incorporate the following two constraints:

- 1. Prior probability is jointly Gaussian,

$$p(G) = \frac{1}{Z}exp(-(G-\mu_G)^T\Lambda^{-1}(G-\mu_G)). \tag{11}$$

- 2. Noise $v^{(i)}$ is an Independent Identically Distributed (IID) Gaussian with a diagonal covariance matrix,

$$p(v^{(i)}) = \frac{1}{Z}exp(-(v^{(i)}-\mu_v^{(i)})^T K^{-1}(v^{(i)}-\mu_v^{(i)})). \tag{12}$$

From Equation (9), the individual conditional probability can be estimated as,

$$p(g^{(i)}|G) = \frac{1}{Z}exp(-(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})^T \times K^{-1}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})). \tag{13}$$

From (9), $g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G$ is IID as a consequence of the fact that $v^{(i)}$ is IID, thus,

$$p(g^{(1)}, \ldots, g^{(M)}|G) = \prod_i p(g^{(i)}|G) = \frac{1}{Z}exp(-\sum_{i=1}^{M}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})^T K^{-1}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})).$$

The estimation problem can then be rewritten as,

$$\widetilde{G} = argmax_G \left(p(g^{(1)}, \ldots, g^{(M)}|G)p(G)\right)$$
$$= argmax_G \frac{1}{Z}exp(-\sum_{i=1}^{M}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})^T K^{-1}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})) \times \frac{1}{Z}exp(-(G-\mu_G)^T\Lambda^{-1}(G-\mu_G)) =$$
$$argmin_G(\sum_{i=1}^{M}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})^T K^{-1}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)}) + (G-\mu_G)^T\Lambda^{-1}(G-\mu_G)).$$

Stage 5: Estimating the solution

The estimation in Stage 4 is an unconstrained optimisation problem. This optimisation can be solved by both iterative steepest descent and iterative conjugate gradients [20]. With a proper choice of the step size and the maximum number of steps, the iterative steepest descent method is capable of converging to the local minimum sharply. However, iterative steepest descent may never reach the true minimum [20]. Instead of employing steepest gradient directions for iterative updating, a conjugate gradients method utilises conjugate directions, which enables the method to converge more accurately in at most n steps, where n is the size of the matrix of the system [20]. Given this, we solve the optimisation problem in Stage 4 by iterative conjugate gradients. Let the cost function, E(g), be defined as,

$$E(G) = \sum_{i=1}^{M}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)})^T K^{-1}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v^{(i)}) + (G-\mu_G)^T\Lambda^{-1}(G-\mu_G).$$

The solution for optimisation can be estimated iteratively as follows,

$$\widetilde{G}_{n+1} = \widetilde{G}_n + \alpha_n \Gamma\widetilde{G}_n, \tag{14}$$

where $\Gamma\widetilde{G}_n$ is defined as,

$$\Gamma\widetilde{G}_n = \triangle\widetilde{G}_n + \beta_n\Gamma\widetilde{G}_{n-1}, \tag{15}$$

where $\triangle\widetilde{G}_n = -\nabla_G E(\widetilde{G}_n)$ and $\beta_n = max(0, \beta_n^{PR})$, and

$$\beta_n^{PR} = \frac{\triangle\widetilde{G}_n^T(\triangle\widetilde{G}_n - \triangle\widetilde{G}_{n-1})}{\triangle\widetilde{G}_{n-1}^T\triangle\widetilde{G}_{n-1}}. \tag{16}$$

α_n is the parameter to minimise $E(\widetilde{G}_n + \alpha_n\Gamma\widetilde{G}_n)$ through a line search. Hence, with an initial estimation $\widetilde{G}_0$, the iterative conjugate gradients estimation $\widetilde{G}_n$ will converge to the true high-resolution G which minimises the cost function $E(G)$.

4. Estimating the statistics of prior probabilities of the features and noise

The estimation solution as explained in Section 3 requires the statistics of noise and the prior probability of HR features to be estimated before hand. This section describes

this prerequisite estimation performed on a training set (details of the training set used in this work are presented in Section 5).

4.1. The statistics of prior probability of HR features

Prior probability of the HR features has been assumed to have a Gaussian form with mean vectors μ_g and covariance matrix Λ given by,

$$\mu_g = \frac{1}{M}\sum_{i=1}^{M} G^{(i)}, \tag{17}$$

$$\Lambda = \frac{1}{M}\sum_{i=1}^{M} (G^{(i)} - \mu_g)(G^{(i)} - \mu_g)^T, \tag{18}$$

where $G^{(i)}$ is the HR features vectors of the ith training image, M is the total number of training images.

4.2. The statistics of noise

From Equation 9, 2D Gabor complex features of noise in the observation equation can be estimated as,

$$v^{(i)} = g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G.$$

The statistics of noise in the form of a mean vector μ_v and a covariance matrix K can be estimated as,

$$\mu_v = \frac{1}{M}\sum_{i=1}^{M}(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G), \tag{19}$$

$$K = \frac{1}{M}\sum_{i=1}^{M}\Big\{(g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v)\times (g^{(i)} - D^{(i)}B^{(i)}W^{(i)}G - \mu_v)^T\Big\}. \tag{20}$$

The statistics of noise and prior probability estimated here are used to bolster the estimation process described in Section 5.

5. Evaluation of the proposed framework

Experiments on face and iris verification are conducted on the MBGC dataset [19] to evaluate the validity of the proposed framework.

For iris, 628 NIR iris portal video of 129 individuals are employed to verify the identity against 8589 NIR high quality still iris images. The resolution of the still iris images is high with approximately 220 pixels across the diameter of the iris boundary circle, while the resolution of the iris in the portal videos is significantly lower with less than 90 pixels across the diameter of the iris. There are variety of degradation factors which reduce the quality of portal iris images as shown in Figure 5.

The dataset is divided into two subsets for training and testing. For training, 5 still images and 1 video sequence per identity are used to estimate the statistics of noise and prior probability of HR features. Parameters of the statistics are estimated as described in Section 4. For testing, the 4 remaining video sequences for each identity are matched against the HR still images. For each video sequence, all frames are evaluated for quality. The quality metrics proposed in [17] are employed to evaluate the quality of each frame. Individual quality factors including focus, off-angle appearance, illumination variation, and motion blur are fused using Dempster-Shafer theory to produce an overall quality score for each frame. Nguyen et al. [17] have shown the optimal performance is achieved by fusing the 5 best quality frames for each video. As [17] also used the MBGC portal dataset, we also select the best five frames for super resolution. However it should be noted that as observed by [17], the optimal number of frames may vary for a different database.

For face, the portal videos in the MBGC dataset focus on capturing eyes for iris recognition, hence the faces in these portal videos rarely contain images of the whole face. While it would be ideal to use actual low resolution imagery, the limitations of existing databases make this difficult and so in this research we use a subset of the MBGC visible dataset to generate synthetic low resolution video sequences for our

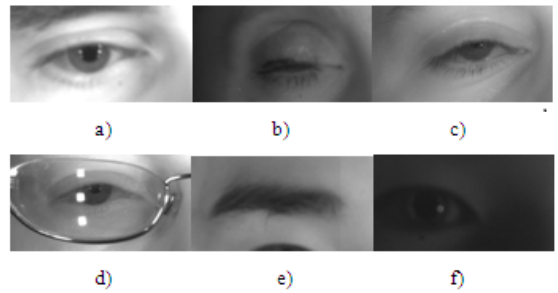
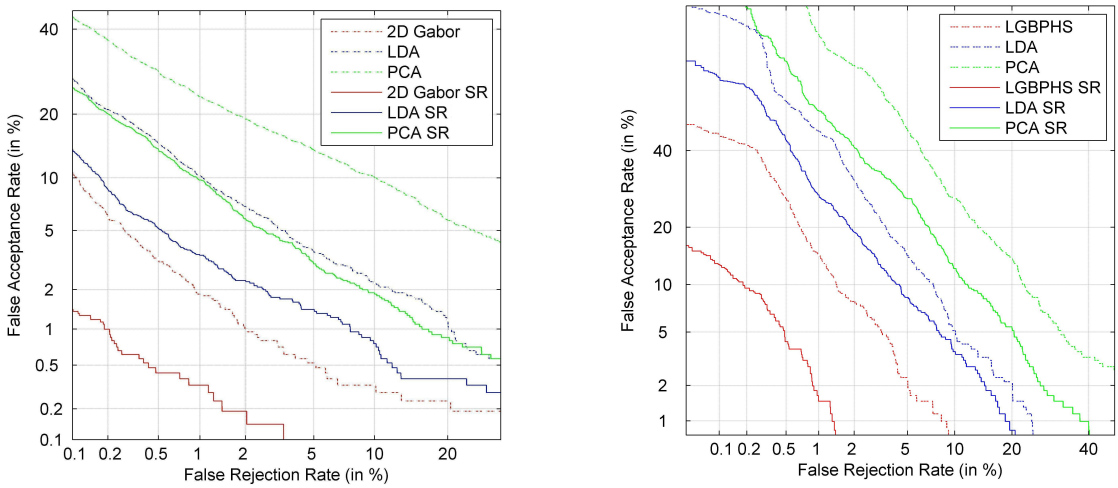


Figure 5. Examples of low quality iris images with a) Out of focus, b) Closed eye, c) Severely occluded by eyelids, d) Glass and reflection, e) Eye not in frame, f) Dark and poor contrast.

Figure 6. Examples of face images in the MBGC visible dataset.



(a) Iris

(b) Face

Figure 7. Linear vs. Nonlinear features in the feature-domain SR approach: Two linear features (LDA,PCA as in [16, 1]) have been employed to compare with the proposed approach using the nonlinear 2D Gabor phase-quadrant features for iris (a), and Local 2D Gabor Binary Pattern Histogram Sequence (LGBPHS) for face (b).

experiments on face super-resolution. The synthetic data has also been employed in other face super-resolution work, such as in [7, 13]. This data has 3482 high resolution images for 129 individuals. The visible face images are captured at high quality with a size of 2616×3904. One high quality visible face image for each identity is used as the gallery image, while five other high quality visible face images for each identity are degraded with warping, Gaussian blurring, and downsampled to a size of 40×40, forming five synthetic low resolution sequences of 16 frames. Two out of five low resolution sequences are used for training, to estimate the statistics of noise and prior probability of the HR features. The remaining three sequences are used for testing. All 16 frames in each sequence are used for super-resolution.

For both face and iris, the complex-valued 2D Gabor features in each image sequence for one identity are extracted by globally convolving each normalised image in the sequence with the Gabor filter. The intermediate Gabor features are then combined using the proposed feature-domain SR approach, to generate a high resolution feature. Subsequently, the super-resolved features are encoded with the nonlinear techniques (phase-quadrant for iris, and LGBPHS for face). Note that there are plethora of different nonlinear techniques used for both iris and face, however, in this paper, we choose to work with phase-quadrant for iris, and LGBPHS for face due to their popularity. It should be noted that all other techniques have the same structure of a global Gabor convolution followed by a nonlinear transformation, and so are equally applicable.

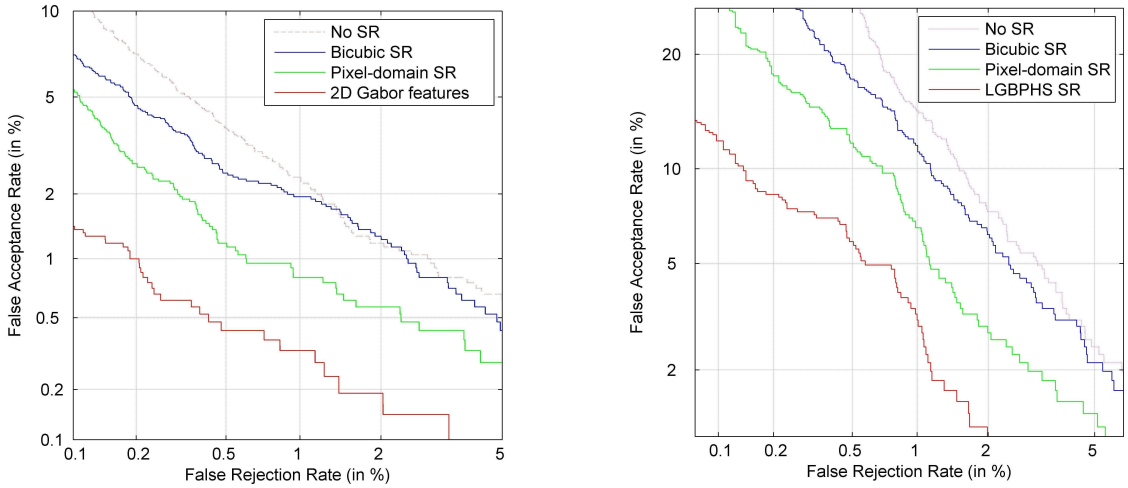
The final features are compared with the gallery features using the hamming distance [4] and the histogram intersection distance [24] for iris and face recognition respectively. Detection Error Trade-Off (DET) plots are employed to show the performance of different approaches.

We conduct experiments to compare the performance of the proposed approach with feature-domain super-resolution using linear features, and the performance of the proposed feature-domain SR approach against equivalent pixel-domain techniques. These experiments are presented in Sections 5.1 and 5.2 respectively.

5.1. Linear vs. Nonlinear features

Linear features including PCA and LDA have been employed for feature-domain SR for iris [16, 1] and face [7]. In this section, the advantage of employing the nonlinear 2D Gabor-based features against the linear PCA and LDA features is demonstrated. Without SR, Gabor-based features outperform PCA and LDA features in the recognition performance for both face and iris as shown in Figure 7. It can be seen that feature domain super resolution improves the performance of all three techniques for both modalities. However, the superior discriminability of the gabor features is clearly evident by the fact that the non-SR gabor techniques outperform the SR-PCA and SR-LDA techniques for both modalities. Applying super resolution to the gabor features results in a further performance improvement, thus highlighting the benefit of being able to perform super-resolution on the more discriminative gabor features.

Employing nonlinear 2D Gabor-based features in the feature-domain SR framework, as proposed in this paper, capitalises on both the boost in recognition performance obtained through the feature-domain SR approach and the dis-



(a) Iris

(b) Face

Figure 8. Recognition performance comparison of the proposed feature-domain SR and other pixel-domain SR. The proposed feature-domain SR outperforms other pixel-domain SR techniques due to the direct super-resolving in the feature domain and the incorporation of specific information from iris models (a), and face models (b)

criminant property of the Gabor features.

5.2. Comparison to pixel-domain SR

In this section, the proposed feature-domain SR framework is compared with other pixel-domain SR approaches including a conventional interpolation SR approach, (bicubic [12]), and a state-of-the-art pixel-domain SR for iris [17] and face [13]. For all pixel based approaches, features are encoded with the non-linear Gabor techniques (phase-quadrant and LBPGHS for iris and face respectively).

Figure 8 shows that the conventional bicubic interpolation approach does not improve the recognition performance considerably. The pixel-domain SR approaches in [17, 13] fuse information from multiple low-resolution images to generate a high-resolution image from which features are extracted, which improves the recognition performance. The proposed framework further improves the recognition performance with the super-resolution processing performed directly in the feature domain and the incorporation of prior knowledge of specific iris/face model. This illustrates the benefits of super-resolving the information that is used for recognition directly as is proposed in this paper.

6. Conclusion

Feature-domain SR has been shown to improve the recognition performance of biometric systems in comparison to pixel-domain SR, through direct super-resolution of the features used for classification, and incorporation of specific prior biometric model knowledge. This paper further improves the performance of feature-domain SR by introducing a new framework to enable feature-domain SR with nonlinear discriminant features (Gabor-based features). By employing nonlinear 2D Gabor-based features, our framework can boost the recognition performance when capitalising on both the boost in recognition performance obtained through the feature-domain SR approach and the highly discriminant property of the Gabor-based features. We have demonstrated the proposed framework on two biometrics (face and iris), and demonstrated similar performance gains in both modalities. The proposed framework can also be used for other biometrics and other nonlinear feature extraction techniques.

In future work, we will examine more nonlinear features and explore additional biometric modalities within the proposed framework.

References

[1] Authors. Conference name and paper title withheld to maintain author anonymity but available to the technical committee on request. *Supplied as additional material supplementary.pdf*, 2011. submitted. 1, 2, 6

[2] S. Baker and T. Kanade. Limits on super-resolution and how to break them. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24(9):1167 – 1183, 2002. 1

[3] J. Daugman. Gabor wavelets and statistical pattern recognition. In *The Handbook of Brain Theory and Neural Networks*, pages 457–461. THE MIT PRESS Cambridge, Massachusetts, London, England, 2002. 2

[4] J. Daugman. How iris recognition works. *IEEE Transactions on Circuits and Systems for Video Technology*, 14:21 – 30,

2004. 2, 6

[5] J. Daugman. New methods in iris recognition. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 37(5):1167 –1175, 2007. 2

[6] G. Fahmy. Super-resolution construction of iris images from a visual low resolution face video. In *Signal Processing and Its Applications, ISSPA 2007. 9th International Symposium on*, pages 1 –4, 12-15 2007. 1

[7] B. Gunturk, A. Batur, Y. Altunbasak, M. Hayes, and R. Mersereau. Eigenface-domain super-resolution for face recognition. *Image Processing, IEEE Transactions on*, 12(5):597 – 606, 2003. 1, 2, 6

[8] Y. Hu, K.-M. Lam, G. Qiu, and T. Shen. From local pixel structure to global image super-resolution: A new face hallucination framework. *Image Processing, IEEE Transactions on*, 20(2):433 –445, 2011. 1

[9] T. T. J. Huang, L. Ma and Y. Wang. Learning based resolution enhancement of iris images. *British Machine Vision Conference*, 1(1):1 – 10, 2003. 1

[10] K. Jia and S. Gong. Multi-modal tensor face for simultaneous super-resolution and recognition. *10th IEEE International Conference on Computer Vision*, Vol. 2:1683 – 90, 2005. 1, 2

[11] K. Jia and S. Gong. Generalized face super-resolution. *Image Processing, IEEE Transactions on*, 17(6):873 –886, 2008. 1

[12] R. Keys. Cubic convolution interpolation for digital image processing. *Acoustics, Speech and Signal Processing, IEEE Transactions on*, 29(6):1153 – 1160, dec 1981. 7

[13] F. Lin, C. Fookes, V. Chandran, and S. Sridharan. Super-resolved faces for improved face recognition from surveillance video. In *Lecture Notes in Computer Science*, volume 4642 LNCS, pages 1 – 10, Seoul, Korea, Republic of, 2007. 1, 6, 7

[14] C. Liu. Gabor-based kernel pca with fractional power polynomial models for face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26:572–581, 2004. 2

[15] C. Liu and H. Wechsler. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE Trans. Image Processing*, 11:467–476, 2002. 2

[16] K. Nguyen, C. Fookes, S. Sridharan, and S. Denman. Feature-domain super-resolution for iris recognition. *18th IEEE International Conference on Image Processing*, pages 3258 – 3261, 2011. 1, 2, 6

[17] K. Nguyen Thanh, C. Fookes, S. Sridharan, and S. Denman. Quality-driven super-resolution for less constrained iris recognition at a distance and on the move. *Information Forensics and Security, IEEE Transactions on*, PP(99):1, 2011. 1, 5, 7

[18] S. Park, M. Park, and M. Kang. Super-resolution image reconstruction: a technical overview. *IEEE Signal Processing Magazine*, 20(3):21 – 36, 2003. 1

[19] P. Phillips, P. Flynn, J. Bevcridge, W. Scruggs, A. O'Toole, D. Bolme, K. Bowyer, B. Draper, G. Givens, Y. M. Lui, H. Sahibzada, I. Scallan, J.A., and S. Weimer. Overview of the multiple biometrics grand challenge. In *Advances in Biometrics. Proceedings Third International Conference, ICB 2009*, pages 705 – 14, Germany, 2009. 5

[20] W. H. Press, S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery. *Numerical recipes : the art of scientific computing*. Cambridge University Press, 2007. 4

[21] A. Serrano, I. de Diego, C. Conde, and E. Cabello. Recent advances in face biometrics with gabor wavelets: A review. *Pattern Recognition Letters*, 31(5):372 – 81, 2010/04/01. 2

[22] J. Yang, J. Wright, T. S. Huang, and Y. Ma. Image super-resolution via sparse representation. *IEEE Transactions on Image Processing*, 19(11):2861 – 2873, 2010. 1

[23] K. Y.S., K. R.P., B. J.K., and S. J.P. Super-resolution method based on multiple multi-layer perceptrons for iris recognition. In *Ubiquitous Information Technologies Applications, ICUT '09. International Conference on*, pages 1 –5, 20-22 2009. 1

[24] W. Zhang, S. Shan, W. Gao, X. Chen, and H. Zhang. Local gabor binary pattern histogram sequence (lgbphs): a novel non-statistical model for face representation and recognition. 1:786 – 791 Vol. 1, 2005. 2, 6