IMAGE QUALITY ASSESSMENT TO ENHANCE INFRARED FACE RECOGNITION

Camilo G. Rodríguez Pulecio⋆ *Hernán D. Benítez-Restrepo*⋆ *Alan C. Bovik*†

⋆Departamento de Electrónica y Ciencias de la Computación,
Pontificia Universidad Javeriana, Cali, Colombia
†Department of Electrical and Computer Engineering,
The University of Texas at Austin, Austin, TX, USA

ABSTRACT

Automatic quality evaluation of infrared images has not been researched as extensively as for images of the visible spectrum. Moreover, there is a lack of studies on the influence of degradation of image quality on the performance of computer vision tasks operating on thermal images. Here, we quantify the impact of common image distortions on infrared face recognition, and present a method for aggregating perceptual quality-aware features to improve the identification rates. We use Natural Scene Statistics (NSS) to detect degradation of infrared images, and to adapt the face recognition algorithm to the quality of the test image. The proposed approach applied to a face identification algorithm based on thermal signatures yielded an improvement of rank one recognition rates between 11% and 19%. These results confirm the relevance of image quality assessment for improving biometric identification systems that use thermal images.

Index Terms— Image Quality, Natural Scene Statistics, Infrared Imaging, Face Recognition, Biometrics

1. INTRODUCTION

Automatic face recognition remains one of the most active fields of computer vision research. Even so, it is still a challenging task especially on uncontrolled and non-cooperative environments, where the performance of autonomous face identification systems is not yet close to that of human viewers [1].

The vast majority of techniques for face identification developed during the last decade rely on images from the visible spectrum. Nevertheless, in recent years there has been a growing interest in algorithms based on different modalities such as 3D, infrared (IR) imaging and hybrid approaches [2]. Automatic face recognition based on Long Wave Infrared (LWIR) images has shown promising results, largely because of the robustness of thermal images to illumination variations and other factors that affect images acquired in the visible spectrum.

The use of image quality assessment (IQA) strategies to augment processing tasks involving thermal images has been studied before [3, 4]. However, to the best of our knowledge, there has been no comprehensive work on analyzing or ameliorating the impact of image degradation on face recognition systems based on IR images. These topics are highly relevant to research on thermal images processing, given the increasing dissemination of affordable IR cameras.

The aim of this work has been to study the influence of four common image distortions on a thermal face identification algorithm, and to design a way to enhance the system, by aggregating IQA features in order to make it more robust to image quality degradation. The face recognition method chosen for this work is based on the thermal signatures approach of Guzman *et. al* [5], which has shown acceptable accuracy with a relatively simple implementation. We used Natural Scene Statistics (NSS) as image quality descriptors, as they have proven to be powerful tools for determining the presence and severity of common image distortions [6–9].

2. RELATED WORK

2.1. Infrared Face Recognition

Two main strategies have been explored for performing face recognition on infrared images: *holistic appearance* and *feature-based* methods [2, 10].

Approaches based on appearance make use of visual face recognition techniques for thermal face identification such as PCA, lineal discriminants and Bayesian analysis [11–13]. These methods are sensitive to intra-subject variations and do not take advantage of IR specific knowledge, so most recent research efforts have focused on feature-based approaches.

One of the most promising techniques employing distinct IR features is based on vascular networks or thermal signatures. Buddharaju *et. al* published early work using this strategy [14], where a structural pattern correlated with the superficial vasculature is extracted from the facial images. Next, the authors locate thermal minutiae points (TMP) as characteristic features, inspired by the minutiae used for fingerprint identification. In a later improvement of their work, the authors refined their method of vascular network extraction, and replaced the TMP based approach with a dual bootstrap Iterative Closest Point algorithm, thereby achieving rank one recognition accuracies greater than 89% [15, 16].

Expanding on the vascular network concept, Guzman *et. al* proposed a thermal signature template (TST) that is generated by combining four thermal signatures (analogous to vascular networks), extracted from different images of the same subject [5]. This TST is used as the unique representation of the individual, and is compared with a thermal signature (TS) of a test image to calculate an identification score. Recognition rates of 90.4% were attained with a dataset of 13 subjects.

The main contribution made here is the development of an effective IQA based method to evaluate and improve face recognition accuracy on distorted IR images.

2.2. Image Quality Assessment

An unresolved problem is the design of methods to assess how recognition accuracy is affected by image distortions [17]. In this

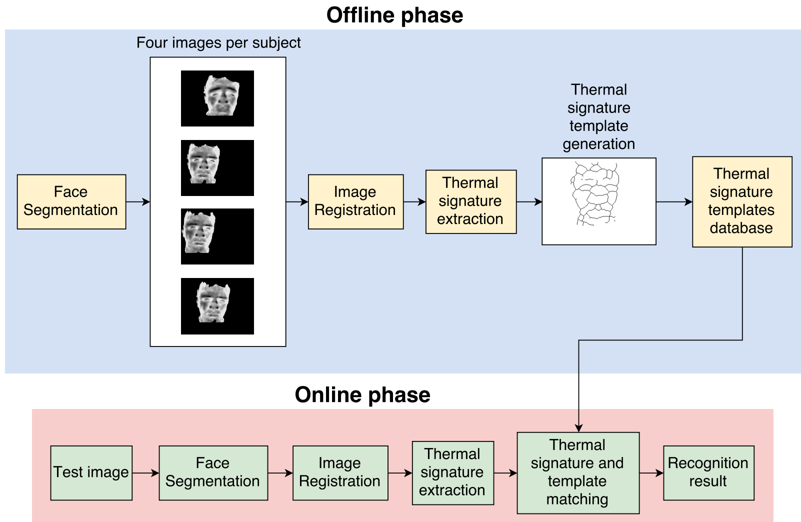


Fig. 1. Infrared face recognition system

direction, one recent study proposed an improvement of face detector performance by augmenting face indicative features with NSS features on images in the visible spectrum [18]. Nonetheless, the application of IQA techniques to IR images has been scarcely studied. One notable effort was reported in [3, 4], where the authors use NSS to model thermal image distortions, classify between visible and IR images, and correct non-uniformity noise. The success of this research inspired us to apply NSS to the problem of infrared face recognition, and try to improve the identification rates of a top-performing IR face recognition model on degraded images.

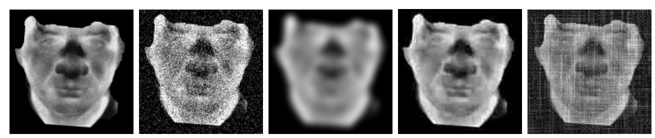
A preliminary effort on including image quality considerations in IR face recognition was presented in [19], where the authors compared the performance of three thermal face identification methods on images distorted with AWGN and NU. However, this study did not include a proposal for enhancing recognition performance nor deployed IQA features.

3. METHODS

3.1. Databases

To evaluate the face recognition algorithm, we used two public databases of IR face images, and a new database generated specifically for this project that we call PUJ. The public databases are IRIS from the University of Tennessee [20], and Collection X1 from the University of Notre-Dame (UND) [21]. Images from 20 subjects from each database were selected to create the gallery set composed of Thermal Signature Templates (TST). These templates are the basis for identification of each individual. The images were chosen to show the face in frontal position, without occlusions, and with good visibility of the distinctive features. The tests were conducted on each database separately.

Distorted versions of each selected image were generated to assess the influence of image quality degradations on the performance of the face recognition algorithm. We applied three severity levels of each of four common distortions to the images: Additive White Gaussian Noise (AWGN), Blur, JPEG compression, and Non-Uniformity (NU). Fig. 2 shows an example of a pristine image from the IRIS database and its distorted versions.



(a) (b) (c) (d) (e)

Fig. 2. Image distortion example. (a) Pristine. (b) AWGN. (c) Blur. (d) JPEG. (e) NU.

3.2. Face Recognition Algorithm

The implemented face recognition algorithm follows the approach described in [5]; a flow diagram of the system is shown in Fig. 1.

The *offline* stage involves the TST database generation from four images of each subject, while the *online* phase consists of matching a test image's TS with each TST.

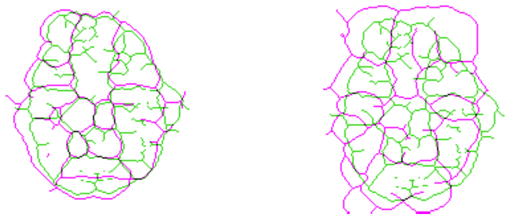
Obtaining a TS comprises several steps: (i) background-foreground segmentation of the image, (ii) registration with respect to a global reference image, (iii) denoising using anisotropic diffusion, and (iv) signature extraction using morphological operations.

The matching of the TST with the TS of the test image is achieved by calculating a score defined as the minimum Euclidean distance between the pixels belonging to each signature. The highest score is compared with a threshold to determine whether there is a positive or negative match. Fig. 3 shows examples for each case.

3.3. Addition of Perceptual Quality-Aware Features

Our strategy for aggregating IQA features to the system, consists of calculating NSS features from each test image, then using them to modify the TS extraction algorithm. In this way, the resultant TS to be matched to the TSTs in the database contains "quality-aware" attributes. This approach is outlined in Fig. 4.

The NSS features extraction is performed by the methods described in [8] and [9], using the software implementation of the NIQE index provided by the authors [22]. The procedure involves calculating Mean Subtracted Contrast Normalized (MSCN) coeffi-



(a) (b)

Fig. 3. Examples of matches between a TS (light-green) and two TSTs (dark-magenta). (a) Positive match. (b) Negative match.

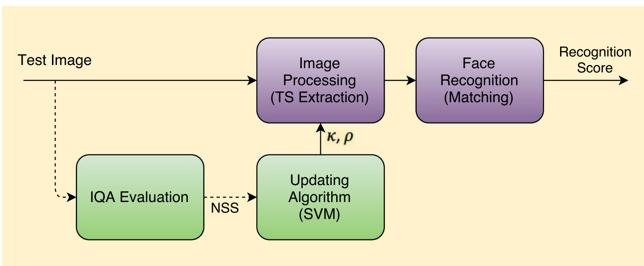


Fig. 4. Proposed IQA-based enhancement method

cients from patches of the image, and estimating the parameters of Gaussian distributions fitted to the histograms of these coefficients. Fig. 5 shows an example of the MSCN histograms of a pristine thermal facial image and its distorted versions. Notice that the shape of the MSCN distribution is modified by the applied distortion; hence, the parameters of the fitted Gaussian model are good descriptors of the type and severity of the image degradation.

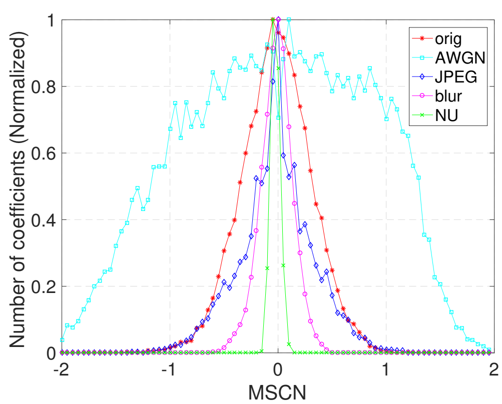


Fig. 5. Histograms of MSCN coefficients from an IR face image and its distorted versions.

To update the TS extraction algorithm, we use an SVM multi-class classifier, which receives the NSS features as inputs, and outputs the optimal values of two parameters governing the image processing, linked to each type and severity of distortion. The chosen parameters were the conductance coefficient (κ) that controls the degree of the anisotropic diffusion, and the radius of the structural element (ρ) used in the morphological operations on the test image. The SVM classifier was trained on samples of NSS features extracted from pristine and distorted images, with optimal values of κ and ρ

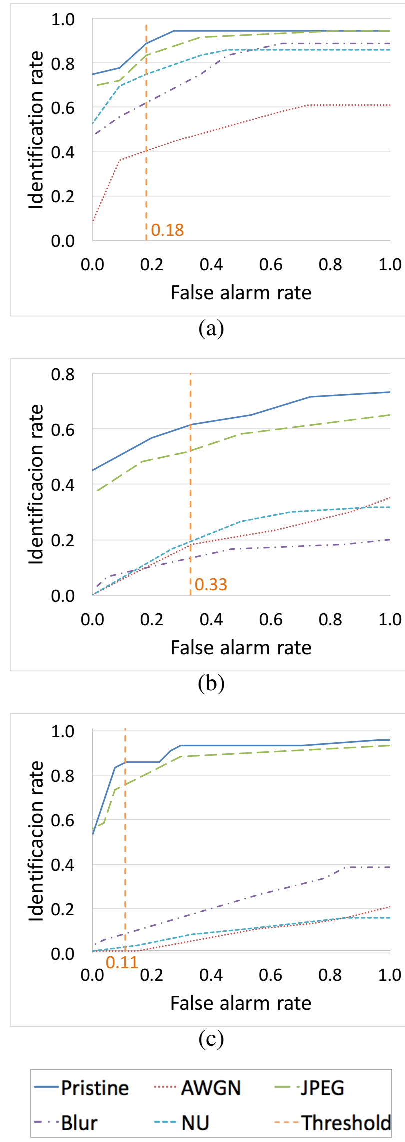


Fig. 6. ROC curves obtained with the original face recognition algorithm evaluated on pristine and distorted images from the (a) IRIS, (b) UND, and (c) PUJ databases.

selected as labels. These values were estimated experimentally, selecting those that yielded the maximum recognition rates from tests with different values of both parameters for each distortion.

4. RESULTS

4.1. Original algorithm (No-IQA)

We first evaluated the rank one recognition accuracy of the face identification algorithm before adding the NSS features on both pristine and distorted images. Tests were conducted on each database, distortion class and severity level; for the sake of clarity, we show only the results for the highest severity levels of distortion in Fig. 6.

The value of the false alarm rate that is indicated by the vertical dashed lines in the figure, corresponds to the matching threshold

	IRIS	UND	PUJ
AWGN	-48%	-48%	-84%
JPEG	-5%	-8%	-11%
Blur	-26%	-48%	-77%
NU	-13%	-41%	-83%

Table 1. Decrease in rank one recognition accuracy on distorted images with the original algorithm.

selected for each database. We chose these thresholds manually, representing a fair compromise between accuracy and false alarm rate. Table 1 shows the maximum decrease in identification rates with respect to the performance on the pristine images, which was estimated for each type of distortion using the chosen threshold.

From the results in Fig. 6 and Table 1, it may be observed that the degradation of image quality has a drastic effect on the recognition rates of the system. Particularly, AWGN, Blur and NU distortions produce the sharpest reductions in accuracy. The specific characteristics of each database cause the observed differences in the results from one another.

4.2. IQA-enhanced algorithm

After integrating the NSS features to the face identification algorithm through the addition of the SVM, as described in Section 3.3, we evaluated the enhanced system with new sets of test images from each database. Experiments were conducted for each distortion type independently, and also for a mixed set, including both pristine and degraded images with all types of distortions. We examined the algorithm performance estimating separately κ and ρ with the SVM classifier, as well as both parameters simultaneously. Fig. 7 shows the results of these tests with respect to rank one recognition on the mixed set.

Table 2 shows the approximate increase in identification accuracy obtained for each distortion with the NSS-enhanced face recognition system, estimated with the thresholds selected previously (vertical dashed lines in Fig. 7). These results confirm that our method improves the performance of the IR face recognition algorithm in the presence of image distortions, specially AWGN and Blur. As expected, the recognition rates on pristine images was not significantly affected by the inclusion of NSS-based IQA features.

	IRIS	UND	PUJ
Pristine	5%	3%	0%
AWGN	20%	17%	10%
JPEG	3%	5%	9%
Blur	28%	31%	9%
NU	3%	17%	10%
Mixed	17%	11%	19%

Table 2. Increase in rank one recognition accuracy after adding NSS features to the face recognition algorithm.

5. CONCLUSIONS

Degradation in image quality negatively impacts the performance of face recognition systems that use IR images. We quantified the decrease in identification accuracy of a leading IR face recognition engine using thermal images from three databases, affected by four frequent distortions. These findings reinforce the importance of studying the influence of image quality on tasks involving IR images.

We verified the feasibility of a quality-aware IR face recognition system robust to image deterioration. Identification accuracy was improved by up to 31% by incorporating NSS features into the algorithm. The results also further validated the suitability of NSS-based metrics for assessing the type and severity of IR image distortions.

As far as we know, this is the first documented effort that studies the effect of image quality degradation on a thermal-based face recognition algorithm, and exploring a method to make it robust against distortions. We hope that this work may encourage further research on using IQA models in thermal imaging applications.

Future work will consider different IR-based face recognition techniques, the inclusion of additional image quality features, tests on larger databases, and a more thorough study of the optimal parameters in the TS extraction process.

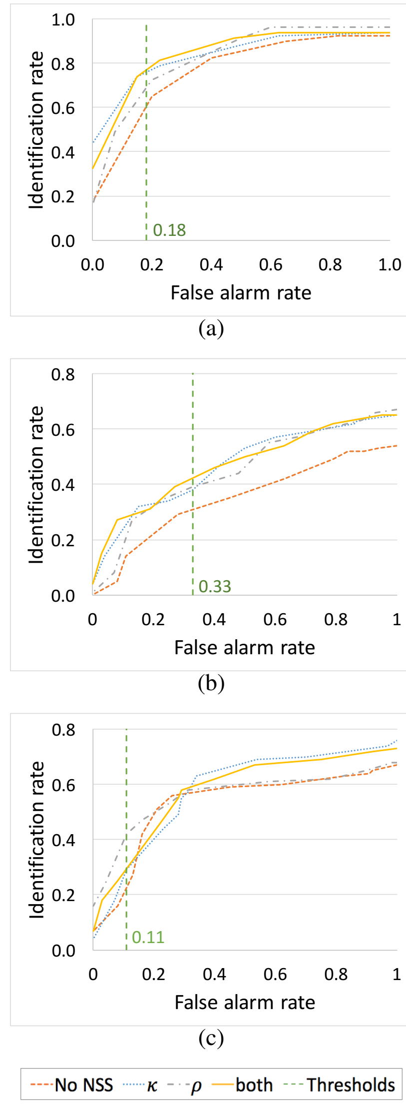


Fig. 7. ROC curves obtained with the face recognition algorithm enhanced by NSS features, evaluated on pristine and distorted images from the (a) IRIS, (b) UND, and (c) PUJ databases.

6. REFERENCES

[1] A. C. Bovik, "Automatic prediction of perceptual image and video quality," *Proceedings of the IEEE*, vol. 101, no. 9, pp. 2008–2024, 2013.

[2] H. Zhou, A. Mian, L. Wei, D. Creighton, M. Hossny, and S. Nahavandi, "Recent advances on singlemodal and multimodal face recognition: A survey," *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 6, pp. 701–716, 2014.

[3] T. R. Goodall, A. C. Bovik, H. Vikalo, and N. G. Paulter, "Non-uniformity correction of IR images using Natural Scene Statistics," in *2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Dec 2015, pp. 230–234.

[4] T. R. Goodall, A. C. Bovik, and N. G. Paulter, "Tasking on natural statistics of infrared images," *IEEE Transactions on Image Processing*, vol. 25, no. 1, pp. 65–79, Jan 2016.

[5] A. M. Guzman, M. Goryawala, J. Wang, A. Barreto, J. Andrian, N. Rishe, and M. Adjouadi, "Thermal imaging as a biometrics approach to facial signature authentication," *Biomedical and Health Informatics, IEEE Journal of*, vol. 17, no. 1, pp. 214–222, Jan 2013.

[6] A. K. Moorthy and A. C. Bovik, "Blind image quality assessment: From natural scene statistics to perceptual quality," *IEEE Transactions on Image Processing*, vol. 20, no. 12, pp. 3350–3364, Dec 2011.

[7] Z. Wang and A.C. Bovik, "Reduced- and no-reference image quality assessment," *Signal Processing Magazine, IEEE*, vol. 28, no. 6, pp. 29–40, Nov 2011.

[8] A. Mittal, A. K. Moorthy, and A. C. Bovik, "No-reference image quality assessment in the spatial domain," *IEEE Transactions on Image Processing*, vol. 21, no. 12, pp. 4695–4708, Dec 2012.

[9] A. Mittal, R. Soundararajan, and A. C. Bovik, "Making a 'completely blind' image quality analyzer," *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209–212, March 2013.

[10] R. S. Ghiass, O. Arandjelović, A. Bendada, and X. Maldague, "Infrared face recognition: A comprehensive review of methodologies and databases," *Pattern Recognition*, vol. 47, no. 9, pp. 2807–2824, 2014.

[11] T. Elguebaly and N. Bouguila, "A bayesian method for infrared face recognition," in *Machine Vision Beyond Visible Spectrum*, vol. 1 of *Augmented Vision and Reality*, pp. 123–138. Springer Berlin Heidelberg, 2011.

[12] Z. Lin, Z. Wenrui, S. Li, and Zhijun, "Infrared face recognition based on compressive sensing and PCA," in *2011 IEEE International Conference on Computer Science and Automation Engineering (CSAE)*, June 2011, vol. 2, pp. 51–54.

[13] A. Seal, D. Bhattacharjee, M. Nasipuri, and D. K. Basu, "Thermal human face recognition based on GappyPCA," in *Image Information Processing (ICIIP), 2013 IEEE Second International Conference on*, Dec 2013, pp. 597–600.

[14] P. Buddharaju, I. T. Pavlidis, P. Tsiamyrtzis, and M. Bazakos, "Physiology-based face recognition in the thermal infrared spectrum," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 613–626, 2007.

[15] P. Buddharaju, I. T. Pavlidis, and P. Tsiamyrtzis, "Physiology-based face recognition," in *IEEE Conference on Advanced Video and Signal Based Surveillance*, 2005, pp. 354–359.

[16] P. Buddharaju and I. T. Pavlidis, "Physiological face recognition is coming of age," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshop 2009*, pp. 128–135, 2009.

[17] Z. Wang, "Applications of objective image quality assessment methods [applications corner]," *Signal Processing Magazine, IEEE*, vol. 28, no. 6, pp. 137–142, Nov 2011.

[18] S. Gunasekar, J. Ghosh, and A.C. Bovik, "Face detection on distorted images augmented by perceptual quality-aware features," *Information Forensics and Security, IEEE Transactions on*, vol. 9, no. 12, pp. 2119–2131, Dec 2014.

[19] R. Donoso, C. San Martín, and H. Méndez-Vázquez, "Face recognition using TOF, LBP and SVM in thermal infrared images," *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications: 16th Iberoamerican Congress, CIARP 2011, Pucón, Chile, Nov. 2011.*, pp. 683–691, 2011.

[20] University of Tennessee, "IRIS thermal/visible face database," `http://www.cse.ohio-state.edu/otcbus-bench/`.

[21] University of Notre-Dame, "Biometrics data sets," Last accesed June 2016. `http://sites.google.com/a/nd.edu/public-cvrl/data-sets`.

[22] A. Mittal, R. Soundararajan, and A. C. Bovik, "NIQE Software Release," `http://live.ece.utexas.edu/research/quality/niqe.zip`, 2012.