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A Study of Highest Perfusion Zones as Biometric Representation

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Abstract. Biometrics focuses on simulate the human ability to associate one or a set of corporal features of a person in a unique way by uses a specific representation, this representation is knows as identity. Visible spectrum face recognition is the identification way more natural which has a higher universality, collectability and acceptability front to the other biometrics modalities, but is weak in the invariance and distinctiveness criterion to be a good biometric. In order to improve the face recognition, the infrared spectrum arises as a good representation to solve these drawbacks in biometric identification. Buddharaju et al., proposed a process by which the vascular net is detected [3] . However, Wu et al. [19, 21], criticized this approach by not take into account the heat transfer between the environment and the person in the time to take the image and proposed a modification of image thermogram and show that it is a better solution to make up for the heat change. This paper is written intending to know if there is a significant difference between both approaches to be used as biometric representation. We found that the normalization of the thermograms, proposed by Wu et al., do not affect the distinctive zones of high blood perfusion to be used as biometric representation.

Keywords. Face recognition, thermal image, perfusion zones, shape description.

1 Introduction

Biometrics focuses on simulate the human ability to associate one or a set of corporal features of a person in a unique way by uses a specific representation, this representation is knows as identity. The biometric identification has become a real solution for many social, corporate and commercial activities where it is necessary the verification of the identity [11, 1, 16].

In principle, any physiological feature can verify or recognize the biometric identity of a person, these features can be group in several modalities as hands, faces, behavior or medical-chemistry features [17].

Visible spectrum face recognition is the identification way more natural which has a higher universality, collectability and acceptability front to the other biometrics modalities, but is weak in the invariance and distinctiveness criterion to be a good biometric [2, 11].

Although face recognition has more of two decades, many of the research has been over visible spectrum [2, 15, 17]. This approach has difficulties when there are lighting variability, chance of pose or different facial expressions.

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In order to improve the face recognition, the infrared spectrum arises as a good representation to solve this drawbacks in biometric identification [6, 12, 8, 15].

This paper is written with the intention to apply the method of higher intensity region of thermogram of Buddaraju over the propose of Wu and test and contrast the performance of this modification with the original propose of Buddharaju [3]. We prove that the perfusion regions with higher intensity are equivalent at the zones of the Buddaraju propose. Our method combines, in first place, the works of Buddaraju and Wu and one simple region shape descriptor is applied to form a nine-dimensional vector feature.

After, it is used the same method over the Buddharaju propose and the performance of both proposes are compared. The UCH image database was employed for this study which has outdoor, indoor and face angle rotations conditions. In order to highlight the efficiency of the proposed face recognition approach, several classification algorithms were used in our study and we proved that both proposes hold enough information to biometric face representation because of the difference in performance accuracy are not significance. However, the Wu thermogram add more computational work.

2 Related Work

Several approaches and techniques have been proposed for a quantitative description. One of the first work was made by Yoshitomi et al. They shown that the infrared spectrum is more robust with the lighting variability problem of the visible [22]. After, Friedrich et al., proposed a method based on eigenfaces as face descriptor of thermograms and found that these kinds of images were less affected by the change of pose or facial expressions [7]. The following works have been focused on different ways to describe the thermograms and the frequency domain is one approach widely used [9, 6]. By another hand, an approach derived is the getting of information physiologic contained inside infrared images.

For instance, Prokoski et al., found that it is possible the detection of the face vascular net in thermograms which could be used as a biometric descriptor [13]. Buddharaju et al., used this idea and proposed a process by which the vascular net is detected. Their hypothesis is based on the existence of zones with high values of intensity in the pixels of the thermogram and that this values they are correlated with the presence of some blood vessel. The method finds the regions with the higher thermogram intensities and they are isolated by morphological transforms. These regions are thinning and its skeleton is formed. In this skeleton are marked the breaching points, called Thermal Minutia Points (TMP). They are used as minutiae points [4, 5, 3].

The work was criticized because the skeleton did not necessarily show blood vessels and it did not take into account the physics and physiological conditions of the heat transfer [19, 18, 21].

Wu takes into account the heat transfer condition in thermograms and suggests changes the name of the regions detected from the vascular net to the perfusion zones. This approach modifies the pixels values of the thermogram and generates a new image which is more robust to temperature changes in which it is taked. Wu and Zhang tested this representation using cosine transform as descriptor and found that can be used as a good biometric [20].

3 Face Recognition Method

In this section, it is described the methodology following for faces recognition based on simple shape descriptor over maximal perfusion zones. Figure 1 shows the methodological architecture.

Step 1: Thermogram transformation into an image of blood perfusion. This step is made by the propose of Wu, where each intensity pixel is modified by (1):

$$W = \frac{\epsilon\sigma(T^4 - T_e^4)}{\alpha c_b(T_a - T)}, \tag{1}$$

where ϵ is the skin emissivity, σ is the Stefan-Boltzmann value, α is the tissue/skin countercurrent exchange ratio and c_b is the blood specific heat which are constants.

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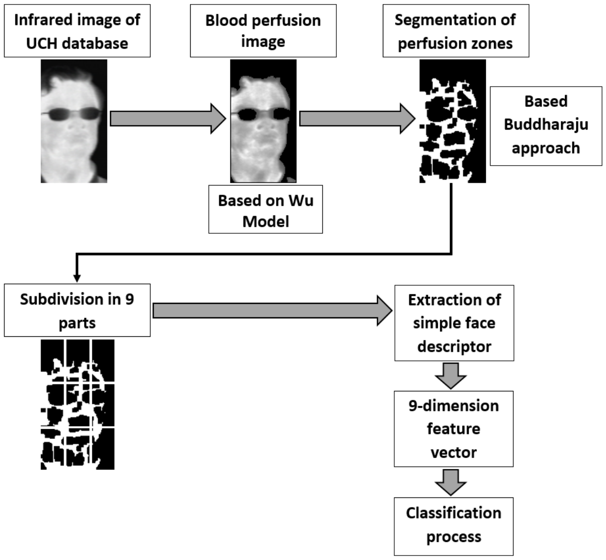

Fig. 1. Diagram of our thermal face recognition process

T is the thermal intensity pixel value, T_a is the artery temperature and T_e is the ambient temperature.

Step 2: It is applied the method of the highest intensity blood vessels extraction proposed by Buddharaju: The anisotropic filter was set up under Matlab platform with a gradient modulus threshold value equal to 60, an integration constant equal to 1/5 and the option 1. After, it was implemented a Tophat morphological transform with a disk as structure element of radius equal to 3. Finally, it was used a closed morphological operation for clear the image with a disk with a radius equal to two.

Step 3: The image is segmented in 9 equal dimensional regions, as it is shown in Figure 1.

Step 4: For each sub-image a simple shape descriptor is extracted, in our case it is use the normalize E factor (NEF) [14]. The NEF uses the internal or external border information to give us a measure of the shape porosity. In our approach, each image is taken as an object with holes. After, a nine feature vector is formed with the NEF values. The example is shown in Figure 1.

Step 5: Finally, the process end with the classification of the database using the NEF description by the following classifiers: Support Vector Machine, K-Nearest Neighbor (K = 3), Parzen, Normal densities based linear (multi-class), Nearest mean linear, Normal densities based quadratic (multi-class), Minimum least square linear, Logistic Linear, Quadratic, Naive Bayes, LC based on PCA expansion on the joint data.

4 Results

For testing the performance of perfusion zones as biometric identification, we used the UCH Thermal data base [10]. This database is ideal because the thermograms are taken in unconstrained environments, with face rotation, indoor, outdoor session and facial expressions. The images used for these tests were images had a spatial size of 81x150 pixel. To measure the effectiveness of this representation, a 4-folds statistical test done by 5 iterations was implemented in the PrTools library under Matlab platform. Table 1 shows the performance by the average recognition rate which is given for each classification algorithm when it is applied our method indoor and rotation conditions. The best overall performance was for a support vector machine and the worse result was for a normal densities based linear algorithm. A standard deviation (SD) got join to the time process for each algorithm.

Table 1. Performance of higher perfusions zones on UCH image database using our propose method

Algorithm	Accuracy	SD	Speed
SVM	89.49%	0.0069	623.162712 s
KNN	61.62%	0.0138	2.793641 s
Parzen	65.80%	0.0081	2.050866 s
NDBL	48.60%	0.0039	7.254782 s
NML	63.26%	0.0081	4.507564 s
NDBQ	75.77%	0.01	3.559874 s
MLQL	59.51%	0.0069	31.038115 s
LL	57.84%	0.0677	34.936810 s
Quadratic	78.68%	0.02	41.189440 s
NB	68.03%	0.0107	1.234846 s
LC	47.71%	0.0081	13.115993 s

With the aim to found some difference between the original propose of Buddharaju and the Wu modification, we tested the same extracted features approach without uses heat transfer equation. The results are described in Table 2. In this case, the support vector machine again got the best classification percentage. However, the difference between both approach are not significative. There are not an important difference with the classification values of the others algorithms.

Table 2. Performance of classification using NEF descriptor on UCH image database when applying only Buddharaju approach

Algorithm	Accuracy	SD	Speed
SVM	89.22%	0.0034	639.940778 s
KNN	60.51%	0.0062	2.979696 s
Parzen	63.13%	0.0056	2.159387 s
NDBL	50.00%	0.0076	7.734073 s
NML	62.61%	0.0088	4.526179 s
NDBQ	74.72%	0.0126	4.040726 s
MLQL	58.06%	0.0065	32.249418 s
LL	54.58%	0.0088	34.873280 s
Quadratic	77.57%	0.0109	41.106188 s
NB	67.84%	0.0102	1.387489 s
LC	49.84%	0.0018	13.063554 s

Finally, we applied our method separately to the Buddharaju and Wu approaches, with the aim to test if there are difference in outdoor condition, using our face descriptor. The results are illustrated in the Table 3, where only the best classification percentage is showed. We could hope that the Wu propose was better than Buddharaju approach. However, we did not find a significative difference in classification rate.

Table 3. Performance of classification using NEF descriptor on UCH image database when applying separately the Buddharaju and Wu approaches

Algorithm	Accuracy	SD	Speed
SVM (Buddharaju)	90.46%	0.0036	583.09 s
SVM (Wu)	90.57%	0.0019	583.46 s

5 Conclusion and Future Work

In this paper, we analyzed how the zones of highest intensity in a modified thermogram can be used as biometric descriptor in combination with the vane net detection method proposed by Buddharaju. For showing this property, a method was designed by partition the vane net image in nine sub-images. Our propose showed a robust behavior to change of temperature, environment, face rotation and physiological condition, properties of the well-know UCH Thermal Face data image base. This robustness is evident when a simple shape descriptor is used to conform a characteristic vector and good percentages in classification accuracy is obtained. Unlike the work of Hermosilla et al. [10], where a study of different description algorithms are tested using the totality of the image, we concentrated the work in lower the computational cost in time and spaces by a reduce representation of the thermogram. The result showed that the representation can be uniquely associated. However, it can observed that the modification make by Wu is not had a great impact when the zones of highest blood intensity are extracted and it is used our approach of description. The limitation of our approach is the kind of descriptor, which is weak in affine transformation and can be more sensitive by the image face angle. However, the work is concerned with the representation, not with the its description. The future work is concerned with applied more complexes descriptor and description methods.

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References

1. **Ashbourn, J. (2015).** *Practical Biometrics, from aspitation to implementation*. Springer-Verlag London, 2 edition.
2. **Bourlai, T. & Hornak, L. A. (2016).** Face recognition outside the visible spectrum. *Image and Vision Computing*, Vol. 55, pp. 14–17.

3. **Buddharaju, P. & Pavlidis, I. (2009).** Physiological face recognition is coming of age. *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 128–135.

4. **Buddharaju, P., Pavlidis, I. T., & Tsiamyrtzis, P. (2005).** Physiology-based face recognition. *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 354–359.

5. **Buddharaju, P., Pavlidis, I. T., Tsiamyrtzis, P., & Bazakos, M. (2007).** Physiology-based face recognition in the thermal infrared spectrum. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 29, No. 4, pp. 613–626.

6. **Farokhi, S., Flusser, J., & Sheikh, U. U. (2016).** Near infrared face recognition: A literature survey. *Computer Science Review*, Vol. 21, pp. 1 – 17.

7. **Friedrich, G. & Yeshurun, Y. (2003).** Seeing People in the Dark : Face Recognition in Infrared Images. *Biologically Motivated Computer Vision, Springer*, Vol. 2525, pp. 348–359.

8. **Ghiass, R. S., Arandjelović, O., Bendada, A., & Maldague, X. (2014).** A unified framework for thermal face recognition. *Neural Information Processing: 21st International Conference*, pp. 335–343.

9. **Ghiass, R. S., Arandjelovic, O., Bendaday, H., & Maldague, X. (2013).** Vesselness features and the inverse compositional AAM for robust face recognition sing thermal IR. *Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence*, AAAI'13, AAAI Press, pp. 357–364.

10. **Hermosilla, G., Ruiz-del solar, J., Verschae, R., & Correa, M. (2012).** A comparative study of thermal face recognition methods in unconstrained environments. *Pattern Recognition*, Vol. 45, No. 7, pp. 2445–2459.

11. **Jain, A. K. & Ross, A. (2008).** *Introduction to Biometrics*. Springer US, Boston, MA, pp. 1–22.

12. **Mehra, S. & Charaya, S. (2016).** Enhancement of Face Recognition technology in Biometrics. *International journal of scientific research and education*, Vol. 4, No. 8, pp. 5778–5783.

13. **Prokoski, F. J. & Riedel, R. B. (1996).** *Infrared Identification of Faces and Body Parts*. Springer US, Boston, MA, pp. 191–212.

14. **Santiago-Montero, R., López-Morales, M. A., & Sossa, J. H. (2014).** Digital shape compactness measure by means of perimeter ratios. *Electronics Letters*, Vol. 50, No. 3, pp. 171–173.

15. **Solanki, K. & Pittalia, P. (2016).** Review of Face Recognition Techniques. *International Journal of Computer Applications*, Vol. 133, No. 12, pp. 20–24.

16. **Tian, Q., Qu, H., Zhang, L., & Zong, R. (2011).** Personal identity recognition approach based on iris pattern. In **Yang, J. & Nanni, L.**, editors, *State of the art in Biometrics*, chapter 08. InTech, Rijeka.

17. **Unar, J. A., Seng, W. C., & Abbasi, A. (2014).** A review of biometric technology along with trends and prospects. *Pattern Recognition*, Vol. 47, No. 8, pp. 2673–2688.

18. **Wu, S., Lin, W., & Xie, S. (2008).** Skin heat transfer model of facial thermograms and its application in face recognition. *Pattern Recogn.*, Vol. 41, No. 8, pp. 2718–2729.

19. **Wu, S.-Q., Fang, Z.-J., Xie, Z., & Liang, W. (2008).** Blood perfusion models for infrared face recognition. In **Delac, K., Grgic, M., & Stewart Bartlett, M.**, editors, *Recent Advances in Face Recognition*, chapter 13. InTech, pp. 183–206.

20. **Wu, S.-Q., Wei, L.-Z., Fang, Z.-J., Li, R.-W., & Ye, X.-Q. (2007).** Infrared face recognition based on blood perfusion and sub-block DCT in wavelet domain. *2007 International Conference on Wavelet Analysis and Pattern Recognition*, volume 3, pp. 1252–1256.

21. **Xie, Z. H., Wu, S. Q., He, C. Q., Fang, Z. J., & Yang, J. (2010).** Infrared face recognition based on blood perfusion using bio-heat transfer model. *2010 Chinese Conference on Pattern Recognition (CCPR)*, pp. 1–4.

22. **Yoshitomi, Y., Miyaura, T., Tomita, S., & Kimura, S. (1997).** Face identification using thermal image processing. *Robot and Human Communication, 1997. RO-MAN '97. Proceedings., 6th IEEE International Workshop on*, pp. 374–379.

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