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***Abstract*—This paper proposes a human thermal face recognition approach with two variants based on Random linear Oracle (RLO) ensembles. For the two approaches, the Segmentation-based Fractal Texture Analysis (SFTA) algorithm was used for extracting features and the RLO ensemble classifier was used for recognizing the face from its thermal image. For the dimensionality reduction, one variant (SFTA-LDA-RLO) was used the technique of Linear Discriminant Analysis (LDA) while the other variant (SFTA-PCA-RLO) was used the Principal Component Analysis (PCA). The classifier's model was built using the RLO classifier during the training phase and in the testing phase then this model was used to identify the unknown sample images. The two variants were evaluated using the Terravic Facial IR Database and the experimental results showed that the two variants achieved a good recognition rate at 94.12% which is better than related work.**

***Keywords*-Thermal IR human faces; Face recognition; Random linear Oracle (RLO);Segmentation-based Fractal Texture Analysis (SFTA)**

I. Introduction

In the last 50 years, face recognition is being one of the most intensively investigated topics in computer vision and psychology. Face recognition systems have found many real-world applications such as surveillance security, forensics, border control, digital entertainment, etc. Progress in the face recognition systems has advanced to an extent that these systems are being shown in real-world settings. This rapid progress is because of a number of factors including: the availability of different databases of facial images, active development of technique and algorithms, and developing various methods for evaluating the performance of the developed face-recognition algorithms. However, classical face recognition systems have many challenges such as the image variation due to differences in head pose, position, and size and due to changing facial expression [1], [2].

Infrared imaging was employed to address the above face recognition problems [3], [4]. At the beginning, Face recognition based on thermal imaging has not received a good attention in the literature comparing with recognition in visible-spectrum imaging. This was because of the following factors: thermal sensors were higher cost than visible cameras/sensors, higher image noise, lower image resolution, and lack of widely available datasets. Recently, these limitations have been less relevant because of the advance of the infrared imaging technology making it attractive to be used face recognition [5].

Infrared imaging could address a number of the key challenges of the visible imaging-based techniques. For example, appearance changes resulting from changing in the illumination or disguises (e.g. facial wear and hair) could be overcome when the thermal images are used [6]. The thermal imaging method works based on the fact that each object emits different ranges of infrared energy and this depends on the object temperature and characteristics. Based on this fact, each object can have different thermal signatures. For example, the human face thermal signature is primarily derived from the pattern of the superficial blood vessels existed under the face skin. Because of the vein and tissue structure of each face are unique for each person thus its thermal image is also unique [7].

Socolinsky et al. used eigenface technique to identify thermal and visible face images. In their experiments, the lower dimensional space of the thermal images consists of only six eigenvectors and achieved 95%, while 36 eigenvectors are needed to achieve the same accuracy of the visible face images [8]. Wilder et al. used different algorithms to identify different expressions of thermal face images. But, they conclude that the performance is not significantly better for one algorithm than the other [9].

In this paper, we propose a face recognition model using

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thermal IR human face images based on Random linear Oracle (RLO) ensembles. Segmentation-based Fractal Texture Analysis (SFTA) algorithm is used to extract features and then dimensionality reduction techniques, LDA and PCA, were used to reduce the dimension of the features to lower dimensional space. The reduced feature were then classified using the RLO ensemble classifier, which is first used to build a classifying model during the training phase and then used to identify a human face in the testing phase.

The rest of the paper is organized as follows. Section II gives an overview about the closed related and Section III introduces the techniques and algorithms used to build our approach, which is presented in Section IV. The experimental results and the discussion are then given in Section V and Section **??**, respectively. Finally, the conclusion is presented in Section VII.

II. Related Work

There are many efforts done for recognizing human face using thermal images, see [**?**]. In this paper, we have limited the related work to the ones [10] and [11], used the same database, to make our proposed approach comparable to this work.

In [10], human Thermal Face Recognition Based on Haar Wavelet Transform and Local Binary Pattern (LBP) feature extraction methods was introduced. PCA was performed separately on the individual feature set for dimensionality reduction. Two different classifiers of multilayer feed forward neural network and minimum distance classifier were used to classify face images. The experiments showed that the recognition rate was 95.09% based on Artificial neural networks (ANNs) classifier using their own database. However, the recognition rate was 94.11% based on minimum distance classifier and 94.11% based on Artificial neural networks (ANNs) classifier using Terravic Facial IR Database.

Also in [11], another thermal Human face recognition approach was proposed. In this approach, the Wavelet transform was used for feature extraction and image dimensionality reduction, by removing redundancies and preserving original features of the image. Then, the reduced feature vectors were fed directly into a series matching classifier. This system is applicable to front views and constant background only. The experiments showed that the recognition rate was 95% using their own database. However, the recognition rate was 93% using Terravic Facial IR Database.

III. PRELIMINARIES

This section gives an overview about the techniques and algorithms used to develop our proposed approach.

A. Segmentation-based Fractal Texture Analysis (SFTA)

SFTA feature extraction algorithm is used to extract the features from grey scale images and it consists of two steps. In the first step, the grey scale image is decomposed into different grey scale images using multi-level threshold algorithm. The multi-level threshold algorithm is used to select different threshold parameters, which are used to decompose the grey scale image. There are many multi-level threshold algorithms including iterative thresholding [12], minimum error thresholding [13], Fuzzy clustering thresholding [14], [15], Entropy-Based Thresholding [16]. In this paper, Two-Threshold Binary Decomposition (TTBD) method is used. In the second step, the features are extracted from each binary image. SFTA features consist of fractal dimension, mean, and size (pixel count), which are computed from the region's boundary of each binary image [17]. More details about the two steps of SFTA are explained in the next sections.

1) Two-Threshold Binary Decomposition (TTBD): The TTBD method is used to decompose the grey scale image (I) into a set of binary images ($I_{bi}, i = 1, 2, \ldots, n_t$), where n_t represents the total number of thresholds, which is defined by the user. Firstly, a set of equally spaced threshold values ($T = t_1, t_2, \ldots, t_{n_t}$) is computed using Otsu' algorithm [18]. The input image (I) is then decomposed into a set of binary images (I_b) as shown in Fig. (1, (b), (c), and (d)) based on applying two threshold segmentation method as in Equation (1). One advantage of the TTBD algorithm is that it segments the objects whose gray level lies among middle ranges of the input image histogram [17].

$$I_b(x, y) = \begin{cases} 1 & \text{if } t_l < I(x, y) \leq t_u, \\ 0 & otherwise \end{cases} \tag{1}$$

where t_l and t_u denote, respectively, the lower and upper threshold values.

2) SFTA extraction algorithm: For each grey scale image that results from the decomposition step, two types of features are extracted. The first type of features are the fractal features which describe the complexity of the object's boundary ($\Delta(x, y)$). The fractal features are extracted from the grey scale image and it is statistics as in Equation (2). The second type of features is the features that are extracted from the boundary of each binary image which results from the grey scale image. In this type, there are two features are extracted, namely, mean and size (pixel count), which are computed from the region's boundary of each binary image.

$$\Delta(x, y) = \begin{cases} 1 & \text{if } \exists(\acute{x}, \acute{y}) \in N_8[(x, y)] : \\ & I_b(\acute{x}, \acute{y}) = 0 \wedge I_b(x, y) = 1, \\ 0 & otherwise \end{cases} \tag{2}$$

where $N_8[(x, y)]$ is the set of eight neighbours for the point (x, y). The value of $\Delta(x, y)$ is equal to one if the corresponding point in the binary image I_b is equal to one and have at least one neighbouring pixel $(\acute{x}, \acute{y})$ equal to zero. Otherwise, the value of $\Delta(x, y)$ will be equal to zero. Thus, the boundary will be one pixel wide. The mean and size of the grey level of each binary image also to complement the extracted features.

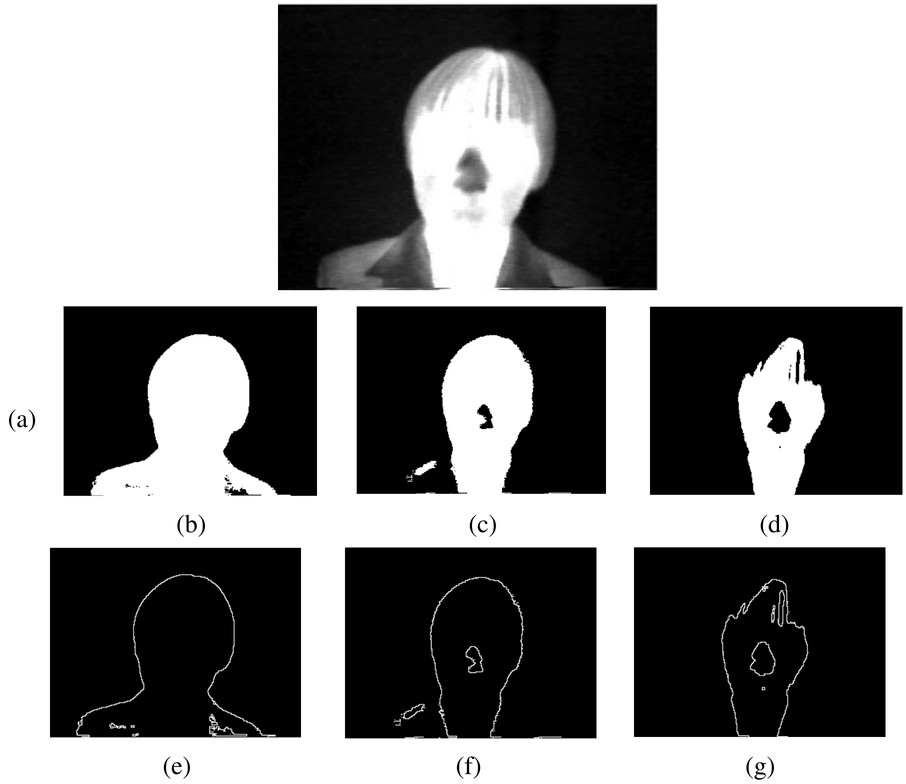

Figure 1. Decomposition of a sample of thermal face images using TTBD algorithm. The resulting set of binary images was obtained using n_t = 3, (a) thermal face image, (b,c, and d) binary images result from decomposing the grey scale image, (e,f, and g) the borders of the binary images (above).

The length of the SFTA feature vector for each grey scale image consists of fractal dimension, mean grey level, and size, which will increase the dimension of SFTA feature vector. Another factor that affects the length of the SFTA feature vector is the threshold parameter, which is defined by the user. The length of the SFTA feature vector proportional to the value of the threshold parameter. Algorithm (1) summarizes the steps of the SFTA feature extraction method.

Algorithm 1 : SFTA Feature Extraction Algorithm [17]

Given an input grey scale image I and threshold n_t.
$T \leftarrow$ MultiLevelOtsu(I, n_t)
$i \leftarrow 0$.
for all (t_l, t_u, where t_l and t_u denote, respectively, lower and upper threshold values) **do**
  $I_b \leftarrow$ TTBD(I,t_l,t_u).
  $\Delta(x, y) \leftarrow$ FindBorders(I_b).
  $SFTA[i] \leftarrow$ FractalDimension(Δ).
  $SFTA[i + 1] \leftarrow$ MeanGreylevel(I_b).
  $SFTA[i + 2] \leftarrow$ PixelCount(I_b).
  $i \leftarrow i + 3$.
end for

B. Dimensionality Reduction Technique

The goal of dimensionality reduction technique is to reduce the dimension of the features to lower dimensional space. There are two types of dimensionality reduction, namely, supervised and unsupervised approaches. In the supervised approaches, the labels of all samples are known and used to find the lower dimensional space, such as in Linear Discriminant Analysis (LDA) [19]. On the other hand, in unsupervised approaches the samples are used without needs for their labels, such as Principal Component Analysis (PCA).

1) Principal Component Analysis (PCA): PCA is used to find a linear transformation, U, which reduces, d-dimensional feature vectors to h-dimensional feature vectors (where $h < d$). PCA has many applications such as dimensionality reduction [20], face recognition [21], ear recognition [22]. The idea of PCA is to find a lower dimensional space which consists of the eigenvectors that satisfy the maximum variance of the given feature vectors. All eigenvectors are mutually orthogonal which are called *principal components*. These principal components are measured and determined based on their corresponding eigenvalues of the covariance matrix [21], [23].

2) Linear Discriminant Analysis (LDA): LDA is used to reduce the dimension and discriminate between classes at the same time. The goal of the LDA is to maximize the ratio of between-class variance to the within-class variance and hence guaranteeing maximum class separability [24]. LDA is used as a dimensionality reduction of feature extraction method in many applications such as face recognition[25], palm-print [26], and ear recognition [27].

C. Random Linear Oracle (RLO) Ensemble Classifier

RLO is one of the ensemble classifiers, which used to combine the individual classifiers. Moreover, it is used a classifier selection approaches [28]. Given an ensemble of classifiers $S = [C_1, C_2, \ldots, C_L]$, where C_i represents the i^{th} classifier in the ensemble and L represents the size of the ensemble. For each classifier (C_i), a random hyperplane or oracle (P_i) is generated and the objects of the labelled data (Z) is divided into two subsets ($+$ and $-$), depending on which side of the hyperplane the data lie on. The two subsets are used to train mini-ensemble, which consists of two classifiers ($C_{i(+)}$ and $C_{i(-)}$). A linear hyperplane (oracle) is used to decide, which of the two classifiers is used to classify the object. Finally, $2L$ classifiers are trained [28], [29].

Given a new object (x), for each individual classifier (C_i) apply the i^{th} hyperplane to x to decide if x is classified using $C_{i(+)}$ or $C_{i(-)}$. The output of all classes are combined using voting method and the new object is assigned to the class which has the largest number of votes [29].

IV. Proposed Model

The proposed model in this research consists of two phases, namely, training and testing as shown in Fig. (2).

A. Training Phase

In this phase, the labelled or training data are collected. The features are then extracted from each image using SFTA feature extraction method. The length of the feature vector that is extracted using SFTA is based on the threshold parameter, which is selected by the user. Thus, increasing the threshold increases the length of the feature vector and may lead to a curse of dimensionality problem. Thus, in the proposed model LDA and PCA dimensionality reduction methods are used to reduce the length of the feature vectors. The features after applying dimensionality reduction methods are then used to build the RLO model, which is used later in the testing phase. The steps of training phase explained in detail in Algorithm (2).

B. Testing Phase

In this phase, the unknown or test image of the thermal face image is collected or captured. Then, extract the features from the test image using SFTA feature extraction method. Project the extracted features on the dimensionality reduction space (i.e. LDA or PCA space). Finally, match the feature vector of the test image after reduction using the model, which is built in the training phase. The details of testing phase are explained in Algorithm (3).

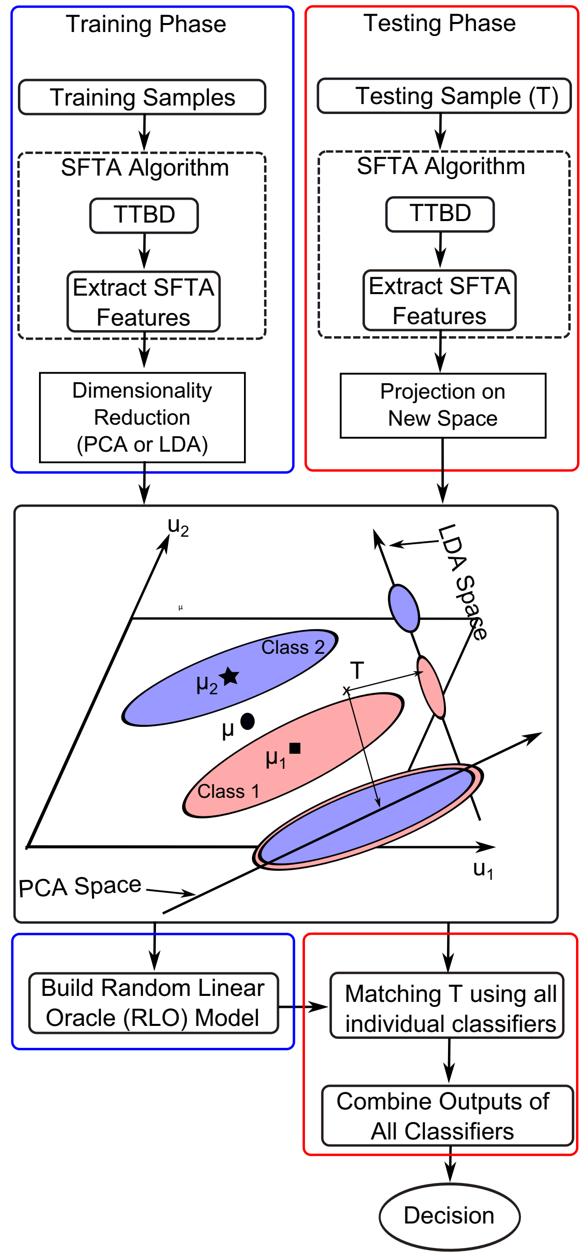

Figure 2. Block diagram of the proposed model.

Algorithm 2 : Training Phase

1: Input all the training thermal face images $\{I\}_{i=1}^{N}$, where N represents the total number of training images and I_i represents the i^{th} training image.
2: Extracting the features from each image (I_i) using SFTA feature extraction method as follows, $J_i = SFTA(I_i)$. Each image is represented by one feature vector ($J_i \in R^M$), where M represents the dimension of the i^{th} feature vector.
3: Use the LDA or PCA to reduce the number of features in each vector to $k, (k < M)$ features. The dimensionality reduction space is dented by $U \in R^k$
4: Use the features after the reduced step to build or design the RLO model.

Algorithm 3 : Testing Phase

1: Input unknown thermal face image (T)
2: Extracting the features from each the test images using SFTA feature extraction method as follows, ($T_{SFTA} = SFTA(T)$)
3: Project the feature vector of the testing image on the dimensionality reduction space as follows, $\Gamma = T_{SFTA}U$
4: Matching or classifying the testing feature vector Γ using the RLO model that is built in the training phase.

V. Experimental Results

The Terravic Facial IR Database was used to evaluate our two variants. The dataset set consists of 20 classes with greyscale images (360 x 240) and each class represents one person. In this paper, we have used 17 classes as three classes were corrupted. For each class, 200 greyscale images were used.

To test the proposed model, three main scenarios were designed for investigating the impact of the following factors on the accuracy ratio of proposed approach.

- Number of classes from the Terravic Facial IR Database. It contains 17 classes for 17 human faces, samples of the database are shown in Figure (3)
- Threshold parameter nt: it is the value at which image is decomposed to nt grayscale images.
- RLO parameter L: It is the number of individual classifiers

Scenario ONE: This scenario is designed to evaluate the proposed approach for different size of the database. During the running of the experiments of this scenario, the parameters of SFTA (the threshold) and the number of individual classifiers (the RLO ensemble size) were one and five, respectively. This scenario was tested for the cases of PCA and LDA variants of our approach and the results are summarized in Table (I).

Scenario TWO: The aim of this scenario is to understand the impact on the face identification accuracy when changing of the threshold parameter of the SFTA feature extraction technique. During the running of the experiments of this scenario, the size of the database 17 classes and the RLO's ensemble size was five. This scenario was evaluated under the two variants (PCA and LDA-based) of the proposed approach and the summary of the results are given in Table (II).

Scenario THREE: It was designed to investigate the accuracy rate of our face identification approach when changing of the ensemble size (i.e. L) of RLO. This scenario is further divided into two sub-scenarios: one to change the value of L while keeping the size of the database equal to 17 classes and the SFTA's threshold ($n_t = 1$) and the second to also change the value of L while keeping the size of the database equal to 17 classes and the SFTA's threshold ($n_t = 3$). Each of these sub-scenarios was evaluated in the case of PCA and LDA variants of our approach. Table (III) summarizes the experimental results of these sub-scenarios.

Figure 3. Samples of Terravic Facial IR Database.

VI. Discussion

From the results of the first scenario, summarized in Table (I), two remarks can be noticed. (1) the more classes were used, the higher accuracy was obtained. This means that our approach would get a higher accuracy if a large database is used. (2) The two variants (PCA-based and LDA-based) of our approach nearly gave the same identification accuracy.

From the results shown in Table (II), the following remarks can be drawn. Firstly, SFTA-LDA-RLO-based approach is slightly better than SFTA-PCA-RLO-based one. Secondly, increasing the value of the threshold parameter of SFTA algorithm does not significantly affect the accuracy

Table I
ACCURACY OF THE TWO PROPOSED PCA-BASED AND LDA-BASED VARIANT WHEN DIFFERENT NUMBER OF CLASSES WERE USED

Dimensionality Reduction method	**No. of Classes**	**No. of Training Images per Subject**	**No. of Testing Images per Subject**	**Accuracy (in %)**
Principal Component Analysis (PCA)	**8**	40	160	86.88
		80	120	86.04
		120	80	86.72
		160	40	91.56
	12	40	160	90.37
		80	120	89.31
		120	80	91.35
		160	40	87.96
	17	40	160	86.25
		80	120	93.58
		120	80	93.75
		160	40	93.38
Linear Discriminant Analysis (LDA)	**8**	40	160	86.88
		80	120	86.49
		120	80	86.86
		160	40	91.56
	12	40	160	90.26
		80	120	89.31
		120	80	91.15
		160	40	87.92
	17	40	160	93.68
		80	120	92.61
		120	80	93.68
		160	40	93.97

Table II
ACCURACY OF THE TWO PROPOSED PCA-BASED AND LDA-BASED VARIANT WHEN DIFFERENT VALUES OF THE SFTA THRESHOLD PARAMETER WERE USED

Dimensionality Reduction method	**SFTA Threshold (n_t)**	**No. of Training Images per Subject**	**No. of Testing Images per Subject**	**Accuracy (in %)**
Principal Component Analysis (PCA)	**4**	40	160	93.71
		80	120	94.12
		120	80	94.12
		160	40	94.12
	5	40	160	94.12
		80	120	92.65
		120	80	94.12
		160	40	94.12
Linear Discriminant Analysis (LDA)	**4**	40	160	94.08
		80	120	92.55
		120	80	94.12
		160	40	94.12
	5	40	160	**94.12**
		80	120	**94.12**
		120	80	**94.12**
		160	40	**94.12**

of the proposed approach. Thirdly, the best accuracy rate, 94.12%, was obtained by the SFTA-LDA-RLO-based approach with the following parameters: SFTA threshold (n_t) was five and RLO ensemble size was equal to five.

From the results obtain by the third scenario, see Table (III), it can be noticed that: 1) increasing the value of the ensemble size of RLO did not have a great impact of the accuracy of both SFTA-PCA-RLO-based SFTA-LDA-RLO-based approaches (notice the accuracy when $L = 7$ and $L = 11$); 2) increasing the training dataset for both proposed variants led to increasing the accuracy rate.

From the results of all three scenarios, it can be concluded that SFTA-LDA-RLO variant is efficient than SFTA-PCA-RLO one and the best accuracy rate (94.12%) was obtained when the parameters of our approach were as follows: SFTA threshold was equal to five and RLO ensemble size was also five and the number of classes was 17 classes.

In comparison with the most related work which used the same dataset, our approach achieving 94.12% was found better than Debotosh's approach [10] achieving 94.11% and Ayan's approach [11] achieving 93% .

VII. CONCLUSION AND FUTURE WORK

This paper proposed a model for human thermal face recognition. The proposed model was based on

Table III
ACCURACY OF THE TWO PROPOSED PCA-BASED AND LDA-BASED VARIANT WHEN DIFFERENT VALUES OF THE ENSEMBLE SIZE OF THE RLO WERE USED.

Dimensionality Reduction method	Ensemble Size (L)	No. of Training Images per Subject	No. of Testing Images per Subject	Accuracy (in %)
Principal Component Analysis (PCA)	**7**	40	160	92.72
		80	120	93.53
		120	80	93.68
		160	40	93.97
	9	40	160	90.96
		80	120	93.73
		120	80	93.68
		160	40	93.97
	11	40	160	91.36
		80	120	93.48
		120	80	93.68
		160	40	93.97
Linear Discriminant Analysis (LDA)	**7**	40	160	92.75
		80	120	93.52
		120	80	93.68
		160	40	93.97
	9	40	160	91.36
		80	120	93.53
		120	80	93.68
		160	40	93.97
	11	40	160	92.72
		80	120	93.53
		120	80	93.68
		160	40	93.97

Segmentation-based Fractal Texture Analysis (SFTA) algorithm for extracting features and Random linearOracle (RLO) ensembles to recognize the face from its thermal image. Two variant approaches for thermal IR human faces recognition were proposed. For classification, both of the proposed approaches used the RLO ensemble classifier. The classifier's model was built using the RLO classifier. In the testing phase, this classifier model was used through the RLO classifier to identify the unknown sample images. Two dimensionality reduction techniques of Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) were used. Experimental results showed that the proposed model achieved a recognition rate of 94.12% for the Terravic Facial IR Database. As a future research, we intend to use one of the parallel processing techniques to increase the processing rate, thus making our model more suitable for the real time applications

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REFERENCES

[1] C. Ding and D. Tao, "A comprehensive survey on pose-invariant face recognition," *arXiv preprint arXiv:1502.04383*, 2015.

[2] A. D. Socolinsky and A. Selinger, "A comparative analysis of face recognition performance with visible and thermal infrared imagery," *Equinox Corp Baltomore MD*, 2002.

[3] Z. Xie and G. Liu, "Infrared face recognition based on lbp cooccurrence matrix and partial least squares," *International Journal of Wireless and Mobile Computing*, vol. 8, no. 1, pp. 90–94, 2015.

[4] Z. Xie, "Infrared face recognition based on lbp histogram and kw feature selection," in *International Symposium on Photonics and Optoelectronics (SOPO 2014). International Society for Optics and Photonics*, vol. 9233, 2014.

[5] A. S. Socolinsky, Diego A. and J. D. Neuheisel, "Face recognition with visible and thermal infrared imagery," *Computer Vision and Image Understanding*, vol. 91, no. 1, pp. 72–114, 2003.

[6] S. Filipe and L. A. Alexandere, "Thermal infrared face segmentation: A new pose invariant method," in *6th Iberian Conference on Pattern Recognition and Image Analysis (IbPRIA)*, vol. LNCS 7887, no. 632639, 2013.

[7] F. B. Zaeri, Naser and R. Dib, "Thermal face recognition using moments invariants," *International Journal of Signal Processing Systems*, vol. 3, no. 4, 2015.

[8] D. A. Socolinsky, L. B. Wolff, J. D. Neuheisel, and C. K. Eveland, "Illumination invariant face recognition using thermal infrared imagery," in *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, vol. 1. IEEE, 2001, pp. I–527.

[9] J. Wilder, P. J. Phillips, C. Jiang, and S. Wiener, "Comparison of visible and infra-red imagery for face recognition," in *Automatic Face and Gesture Recognition, 1996., Proceedings of the Second International Conference on*. IEEE, 1996, pp. 182–187.

[10] S. G. M. N. Debotosh Bhattacharjee, Ayan Seal and D. K. Basu, "A comparative study of human thermal face recognition based on haar wavelet transform and local binary pattern," *Computational Intelligence and Neuroscience*, vol. 2012, no. 261089, 2012.

[11] D. B. M. N. Ayan Seal, Suranjan Ganguly and D. kr Basu, "Thermal human face recognition based on haar wavelet transform and series matching technique," in *Multimedia Processing, Communication and Computing Applications, Lecture Notes in Electrical Engineering*, vol. 213, no. 155-167, 2013.

[12] T. Ridler and S. Calvard, "Picture thresholding using an iterative selection method," *IEEE transactions on Systems, Man and Cybernetics*, vol. 8, no. 8, pp. 630–632, 1978.

[13] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, no. 285-296, pp. 23–27, 1975.

[14] N. Ramesh, J.-H. Yoo, and I. Sethi, "Thresholding based on histogram approximation," *IEE Proceedings-Vision, Image and Signal Processing*, vol. 142, no. 5, pp. 271–279, 1995.

[15] C. Jawahar, P. K. Biswas, and A. Ray, "Investigations on fuzzy thresholding based on fuzzy clustering," *Pattern Recognition*, vol. 30, no. 10, pp. 1605–1613, 1997.

[16] G. Johannsen and J. Bille, "A threshold selection method using information measures," in *Proceeings of International Conference on Pattern Recognition (ICPR)*, vol. 82, 1982, pp. 140–143.

[17] A. F. Costa, G. Humpire-Mamani, and A. J. M. Traina, "An efficient algorithm for fractal analysis of textures," in *25th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*. IEEE, 2012, pp. 39–46.

[18] P.-S. Liao, T.-S. Chen, and P.-C. Chung, "A fast algorithm for multilevel thresholding," *Journal of Information Science and Engineering*, vol. 17, no. 5, pp. 713–727, 2001.

[19] A. Tharwat, T. Gaber, A. E. Hassanien, M. Shahin, and B. Refaat, "Sift-based arabic sign language recognition system," in *Afro-European Conference for Industrial Advancement*. Springer, 2015, pp. 359–370.

[20] B. Moore, "Principal component analysis in linear systems: Controllability, observability, and model reduction," *IEEE Transactions on Automatic Control*, vol. 26, no. 1, pp. 17–32, 1981.

[21] M. A. Turk and A. P. Pentland, "Face recognition using eigenfaces," in *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1991. (CVPR'91)*. IEEE, 1991, pp. 586–591.

[22] A. Tharwat, A. Ibrahim, and H. Ali, "Personal identification using ear images based on fast and accurate principal component analysis," in *8th International Conference on Informatics and Systems (INFOS)*. IEEE, 2012, pp. MM–56.

[23] T. Gaber, A. Tharwat, V. Snasel, and A. E. Hassanien, "Plant identification: Two dimensional-based vs. one dimensional-based feature extraction methods," in *10th International Conference on Soft Computing Models in Industrial and Environmental Applications*. Springer, 2015, pp. 375–385.

[24] M. Welling, "Fisher linear discriminant analysis," *Department of Computer Science, University of Toronto*, vol. 3, 2005.

[25] J. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, "Face recognition using lda-based algorithms," *IEEE Transactions on Neural Networks*, vol. 14, no. 1, pp. 195–200, 2003.

[26] J.-R. Cui, "Multispectral palmprint recognition using image–based linear discriminant analysis," *International Journal of Biometrics*, vol. 4, no. 2, pp. 106–115, 2012.

[27] L. Yuan and Z.-c. Mu, "Ear recognition based on 2d images," in *First IEEE International Conference on Biometrics: Theory, Applications, and Systems, (BTAS)*. IEEE, 2007, pp. 1–5.

[28] L. I. Kuncheva and J. J. Rodriguez, "Classifier ensembles with a random linear oracle," *IEEE Transactions on Knowledge and Data Engineering*, vol. 19, no. 4, pp. 500–508, 2007.

[29] L. I. Kuncheva, *Combining pattern classifiers: methods and algorithms*. John Wiley & Sons, 2004.