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Simple and Novel Approach for Image Representation with Application to Face Recognition

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Abstract: In this paper, a new statistical image descriptor for the face recognition problem is proposed. To the best of our knowledge, no one has attempted to implement this approach before. The idea is simple and straight forward. For each face image, a feature descriptor is formed by concatenating 4 vectors together. These four vectors are formed by taking the sum of pixels in four different directions, namely; row sum (0^o), column sum (90^o), diagonal sum (45^o) and antidiagonal sum (-45^o). For test purposes, the generated feature descriptor is used in face recognition problem. The experiments are carried out on two different face databases namely; ORL and PUT databases. Simulation results show that the proposed approach gave a comparative performance to the well-known feature extraction algorithms in face recognition.

Keywords: *Image representation; local binary patterns; principal component analysis; face recognition.*

1. Introduction

The human face plays a significant role in the identification of people in social interactions. As a biometric, face and face recognition technology has been drawing a lot of attention for the last few years with the potential for a wide range of applications.Face recognition is usually preferred over the other biometrics such as iris and fingerprints due to its easiness of acquiring the subject's samples from a distance especially with non-cooperative ones. One of the drawbacks of the existing recognition systems is the computational complexity when considering real-time applications. The general problem of such systems is their computational cost in data pre-preparation stage and projection into other spaces such as eigenspace [1, 2], fisherspace [3, 4], wavelet transform [5, 6] and/or cosine transform [7]. On the other hand, many researchers have used statistical approaches such as the grey-level co-occurrence matrix [8] and its variants for the extraction of features in texture classification [9-11] and object recognition [12, 13]. Local binary patterns algorithm is another powerful statistical algorithm that is widely used by researchers for image representation [14]. Statistical approaches have less computational time compared to the conventional transform-based methods. This is a plus feature when we are dealing with a large images and big databases.

The idea behind this paper is to introduce a new statistical feature descriptor for image representation that combines the low computational complexity and the high performance at the same time. The idea is simple and straight forward. For each face image, a feature vector is formed by concatenating 4 vectors namely; row-wise sum, column-wise sum, diagonal-wise sum and antidiagonal-wise sum. The generated feature vector is then used for classification. The proposed approach is compared with well-known face recognition technique Principal Component Analysis (PCA) [1,2] and Local Binary Patterns (LBP) [15] which are used in statistical pattern recognition and signal processing for dimensionality reduction and feature extraction.

Remainder of this paper is organized as follows: Section 2 discusses the proposed approach in details. The experimental results and discussions are given in Section 3, followed by computational complexity comparison between our approach and LBP approach. The conclusions are drawn in the final section

2. Proposed Methodology

The idea behind the presented paper is to use another statistical feature for image representation. For each image, a feature vector is formed by concatenating 4 vectors.

Detailed stages of the proposed approach for feature descriptor generation are shown in Fig. 1. Further improvement to the proposed approach was done by utilizing the partitioning idea used in LBP approach. The image is divided to Rnon-overlapping regions and the proposed approach is applied for each region separately. The final feature descriptor will be obtained by concatenating all the R feature descriptors generated from the R regions. At the end, the feature descriptor values are normalized to have their range between 0 and 1.

Fig. 2 shows an example of face image and its corresponding feature descriptor using the whole image without dividing it to regions ($R = 1$). Fig. 3 shows an example with face divided into different number of regions ($R = 1, 4, 9, 16$ and 25). The feature descriptor concatenation process for each value of R is shown, respectively.

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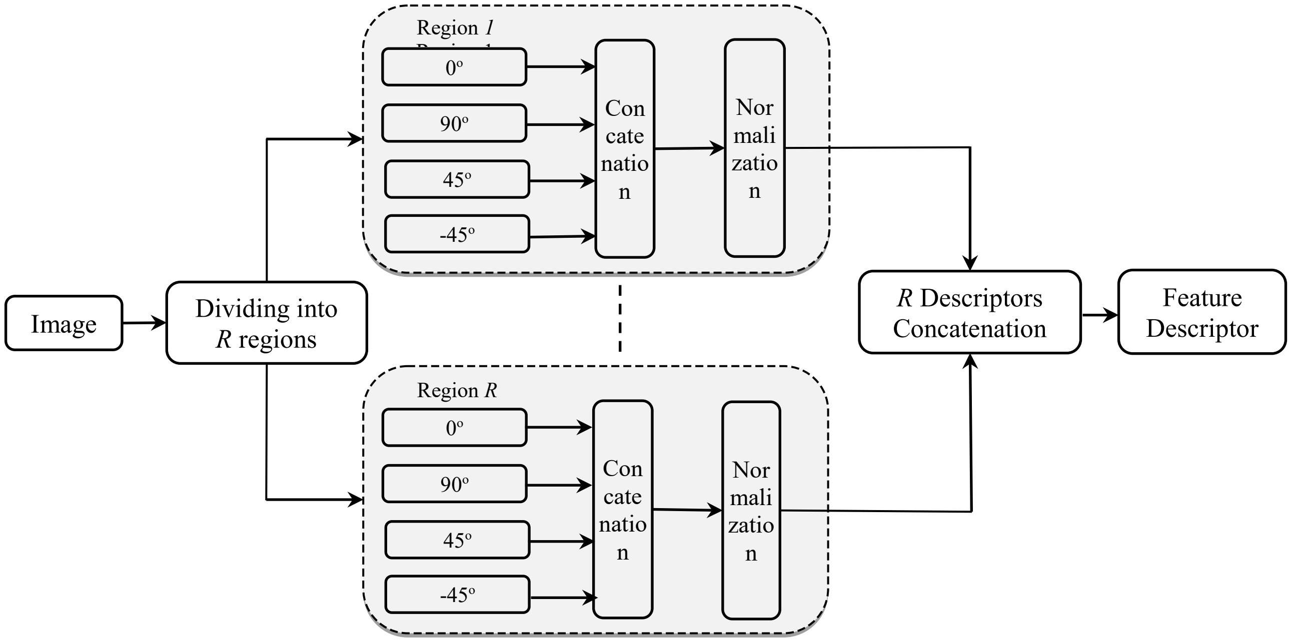

Figure 1. Stages of the proposed approach for feature descriptor generation.

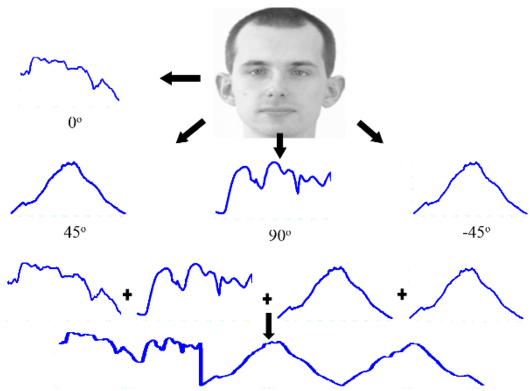

Figure 2. Example of feature descriptor generation process (R=1).

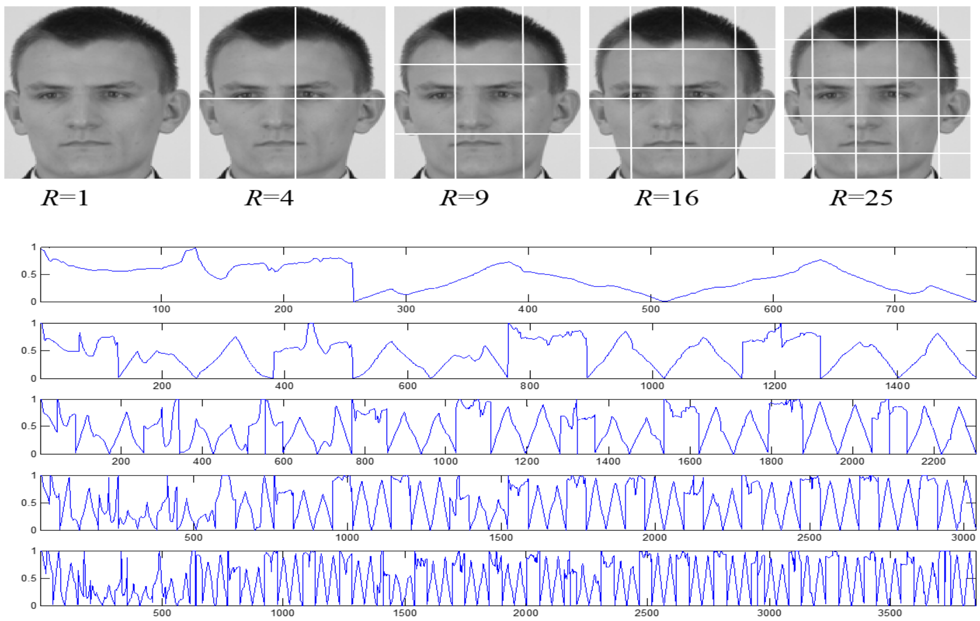

Figure 3. Example of face image with its corresponding normalized feature descriptors generated using the proposed approach (R=1, 4, 9,16 and 25, respectively).

Table 1. Performance comparison between LBP and the proposed approach using different number of training images, different number of regions (*R*) and different classifiers for ORL database.

Approach	# of training images	*R=1*			*R= 9*			*R=16*			*R=25*		
		δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}
LBP	1	52.89	49.22	53.25	68.47	68.14	72.81	58.19	62.33	70.22	65.97	62.86	67.47
	2	66.09	63.53	67.34	83.00	81.91	84.72	74.63	77.97	84.63	82.41	79.66	83.25
	3	75.64	73.18	76.68	89.89	89.54	91.21	83.89	86.96	91.36	88.54	86.68	89.68
	4	81.50	78.71	82.58	93.63	93.63	95.21	88.92	90.71	95.17	92.25	90.38	92.96
	5	84.15	82.20	85.20	95.25	95.20	96.70	91.85	93.10	97.25	94.15	92.20	94.60
	6	88.19	86.50	89.25	96.25	96.38	97.56	93.69	94.19	98.13	95.06	93.63	94.86
	7	90.83	89.00	91.83	97.08	97.42	98.17	94.67	94.75	98.58	96.25	94.75	95.25
	8	92.00	90.38	93.25	97.50	97.88	98.38	95.38	95.25	98.38	97.00	95.63	95.75
	9	93.25	91.25	95.00	98.50	98.50	98.75	96.25	95.75	99.00	97.00	96.50	96.25
Proposed	1	63.72	63.00	64.47	69.39	67.03	66.64	69.67	67.28	66.75	71.36	68.64	67.31
	2	79.19	78.19	78.63	81.75	80.28	80.34	82.63	81.84	81.50	83.88	82.25	81.63
	3	87.64	86.86	85.29	88.39	87.12	87.43	89.96	88.93	88.25	90.36	88.93	88.26
	4	92.67	91.79	90.08	92.21	91.38	91.63	93.58	92.79	92.29	93.83	92.96	92.50
	5	94.75	93.40	91.90	93.85	93.20	93.30	95.20	94.50	94.10	95.25	94.30	94.00
	6	96.31	95.63	93.81	95.88	95.13	95.00	96.38	95.88	95.44	96.50	96.00	95.88
	7	97.92	97.08	95.75	97.17	96.92	96.25	97.42	97.17	96.83	97.50	97.00	97.08
	8	98.75	97.75	96.75	97.63	97.50	97.13	98.13	97.75	97.00	97.88	97.25	97.50
	9	99.00	98.25	96.75	98.25	98.25	97.50	98.75	98.50	97.75	98.75	98.00	97.75

Table 2. Performance comparison between LBP and the proposed approach using different number of training images, different number of regions (*R*) and different classifiers for PUT database

Approach	# of training images	*R=1*			*R= 9*			*R=16*			*R=25*		
		δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}	δ_{l_1}	δ_{l_2}	δ_{cos}
LBP	1	82.31	82.67	87.86	83.82	81.17	87.64	83.89	82.67	89.56	80.33	79.39	83.44
	2	91.38	91.09	93.92	92.13	90.75	94.19	92.53	91.66	95.69	90.50	89.22	91.94
	3	94.79	94.25	95.96	96.14	94.50	96.89	96.57	95.50	97.68	94.86	93.21	95.79
	4	96.58	96.08	97.33	97.71	96.67	98.04	97.71	97.38	98.71	96.33	95.50	97.25
	5	97.45	97.15	97.80	98.30	97.35	98.30	98.05	98.00	98.90	97.15	96.40	97.70
	6	98.31	98.06	98.56	99.00	98.19	99.00	98.88	98.56	99.13	98.06	97.25	98.19
	7	99.08	98.67	99.00	99.42	98.67	99.25	99.25	98.92	99.17	98.50	98.00	98.42
	8	99.88	99.63	99.63	99.87	99.38	99.50	99.50	99.38	99.38	99.13	98.62	99.00
	9	100	99.75	99.75	100	99.75	99.75	99.75	99.75	99.50	99.50	99.25	99.25
Proposed	1	84.97	83.69	81.89	86.81	84.69	82.58	87.53	85.36	83.28	87.53	84.78	82.92
	2	92.47	91.84	90.25	93.31	91.97	90.34	93.94	92.34	90.50	94.09	91.97	90.72
	3	96.11	95.82	95.14	96.82	96.04	95.25	97.00	96.00	95.07	97.32	95.82	94.96
	4	97.54	96.92	96.50	97.92	97.42	96.58	97.88	97.29	96.54	98.29	97.17	96.25
	5	98.20	97.85	97.35	98.20	97.95	97.40	98.30	97.95	97.30	98.65	97.80	97.10
	6	98.69	98.44	98.19	98.69	98.50	97.94	98.81	98.56	97.94	99.13	98.56	97.81
	7	99.17	98.83	98.75	99.08	99.00	98.25	99.08	99.00	98.25	99.33	99.08	98.25
	8	99.50	99.25	99.13	99.50	99.38	98.63	99.50	99.38	98.50	99.75	99.25	98.25
	9	99.75	99.50	99.50	99.75	99.50	99.00	99.75	99.50	99.00	100	99.75	99.00

The four vectors V_{RS} $V_{CS}V_{DS}$and $V_{AS}$are formed by taking the sum of pixels in four different directions,respectively, namely; *RS* row sum (0^{o}), *CS* column sum (90^{o}), *DS* diagonal sum (45^{o}) and *AS* antidiagonal sum (-45^{o}) to form the final feature vector V_F as shown in (1)-(5) for $N \times N$ image :

$$V_{RS} = [x_1, x_2 , \dots \dots , x_N] \quad (1)$$

$$V_{CS} = [x_1, x_2 , \dots \dots , x_N] \quad (2)$$

$$V_{DS} = [x_1, x_2, \dots \dots , x_{2N-1}] \quad (3)$$

$$V_{AS} = [x_1, x_2, \dots \dots , x_{2N-1}] \quad (4)$$

$$V_F = [V_{RS} V_{CS} V_{DS}\ V_{AS}] \quad (5)$$

where x represents the pixel values in the corresponding direction. Normalization of vectors before concatenation is ignored given that all four vectors are in the samevalues range.

3. Results and Discussion

The simulations and experiments are conducted on two different face databases namely; ORL face database and PUT face database [16] based on our preliminary experiments in [17]. Number of people in ORL database is 40 persons and we limit it in PUT database to the same number with 10 images per person in both databases. Fig. 4 shows face examples from ORL face database while Fig 5. shows face examples from PUT face database. Image dimensions of both databases are resized to 128×128.

Figure 4. Face image examples from ORL face database.

Figure 5. Face image examples from PUT face database.

Simulation results of experiments conducted on ORL and PUT face databases are recoded in Table 1 and Table 2, respectively.The proposed approach was compared with the well-known LBP algorithm. Different number of regions were used regions ($R = 1, 9, 16$ and 25). Number of training images in both tables was changing from $n = 1$ to $n = 9$, while the rest $10 - n$ images are used for testing. The similarity measures where used for classification are $\delta_{l_1}, \delta_{l_2}$ and δ_{cos} distances. Results in Table 1 show that our approach is performing better than LBP with $R = 1$ and $R = 25$, while LBP gave better results with $R = 9$. For $R = 16$ our approach performed better with δ_{l_1} and δ_{l_2} measures and LBP was better with δ_{cos} measure.

Nearly similar observations can be derived from Table 2. Our approach almost performed better that LBP for all R values for δ_{l_1} and δ_{l_2} measures while LBP performed better with δ_{cos} measure.

For better understanding and interpretation of the results, all results from Tables 1 and 2 are averaged all over the different number of training images and recorded in Table 3 for both ORL and PUT face databases. It's worth noticing that δ_{cos} similarity measure gave the best performance for both databases usingLBP algorithm. On the other hand, δ_{l_1} similarity measure provided the best performance for both databases usingthe proposed algorithm. In general, the proposed approach gave better average performance with $R = 1, 16$ and 25 regions. Using $R = 9$ regions, LBP gave better average performance.

Table 3. Average recognition rates for LBP and the proposed approach for ORL and PUT databases.

# of Regions		LBP ORL	LBP PUT	Proposed ORL	Proposed PUT
1	δ_{l_1}	80.5052	95.5300	89.9943	96.2598
	δ_{l_2}	78.2184	95.2609	89.1050	95.7941
	δ_{cos}	81.5988	96.6447	88.1587	95.1883
9	δ_{l_1}	91.0637	96.2637	90.5008	96.6752
	δ_{l_2}	90.9525	95.1570	89.6425	96.0490
	δ_{cos}	92.6112	96.9512	89.4679	95.1081
16	δ_{l_1}	86.3842	96.2361	91.3007	96.8651
	δ_{l_2}	87.8902	95.7558	90.5148	96.1538
	δ_{cos}	92.5227	97.5219	89.9903	95.1532
25	δ_{l_1}	89.8474	94.9290	91.7002	97.1214
	δ_{l_2}	88.0301	94.0941	90.5918	96.0201
	δ_{cos}	90.0093	95.6635	90.2138	95.0291

Fig. 6 represents performance comparison between LBP, PCA and proposed approach using ORL database with $R = 25$. The Number of training image n was set to 5. The proposed approach outperformed the other 2 algorithms with 95.25%, 94.3%and 94% using $\delta_{l_1}, \delta_{l_2}$ and δ_{cos} similarity measures, respectively.

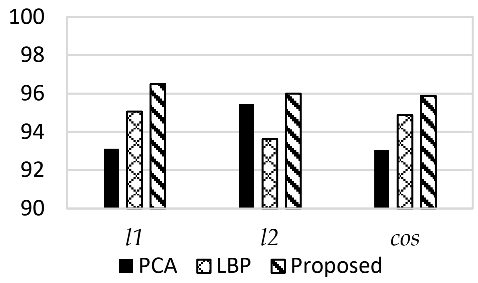

Figure 6. Performance comparision between PCA,LBP and the proposed approach using ORL face database($R = 25$).

4. Conclusion

Simple and novel feature descriptor for image representation was proposed in this paper. It mainly depends on the sum of the pixels values in four different directions. The proposed approach can be applied by dividing image into different number of regions same as the LBP algorithm. The new feature descriptor was tested on the face recognition problem. Simulation results of experiments were conducted on ORL and PUT face databases. The simulation results support our earlier preliminary findings. It indicates the high performance of the proposed feature descriptor and at the same time its low complexity compared to other well-known feature extraction algorithms. For future study, neural network, SVM, fuzzy based classifiers can be used for classification. This approachcan be extended and investigated for otherpattern recognition problems.

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