A NOVEL METHOD OF EXPORATION & ANAYLYSIS FOR PERIOCULAR RECOGNITION

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ABSTRACT

A novel method of exploration and analysis for periocular recognition data that takes into consideration the structure of the periocular region as well as information from multiple scales.

Perform experimentation to compare the performance of the new method to existing methods of periocular feature extraction. The periocular region are more discriminative than others. Using this knowledge, a novel block placement method for LABFs was proposed, and Two different datasets were selected of Facial Recognition Grand Challenge and Facial Recognition Technology Database. When using only features extracted from each individual sub-region, the results of biometric experiments. We suggest that LBP features are most discriminative in the upper eyelid, lower eyelid, tear duct, and outer corner, while LPQ features are most discriminative in the inner eyebrow, outer eyebrow, and skin , we could be serve as preliminary or training data for a biometric system that considers the structure of the periocular region in the determining recognition accuracy.

Keywords- Periocular, Novel Method, Recognition Data, Perform Experimentation, Grand Challenge, Technology Database, discriminative.

I INTRODUCTION

A novel method of exploration and analysis and how it influences the performance of an LABF-based periocular recognition system. The experiments presented that some sub-regions of the periocular region are more discriminative than others. Using this knowledge, a novel block placement method for LABFs was proposed. When using only features extracted from each individual sub-region, the results of biometric experiments and we suggest to that LBP [1] features are most discriminative in the upper eyelid, lower eyelid, tear duct, and outer corner, while LPQ features are most discriminative in the inner eyebrow, outer eyebrow, and skin. The performance of LABFs at multiple scales was examined. Previous research looked at only a single, commonly the smallest, scale and discarded potentially useful information.

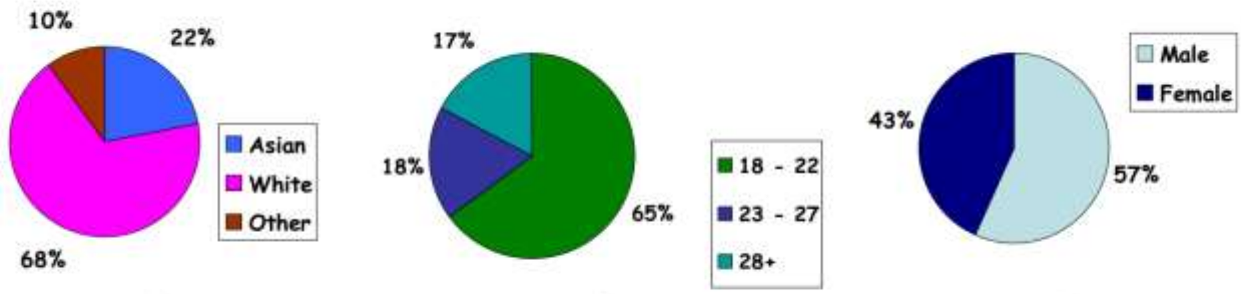
The modifications made to the original LABF algorithms resulted in little increase in computation complexity, yet demonstrated a significant difference in performance in a basic biometric experiment. A Novel method exploration and analysis can be used in conjunction with the method developed a novel algorithm for periocular feature extraction that incorporates the discriminative power of features from multiple scales.

These two areas of exploration are specific to the periocular region and can be used in conjunction to form the basis of a biometric feature extraction algorithm. This algorithm utilizes unique properties of the periocular region to provide a boost to recognition system performance over existing and more generalized methods.

II DATA

There are two different datasets use to first facial recognition grand challenge (FRGC) and second facial recognition technology (FERET)[2]. The FRGC database [3] consists of high resolution color images of a large number of subjects mostly between ages 18 and 22, collected over a two year period from multiple recording sessions involving controlled and uncontrolled lighting conditions, and with an expression and without. A recording session is the set of all images of a subject taken each time the subject's biometric data is collected.

A typical FRGC recording session consists of four frontal face, controlled lighting still images, two frontal face, uncontrolled lighting still images, and one three-dimensional image. The controlled lighting images were taken in a studio setting (two or three studio lights) and with two facial expressions (smiling and neutral). In controlled conditions, the distance between the subject and the camera is approximately the same. The still images were taken with a 4 Megapixel Canon Power Shot G2 and have a pixel resolution of either 1704×2272 or 1200×1600 pixels. The images are stored in JPEG format with storage sizes ranging from 1.2 Mbytes to 3.1 Mbytes. FRGC Experiment 1 is an experimental protocol and data subset that is widely used to compare different biometric recognition methods. FRGC Experiment 1 is a set of 16,029 still, high resolution, frontal face images taken under controlled lighting conditions. It was chosen for this work because the large face images will lead to relatively large periocular region images. FRGC Experiment 1 measures performance on the



(a) (b) (c)

Figure 1: Demographics of FRGC validation partition by (a) race, (b) age, and (c) sex [40].
classic face recognition problem: recognition from frontal facial images taken under controlled illumination.

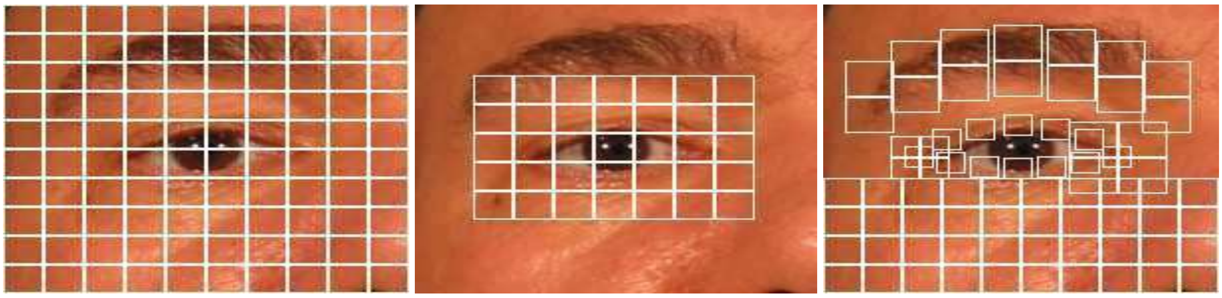
FRGC Experiment data is divided into training and validation partitions. Images in the validation partition were collected during the 2003-2004 academic year and cover 466 subjects from 4,007 subject sessions. The demographics of the validation partition are given in Figure 1. The training set consists of an additional 12,776 images taken from 226 of the same subjects in a single recording and used with feature extraction algorithms that require a trained model. This work also uses the FRGC Experiment data subset, a collection of images taken under uncontrolled lighting situations. Experiment is a set of 8,014 still, high resolution, frontal face images taken from the same 469 subjects as Experiment images were taken either in an indoor hallway with only the overhead ceiling lights, or outside with only the sun illuminating the face. The Experiment protocol calls for using the Experiment dataset as the gallery set and the Experiment set as the probe set.

The FERET database [2] consists of gray-scale and color images of faces captured. The mission of FERET was to assist researchers in the development of early facial recognition systems by providing the best set of test data available at the time. Many of the subjects present in the FERET dataset were photographed in many different poses and with different facial expressions. The experiments of this chapter only make use of frontal face images. This subset consists of 1,980 frontal face images taken from 990 subjects.

III METHOD

A novel feature extraction method is presented in this chapter for use with periocular region data. This method is the logical fusion of the methods have the potential to work together in such a way that the proposed method will offer an increase in performance over existing periocular feature extraction[1] methods. As a reminder, the basic components of a biometric recognition algorithm are image preprocessing, feature extraction, feature comparison, and classification. Both elements of the proposed approach influence the feature extraction

The first part of the proposed approach comes from the new block configuration method of basic block placement as the original LBP implementation of face recognition [4]. The blocks have all been rectangular regions of the same size that border each other in a grid pattern and do not overlap. Instead, blocks are placed so that they correspond to physical sub-regions of the periocular region. These sub-regions of the periocular region are the upper eyelid, the lower eyelid, tear duct, outer corner, inner eyebrow, outer eyebrow.



(a) (b) (c)

Figure 2 Different models for block placement when using LABF: (a) Miller (b) Park (c) Proposed skin.

The suggested feature extraction method used varies based on the sub-region. Based on the results from LBP features are extracted from the upper eyelid, lower eyelid, tear duct, and outer corner. LPQ features are extracted from the inner eyebrow, outer eyebrow, and skin. The second part of the proposed approach involves using modified LBAFs to extract features from multiple scales. The experimental results presented in used a weighted fusion of features from multiple scales to present the optimal results for those experiments.

It is expected that these sub regions will be more discriminative than previous standard approaches. Second, the blocks are of variable size, because not all structural elements of the periocular region are the same size. For instance, the eyebrow is much wider than the eyelid. The size of the each block is determined so that a particular sub-region of the periocular region and only that sub-region is contained in the block. The location of the blocks that cover a sub-region of the periocular region as placed so that they cover the physical feature they are intended to cover based on the mean images shown in Figures

	Left			Right		
Sub-region	LBP	HOG	LPQ	LBP	HOG	LPQ
upper eyelid	71.2446	53.6481	69.0987	70.8155	52.5751	68.8841
lower eyelid	59.2275	36.0515	57.2961	60.9442	42.7039	59.4421
tear duct	70.3863	47.6395	59.8712	68.6695	45.4936	58.7983
outer corner	81.9742	59.4421	74.4635	82.8326	58.7983	75.1073
inner eyebrow	77.8970	71.4592	87.3391	78.3262	69.9571	84.9785
outer eyebrow	81.3305	72.7468	87.3391	80.4721	74.4635	88.6266
skin	90.9871	90.1288	93.7768	91.4163	91.8455	95.7082

Table 1: Rank-1 recognition rates of experiments using FRGC images and only features from certain subregions of the periocular region.

IV ALGORITHM

LABF perform equally in each sub-region within the experiments of each feature extraction [1] method has types of patterns that it is intended to quantify, and these patterns express themselves differently in the different sub-regions of the periocular region. Experiments should be conducted to test the relative performance of each of the LABF within the different sub-regions. If the performance of each LABF is significantly different within the sub-regions, then an algorithm could be developed, using the proposed periocular structure based block arrangement, to make the best use of the specific patterns found in each sub-region, instead of treating the whole periocular region the same.

This approach has the potential to improve the performance of periocular-based biometric systems by using a method fitted to the unique aspects of the periocular region. To perform an analysis of the algorithmic performance of different LABF within different subregions of the periocular region, basic biometric experiments were conducted. In these experiments, features extracted from only one sub-region of the periocular region are considered so that the performance of each sub-region can be analyzed individually.

The results are from biometric experiments using concatenated feature vectors of multiple blocks from the same sub-region. Table 2 shows the Rank-1 recognition rates of these experiments performed using images from the FRGC dataset. Table 2 shows the same using FERET images. For the upper eyelid, lower eyelid, tear duct, and outer corner, LBP features give the best performance in these experiments using both left and right periocular region images and using both FRGC and FERET [5] images. These results point to the observation that LBP features are more discriminate in this region than other feature types

	Left			Right		
Sub-region	LBP	HOG	LPQ	LBP	HOG	LPQ
upper eyelid	45.4545	27.9798	44.1414	47.4747	28.6869	46.2626
lower eyelid	34.9495	20.3030	30.8081	34.2424	18.4848	32.0202
tear duct	53.5354	32.7273	48.4848	52.1212	32.5253	49.0909
outer corner	54.1414	34.0404	45.7576	53.6364	35.5556	47.7778
inner eyebrow	69.6970	62.8283	78.4848	69.3939	62.3232	80.0000
outer eyebrow	63.9394	56.8687	73.2323	64.5455	54.8485	73.0303
skin	73.4343	71.3131	75.2525	71.0101	68.5859	73.4343

Table 2: Rank-1 recognition rates of experiments using FERET images and only features from certain sub-regions of the periocular region.

For the inner eyebrow, outer eyebrow, and skin, LPQ features give the best performance in these experiments using both left and right periocular region images and using both FRGC and FERET images. This would suggest that LPQ features are more discriminate in these regions than other feature types. The performance numbers seen within a single feature extraction method do not seem to correspond to the figures In most cases the skin under the eye area is the best performing sub-region, but patches in the skin area to be very high performing. The figures are showing the performance of a single patch, while the results shown here come from a concatenation of the features from 40 patches. In fact, the skin area contains the most patches while other areas, like the eyebrow, contain less patches and do not see a drastic decrease in performance compared to the skin. One explanation for this behavior would be that the features found in the eyebrow, for instance, are more discriminative than the features found in the skin, and that the performance of the skin sub-region is due inlarge part to the large number of patches.

V RESULTS

The experiments presented in biometric experiment guidelines and results are reported for experiments using methods from Miller *et al.* [6] and Park *et al.* [7]. Rank-1 recognition rate, equal error rate, verification rate at 0.1% false accept rate, and three different LABF methods on FRGC Experiment using both the Miller *et al* and Park *et al.* methods. Table.2 shows the same performance metrics for the proposed method. It can be seen that the proposed approach provides better performance results than any of the other approaches.

	Left Periocular				Right Periocular			
				LBP				
	Rank-1	**EER**	**VR at 0.1% FAR**	**D'**	**Rank-1**	**EER**	**VR at 0.1% FAR**	**D'**
Miller	**99.7068**	**8.8323**	**64.8841**	**2.7331**	**99.7005**	**8.2016**	**69.7151**	**2.4401**
Park	**98.6960**	**10.8464**	**46.2132**	**2.8250**	**98.8520**	**10.4823**	**48.6871**	**2.5137**
				HOG				
	Rank-1	**EER**	**VR at 0.1% FAR**	**D'**	**Rank-1**	**EER**	**VR at 0.1% FAR**	**D'**
Miller	**99.6069**	**8.0829**	**69.6951**	**2.8350**	**99.6444**	**7.5245**	**72.2473**	**2.9378**
Park	**98.7834**	**10.3863**	**61.3708**	**2.5107**	**98.8208**	**9.9537**	**62.6322**	**2.5849**
				LPQ				
	Rank-1	**EER**	**VR at 0.1% FAR**	**D'**	**Rank-1**	**EER**	**VR at 0.1% FAR**	**D'**
Miller	**99.7692**	**7.1183**	**75.9181**	**2.8654**	**99.7816**	**6.7227**	**76.6574**	**2.9439**
Park	**98.9706**	**11.0274**	**47.7062**	**2.4111**	**99.0454**	**10.5711**	**49.4899**	**2.4872**

Table 3: Results of experiments using existing feature extraction methods on images from the FRGC Experiment dataset

	Left Periocular				Right Periocular			
	Rank-1	EER	VR at 0.1% FAR	D’	Rank-1	EER	VR at 0.1% FAR	D’
Proposed	99.9321	6.9887	78.1764	2.9854	99.9798	6.6785	79.5894	3.1154

Table 4 Results of experiments using the proposed method on images from the FRGC Experiment 1 dataset

	Left Periocular				Right Periocular			
LBP								
	Rank-1	EER	VR at 0.1% FAR	D’	Rank-1	EER	VR at 0.1% FAR	D’
Miller	90.2020	4.9208	80.7071	3.2319	87.2727	5.2477	77.3737	3.2113
Park	72.7273	15.7522	47.4747	1.9316	72.8283	16.0677	45.2525	1.9190
HOG								
	Rank-1	EER	VR at 0.1% FAR	D’	Rank-1	EER	VR at 0.1% FAR	D’
Miller	87.1717	5.0597	80.6061	3.3462	86.6667	5.3547	78.6869	3.3305
Park	70.6061	9.1828	62.3232	2.7286	70.0000	9.4609	61.3131	2.6758
LPQ								
	Rank-1	EER	VR at 0.1% FAR	D’	Rank-1	EER	VR at 0.1% FAR	D’
Miller	92.0202	4.6486	83.9394	3.2062	92.2222	4.8796	83.4343	3.1487
Park	77.1717	15.5542	56.8687	1.9655	77.2727	16.2383	55.9596	1.9133

Table 5. Results of experiments using existing feature extraction methods on images from the FERET dataset

	Left Periocular				Right Periocular			
	Rank-1	EER	VR at 0.1% FAR	D’	Rank-1	EER	VR at 0.1% FAR	D’
Proposed	94.0667	4.0462	85.1113	3.5005	93.8887	4.3232	84.9190	3.8682

Table 6: Results of experiments using the proposed method on images from the FERET dataset

In experiments using both FRGC and FERET images, the proposed method produced a higher R @ 0.1% FAR than either of the commonly used methods. The increase was between 1% and 3%. This performance comparison is given in regard to experiments that use periocular images only. A comparison to experiments that use face images would be an inappropriate comparison because the proposed method is intended to be used with periocular region images only. It is possible to conduct similar analysis on features extracted from the full face and produce a method similar to the one proposed in this chapter but such work falls outside of the scope of this dissertation. Also, we are not suggesting that the periocular region be used to replace the face when face data is available and collected in ideal settings.

VI CONCLUSIONS

These datasets are typically much smaller than either FERET or FRGC and not publicly available. Collecting our own set of biometric data for the experimentation of this dissertation was infeasible. Datasets such as the FRGC took over three years and many researchers to compile. Datasets to the scale of FRGC are collected for the sake of collecting the data and not with specific scientific research in mind because of the time investment required. Even though the data used to explore aspects of the periocular region. and the data used to test the proposed method overlap, the observations made in each chapter come from using more than one dataset and using more than one feature extraction algorithm. Many of the observations are consistent across these variables which suggests that the observations would likely be made from experimentation with any periocular data. One suggested area of future work would be to test the proposed method on a new and larger set of periocular data. The contributions of this dissertation to the state of biometrics research are much more significant than a method that provides improved performance in one biometric problem.

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BIOGRAPHY

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