Using Iris Texture to Predict Ethnicity: A Pattern Recognition Approach

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***Abstract*—Predicting ethnicity using the texture of an iris has become an interesting topic for researchers in the recent past. Artificial intelligence, Neural Network, Computer Vision and many other Machine Learning paradigms have been taken into consideration while classifying ethnicity using the iris texture. In addition, there have been many studies where it classifies the age, gender and other biometrics of a person compared to the ethnicity of a person. The purpose of this paper is to highlight and acknowledge how several researchers have studied in this field by differentiating and understanding their methods, algorithms and its subsequent outcomes.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

The study of iris biometrics results in a coded text of the iris which is obtained from the texture of the iris. This coded text is further analyzed to identify a person or age of a person or even gender of that person. [2] However, a small amount of research has been done regarding soft biometrics of the iris such as ethnicity. [1] This paper completely revolves around the previous excellent research work of the topic: ethnicity classification and prediction based on the texture of the iris. Additionally, this paper addresses and explains all the iris image datasets, various algorithms and its correspondent experiment results that were carried out by the researchers over the last two decades. The paper is organized in this manner where section II comprises detailed review work of the topic ethnicity prediction done by several researchers across the world. Section III depicts a summary table that elaborates and compares the different datasets, techniques and their accuracy that were achieved by the researchers. Lastly, a conclusion and future work is also provided in section III to provide a closure in predicting and classifying ethnicity.

II. Detailed Literature Review

A. Infrared Illumination to detect ethnicity

Stephen et al. [2] have used near-infrared illumination in order to take images of the iris to make an improved detection of ethnicity. They took Asians and Caucasians as their experiment subjects. From their experiment they could claim that their performance was better compared to those previous researchers. Also, they came up with the fact that predicting ethnicity for a female subject is arduous than male subjects

1) Datasets: The experiment was done with a collection of 1200 feature vectors data, where Asians and Caucasians were taken as subjects. From each of the subjects, five images of both of the iris were taken. Images were captured using the sensor called LG 4000 and its near-infrared illumination ability

makes it possible to produce 480x640 images. For segmentation and creating a normalized picture, IrisBee software was used. In order to avoid biases in their experimental result they have used the person-disjoint train and test data. This was done by randomly dividing the iris dataset into 10 sections, where each section consisted of images for 6 individuals of each different ethnicity.

2) Algorithm: Computation of texture features are done independently in order to classify the contrast between iris-sclera (white portion of the eye) and pupil-iris. Similarly, texture features are also calculated using some of the basic texture filters that include: 'spot detectors', 'line detectors', 'S5S5', 'R5R5' and 'E5E5'. Each of the texture filters are then computationally summarized using five statistical measures. The five statistical measures are: mean value of the filter response, standard deviation, 90th percentile, 10th percentile and the range between 90th and 10th percentile. Thereby, resulting in 450 features with a grand total of 882 features. Numerous classifiers that were available in the Weka package were deployed to classify ethnicity. Altering the parameters in some of the classifiers has resulted in performance gains. Although, with the default parameters in the Weka's system, that SMO (Sequential Minimum Optimization) algorithm has achieved the highest accuracy of 90.58% in predicting ethnicity. Random Forest and Bagged FT were also very close in predicting ethnicity. Naive Bayes had the lowest accuracy of 68.42% in predicting ethnicity. Furthermore, they have run the experiment once more by 10 fold cross-validation but this time without the condition of person-disjoint. The whole idea of person-disjoint condition is done to avoid the duplication of images for both training and test dataset.

3) Experimental Results: Without the condition of person-disjoint there has been an improved accuracy of 96.17%. Stephen et al. [2] has found an enhanced accuracy compared to the works of previous researchers. The success in predicting Asian and Caucasian ethnicity with the aid of subject-disjoint 10-fold cross validation on a collection of 1200 images data has exceeded 90%.

B. 2D Gabor Filter

Qui et al. [3] believes that the iris texture of an individual is interconnected with their iris texture. Iris is the coloured tissue at the front of the eye that contains the pupil in the centre. Qui and his team looked into huge amounts of iris images of Asians and non-Asians. They discovered that these iris patterns varied from one another in terms of the statistical analysis of the iris texture. Thus, in short their reason to find a new way of predicting ethnicity is that at a small scale, the features of iris texture are not dictated by genetics. Their proposed algorithm requires 2D gabor filters to get the global texture information and AdaBoost is used to learn the different categorization principle from the group of the candidate feature set

1) Datasets: For their experiment they used databases from Chinese Academy of Sciences Institute of Automation (CASIA v2), University of Palackeho and Olomopuc (UPOL) and University of Beira Interior (UBIRIS). The CASIA database consisted of 2400 iris images of Asiand and UPOL and UBIRIS consisted of 1582 iris images of non-Asian. The images in the CASIA database were 8 bit depth grey images; thus, the images from UPOL and UBIRIS were also converted into that format to make the experiment more reliable.

2) Algorithm: The ethnic classification algorithm requires three steps: Image preprocessing Global Texture Analysis and Training. Image Preprocessing: All iris recognition systems require this step. The step includes localization, normalisation and enhancement. The image consists of the eyelids and eyelashes, thus, to cut out those portions only the inner ¾ of the lower half of an iris region is used. This region is called the region of interest (ROI) and it is used for feature extraction. Qui and his team used a 60 x 256 pixel image for their ROI and it is then split into two equal regions, region A and region B. Global Feature Extraction: To extract the global feature from the ROI multichannel Gabor filtering. The input image (ROI), which consists of image points, is coiled together using a 2D Gabor filter to acquire a Gabor filtered image. The output of the Gabor filter in each image point can be combined into a single quantity called the Gabor energy. From this output, it was found that Asians have substantial texture in region A whereas for non-Asians the texture was rich in both the regions, region A and region B. Therefore, a high pass filtering system can be used to extract the differences between different races. Qui and their team designed a bank of Gabor filters to get the Gabor energy features. The frequency domain of the Gabor filters are of central symmetry thus only the half of the frequency plan is needed. By using four different values of orientation θ, 0, π / 4 , π / 2 , and 3π / 4, 240 pairs of Gabor channels were discovered. The pair of Gabor filters helped to get Gabor's energy image. From the Gabor energy values the average of region A and region B was calculated. Two statistical parameters of the Gabor energy picture, Gabor Energy (GE) and Gabor Energy Ratio (GER), are retrieved in order to define the global texture data associated with the ROI. Training: A lot of the features have been extracted for each iris image, but not all the features are kept. The image goes through a rigorous process which disposes of most of the features. Then the AdaBoost algorithm is used to collect features automatically and train the classifier.

3) Experimental Results: The Gabor energy features helped to achieve a correct classification rate of 79.44% and the Gabor energy ratio features achieved a CCR of 84.95%. However, when features from both Gabor energy and Gabor energy ratio are used they achieved a higher CCR of 85.95%. Even though the classification rate is high there are some obvious errors: UBIRIS is a noisy image database and it has many images that are not focused. The ROI might be obstructed by eyelids and eyelashes. There are outliers in both classes.

C. Binarized Statistical Image Feature & Local Binary Patterns

Ross A. and Bobeldyk D. [4] focused mainly on iris biometric attributes. As it is difficult to detect the rich texture of dark colored iris in the visible wavelength, Ross A and Bobeldyk

D. used images of iris that was imaged in the Near Infrared (NIR) spectrum as infrared has a longer wavelength. The long wavelength helped to penetrate deeper into the iris of dark-colored eyes. Moreover, the NIR picture capture procedure doesn't excite the pupil, thus the iris texture is protected from being unnecessarily altered by pupil dynamics.

1) Datasets: To carry out this experiment three datasets were used. The largest one is BioCOP2009 which was collected at West Virginia University and the other two were used for cross testing in order to display the generalizability of the proposed methods. Those datasets are Cosmetic Contact dataset and GFI dataset which were collected at Notre Dame University. All the datasets went through preprocessing and geometric alignment.

2) Algorithm: The main goal of this paper [4] is to demonstrate the usefulness of straightforward texture descriptors for feature prediction. The texture descriptors that performed well in extracting iris texture features from Outex and Curet texture dataset are local binary patterns (LBP) and binarized statistical image features (BSIF) along with local phase quantization (LPQ).

LBP: By comparing the values of each pixel in a picture with each of its corresponding neighbours, LBP [44] encodes local texture information. As a consequence, a binary code is created whose length is determined by how many adjacent pixels are taken into account.

The LBP code is created for each pixel in the image by first converting the binary sequence into a decimal value. LPQ: By leveraging an image's phase data, LPQ [46] encodes local texture data. The phase information from the 2-D Discrete Fourier Transform is utilized to construct an 8-bit binary code at each pixel point using a sliding rectangular window. A 256-dimensional vector of features is produced by creating a histogram of the produced data.

BSIF: As a texture descriptor, BSIF was initially developed by Kanala and Rahtu [45]. By organizing the picture using pre-made filters, BSIF casts the image into a domain. 13 natural photos were used to produce the pregenerated filters. The 13 natural photos are randomly picked to yield 50,000 patches of size k x k. Only the most significant n elements are kept after using principal component analysis. Then, independent element analysis is used to create n filters with a size of k x k. The pregenerated filters for k = { 3, 5, 7, 9, 11, 13, 15, 17 } and n = { 5 - 12}.

The picture has been compressed with each of the n pregenerated filters, and the response is converted into a binary. A '1' is produced if the answer is larger than zero. A '0' is produced if the answer is less than or equal to zero. The replies are combined to create a binary string, which is then transformed into a decimal number (the BSIF code). The resultant decimal number would be '19', for instance, if the n binary replies were { 1, 0, 0, 1, 1 }. The BSIF response will therefore vary from 0 to 2n - 1 for n filters.

Each of the NIR retinal pictures from our suggested technique is given a texture description before being tessellated into 2020 pixel sections. This patterning was carried out to make sure that the feature vector that was being produced had spatial data. Each tessellation's histogram was created, normalized, and concatenated into a single feature vector. The original NIR ocular picture was subjected to a geometric adjustment in order to offer uniform spatial data throughout every image.

3) Experimental Results:

i. BIOSCOPE2009: As a trade-off between prediction accuracy and computational processing time, the 8-bit BSIF was chosen in this study. The findings with 9-bit or 10-bit BSIF would be marginally better, but considering the size of the BioCOP2009 dataset, the additional memory and processing time needed to run each experiment were fairly significant. Using the retrieved BSIF features, an SVM classifier was honed on each of the 5 training sets. Each SVM model's classification of the experimental information was done. the accuracy of the predictions made using filters with sizes between 3 x 17 squares. Although the forecast accuracy changes significantly for each of the several filter sizes, there is no appreciable performance difference between them.

ii. IRIS-EXCLUDED OCULAR REGION VS. IRIS-ONLY REGION: When using BSIF to determine race, the iris-only region is more accurate than the iris-excluded ocular region, however when predicting gender, the converse is true.

iii. CROSS DATASET TESTING: A technique frequently performs well when both training and evaluation are carried out on the same dataset. We trained on the BioCOP2009 dataset and tested on the previously mentioned CCD1 and CCD2 datasets in order to show the generality of the suggested method. The pictures in CCD1 and CCD2 were classified using the 5 trained SVM models that were created using the BioCOP2009 dataset. It should be noted that although participants from the CCD1 and CCD2 datasets were categorized as "White," those from the BioCOP2009 dataset were given the "Caucasian" designation. Images of individuals with contacts, without contacts, and with cosmetic contacts may be found in the CCD1 and CCD2 collections. Without contacts, CCD1 and CCD2 each carry 500 left and 500 right eye pictures and 200 left and 200 right eye images, respectively. In our studies, only the photos devoid of interactions were utilized.

REFERENCES

[1] S. Lagree and K. W. Bowyer, "Predicting ethnicity and gender from iris texture," 2011 IEEE International Conference on Technologies for Homeland Security (HST), Waltham, MA, USA, 2011, pp. 440-445, doi: 10.1109/THS.2011.6107909.

[2] G. P. Mabuza-Hocquet, F. Nelwamondo and T. Marwala, "Ethnicity Prediction and Classification from Iris Texture Patterns: A Survey on Recent Advances," 2016 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2016, pp. 818-823, doi: 10.1109/CSCI.2016.0159.

[3] Qiu, X., Sun, Z. and Tan, T. (2006). Global Texture Analysis of Iris Images for Ethnic Classification. International Conference on Biometrics.

[4] D. Bobeldyk and A. Ross, "Analyzing Covariate Influence on Gender and Race Prediction From Near-Infrared Ocular Images," in IEEE Access, vol. 7, pp. 7905-7919, 2019, doi: 10.1109/ACCESS.2018.2886275.

[5] Singh, M., Nagpal, S., Vatsa, M., Singh, R., Noore, A., Majumdar, A. (2017). Gender and ethnicity classification of Iris images using deep class-encoder. 2017 IEEE International Joint Conference on Biometrics (IJCB), 666-673.

[6] A. Zarei and D. Mou, ”Artificial Neural Network for Prediction of Ethnicity Based on Iris Texture,” 2012 11th International Conference on Machine Learning and Applications, Boca Raton, FL, USA, 2012, pp. 514-519, doi: 10.1109/ICMLA.2012.94.
[7] M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.