International Journal of Research Publication and Reviews, Vol 3, no 6, pp 3776-3778, June 2022

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Face Detection Ethnicity Classification

C.Chandraleka[1], Mr.R.Sathish Kumar[2]

[1]Master of Computer Application, Krishnasamy College of Engineering & Technology ,Cuddalore

[2]MCA,M.Phil.,Assistance Professor, Assistant Professor, Master of Computer Application, Krishnasamy College of Engineering & Technology, Cuddalore

ABSTRACT

Human facial images provide the demography information, such as ethnicity. Conversely, ethnicity plays an important role in face-related application. Image-based ethnicity identification problem is addressed in a machine learning framework. Nowadays, ethnicity classification has a wide application area and is a prolific area of research. This paper gives an overview of recent advances in ethnicity classification with focus on Convolutional Recurrent Neural Networks. (CRNNs) and proposes a new ethnicity classification method using only the middle part of the face and CRNN. Ethnicity detection plays an important role for pre-identify and re-identify people with different demographic background. The first level of fusion is feature fusion which fused two important local features which are Local Binary Pattern (LBP). The proposed model was tested using holdout testing method on UTK Face dataset.

Keywords: Deep Convolutional Neural Networks (DCNN), Convolutional Recurrent Neural Networks. (CRNNs)

1. INTRODUCTION

The human face is a highly rich stimulus that provides diverse information for adaptive social interaction with people. Humans are able to process a face in a variety of ways to categorize it by its identity. Nowadays, face recognition has become almost inevitable in real-world applications in the fields of security, biometrics, entertainment industry and others in order to identify a person [1]. Ethnicity is the most important notable and prevailing human trail. This soft biometric could be explained using a chain of social cognitive and perceptual tasks of ethnicity. Effective extraction of visual features and contents to provide a meaningful index and access to such image data as per the requirement of the user plays important in many fields of image processing applications. CRNN requires to combine method that detects and represent the content based features and database techniques to efficiently index and retrieve the relevant images based on those features as well as learning capabilities to include new data entries. Face image retrieval is a process to search face images from large scale face database which are similar to a given query image [2]. Content-based face image retrieval process requires building a large face database where each image along with its feature descriptor is stored. Face image retrieval based on Face Image Retrieval using Multi-Task Cascaded Convolutional Neural Network (MTCNN).

2.RELATED WORK

Guo et al. [1] use the biologically-inspired features (BIF) with (or without) manifold learning to study the ethnicity classification with variations of gender and age. Their experiments are conducted on the whole MORPH-II database with about 55,000 face images, in which White faces make up 19 %, Black faces provide 77 %, and the remaining faces (4 %) belong to Asian, Indian, Hispanic and other.

W. Zhao .et.al[2]Enormous methods have been applied in ethnicity classification, which can achieve a high accuracy and perform effectively. It is well accepted that good results can be gained when the training and test images have the same gender; but in most cases, the gender of the test images is not known in prior. For the experiment in five races classification within the cases of unknown genders and age, they can predict ethnicity on Black and White races

3. CONVOLUTIONAL RECURRENT NEURAL NETWORK (CRNN)

The approach proposed in this paper consists of several stages. First, all of the training images are preprocessed, which is described in more detail in Section. After preprocessing, the filtered dataset with cropped images is created. Here, the approach for ethnicity classification with plotted landmarks (Fig 1) goes to the landmark annotation step after which a new dataset with annotated landmarks is created. The approach for ethnicity classification without plotted landmarks omits this step and goes to data normalization and augmentation. The steps omitted in the approach without plotted the CRNN. After CRNN training and validation, testing is conducted. First part is to input an image which is preprocessed in the same way as training images, then landmarks are annotated (only in the approach with plotted landmarks), images normalized and the trained CRNN makes a prediction of ethnicity. Based on the previous research and observation through study of other papers, in which landmarks are not often used in combination with deep neural networks, one of the aims of this paper is to investigate if landmark plotting can contribute to ethnicity classification models.

Convolutional Recurrent Neural Network (CRNN) are derived from basic neural networks. In neural networks, there are three types of layer, input, hidden and output. Each layer have several neurons stacked in it which takes input from the previous layers. In each layer, a neuron acts as a linear classifier. Each neuron performs some mathematical operation, usually computes a dot product of input with its respective weight, adds biasing, and applies a non-linearity. Circles in each layer represent one neuron. The output is fed into the neuron of next layer. Usually neurons between two adjacent layers are fully connected, and neurons within a single layer are not interconnected. Architecture of a 3-layer neural network is shown in Fig 1.

3.1 MULTI-TASK CONVOLUTION NEURAL NETWORK (MTCNN)

For this study MTCNN is used. The architecture of this model is based on the opting this network is that it is pre trained on a large face dataset of 2.6 million images. It presents comparable accuracy to state of the art networks, which are very deep than this, on benchmarks like Local Binary Pattern (LBP).

3.2 LOCAL BINARY PATTERN (LBP)

The combination between several features to get reasonable results is not new but the challenges make this task very hard to achieve. Our challenge leads us to combine two features after several tests and depending on the classification results. The feature extraction fused on one of the powerful texture classification features. Which is called Local Binary Pattern (LBP). The LBP feature is used to segmentation of the image, then identify the ethnicity classification location.

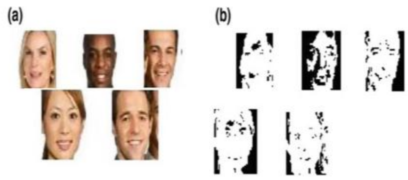

Fig. 3: (a) MTCNN detect the faces, next cut the faces images (b) LBP skin segmentation.

Fig. 4: CRNN ethnicity classification of the location.

3.3 VISUALIZATION

Fig 5.1 shows CRNN result plot of the whole database and the features extracted from LBP Face network. The spatial distance indicates the similarity between the images and show strong clustering of images from same class. Although the feature vector, which is 4096- dimensional, is shown in 2D space it still shows superiority of network in increasing inter-class reparability and intra-class compactness.Therefore, processing only that part of the face allows smaller resource consumption while the accuracy (80.34% on the UTK Face) is still slightly better than in the state-of-the-art using the whole face (78% on the UTK Face dataset). The developed CRNN has been tested using holdout method on two different datasets (UTK Face and Fair Face) and the results are compared with state-of-the-art methods which shows an improvement in accuracy, while decreasing preprocessing and training time. Landmarks were applied to deep neural networks (CRNNs) which showed no significant differences in the results of CRNN networks, but only increased the time and resources necessary for image preprocessing, training and testing the CRNNs.

4. CONCLUSION

The results of ethnicity classification both with and without plotted landmarks were analyzed and compared. In order to determine the initial ability of landmarks in ethnicity classification, previous research on this topic has been studied, which has shown sufficient differences in the characteristic features of persons between different ethnicity classes to distinguish them. Accordingly, and with the observed increasing trend of using neural networks to solve this and related problems, neural networks were selected as the main driver of research . The scientific contribution of the paper can be seen in the development of a new CRNN for ethnicity classification into five ethnicities (White, Black, Asian, Indian and Others) using only the middle part of the face. The area of the face around the nose and eyes has been observed to contain the most visual data that allows successful ethnicity classification .

REFERENCES

1. L. Fracas, Anthropometry of the Head and Face, Raven Press, 2nd ed., 1994.

2. D. Endow, Facial Growth, W.H. Saunders, 3rd ed., 1990.

3. R. Maples and J. Kravitz, “Recognition for faces of own and other race,” J.Perc.Soc.Psychol.13, pp. 330–334, 1969.

4. J. Brigham and P. Barkowitz, “Do ’they all look alike?’ the effect of race, sex, experience and attitudes on the ability to recognize faces,” J. Appl. Soc. Psychol 8, pp. 306–318, 1978.

5. A. Golby, J. Gabrieli, J. Chiao, and J. Eberhardt, “Differential responses in the fusiform region to same-race and other-race faces,” Nature Neuroscience 4(8), pp. 845–850, 2001.

6. A. Puce, T. Allison, J. Gore, and G. McCarthy, “Face-sensitive regions in human extrastriate cortex studied by functional mri,” J. Neurophysiol. 74, pp. 1192–1199, 1995.

7. A. O’Toole, K. Deffenbacher, D. Valentin, and H. Abdi, “Structural aspects of face recognition and the other race effect,” Memory & Cognition 22, pp. 208–224, 1994.

8. A. O’Toole, A. Peterson, and K. Deffenbacher, “An other-race effect for classifying faces by sex,” Perception 25, pp. 669–676, 1996.

9. W. Zhao, R. Chellappa, A. Rosenfeld, and P. Phillips, “Face recognition: A literature survey,” CVL Technical Report, University of Maryland , Oct. 2000.

10. Viisage, . Littleton, MA.

11. Identix, . Minnetonka, MN.

12. P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection,” IEEE Trans. Pattern Analysis and Machine Intelligence 19, pp. 711–720, Jul. 1997.

13. M. Turk and A. Pentland, “Eigenfaces for recognition,” Journal of Cognitive Neuroscience 3, pp. 71–86, Mar. 1991.

14. P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, “The feret evaluation methodology for face-recognition algorithms,” IEEE Trans. Pattern Analysis and Machine Intelligence 22(10), pp. 1090–1104, 2000.

15. M. Kirby and L. Sirovich, “Application of the Karhunen-Lo´eve procedure for the characterization of human faces,” IEEE Trans. Pattern Analysis and Machine Intelligence 12, pp. 103–108, Jan. 1990.