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Face Recognition using Unsupervised Feature Learning (UFL) Approach

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Abstract: In our paper, we propose a facerecognition system that uses joint feature learning that helps us learn feature representation directly from raw pixels. Unsupervised feature learning enables us to recognize faces even in unconstrained environment like varying poses and expressions. Firstly, we input an image or video into our system. Then we pre-process it by converting it into a gray-scale image. This is to reduce the complexity of the computation. Then we apply Face Detection algorithm (Viola Jones Algorithm) to detect the faces in the input image. After this process, we get the all the faces in the image along with the count of it. Then we adopt Gradient Boost Algorithm (Feature Extraction) to extract the features from the faces obtained in the previous step. This is followed by Correlation matching in which, the features obtained are matched with a template of the face to be recognized. If it matches, it signifies that the face is available in the input frame. Or else the face to be recognized is not available in the given image. The final step is using Support Vector Machines classifiers that are used for the actual authentication process. If this step is complete, the recognized face is given as output. Here, the usage of Viola Jones Algorithm has shown an overall increase in accuracy and reduction in computation time.

Key words: Joint feature learning · Facedetection · Face recognition

INTRODUCTION

In imaging science, an image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows [1]. And an image processing is processing of enhancing an image or extracting an images using mathematical operations by using the signal processing. Here an input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an image or a set of distinctiveness or parameters related to the image [2]. One is analog image processing, it can be used for the hard copies likes printout and photographs. Another one is digital image processing, it manipulate the digital images by using computers.

Here we use as the digital method for facial recognition system that is a computer application system capable of identifying or verifying a person from a image or a video framework from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database [3]. It is characteristically used in security system and can be compared to other biometrics such as fingerprint or eye iris recognition systems.

The main process in face recognition system is feature learning or representation learning that is a set of techniques that learn a feature [4], a transformation of unrefined data input to a representation that can be effectively demoralized in machine learning. Feature learning is motivated by the fact that machine learning tasks such as classification often require input that is precisely and computationally convenient to process. However, real-world data such as images [5], video and feeler measurement is usually complex, redundant and highly variable. Thus, it is necessary to discover useful features or representations from unprocessed data. Traditional hand-crafted features often require expensive human.

The Unsupervised method is describehidden structure fromunlabeled data. Unsupervised learning is closely related to the problem of density of estimation in statistics [6]. However unsupervised learning also encompasses many other techniques that hunt for to summarize and explain key features of the data. Many methods employed in unsupervised learning are based on data mining methods used to preprocess data. The goal of unsupervised featurelearning is often to discover low-dimensional features that capture some structure essential to the high-dimensional input data.

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When the feature learning is performed in an unsupervised way [7], it enables a form of semi supervised learning where first, effort and often rely on expert knowledge. Also, they normally do not simplify well. This motivates the design of capable feature learning techniques, to automate and generalize this.

Feature learning can be divided into two types: Supervised and Unsupervised feature learning, related to these categories in machine learning generally. In supervised feature learning, features are learned from labeled input data. Examples include neural networks, multilayer perceptron [8] and (supervised) dictionary learning. In unsupervised feature learning, features are learned from unlabeled input data. Examples include lexicon learning, independent component analysis, auto encoders, matrix factorization and various forms of clustering.

In Supervised method dictionary learning is to learn a set (dictionary) of representative elements from the input data such that each data point can be represented as a partisan sum of the representative elements. The dictionary elements and the weights may be found by minimizing the average representation error (over the input data), together lightly (i.e., the representation of each data point has only a few nonzero weights) [9].Supervised dictionary learning exploits both the structure primary the input data and the labels for optimizing the dictionary elements. Features are learned from an unlabeled dataset, which are then in use to improve performance in a supervised setting with labeled data.

The next notable process is the face detection. It is a computer technology, locates and identifies human faces in digital images. In Face detectionAn input image is scanned at all possible locations and scales by a subwindow. Face detection is posed as classifying the pattern in the subwindow as either face or nonface. The face/nonface classifier is learned from face and nonface training examples using statistical learning methods. After the face detection, feature extraction starts from an initial set of measured data and builds resulting values (features) intended to be informative and non-redundant, facilitating the subsequent learning and simplification steps and in some cases leading to better human interpretations. Feature extraction is related to dimensionality decrease. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both base and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a compact set of features (also named a features vector). This process is called feature extraction. The extracted features are expected to contain the related information from the input data, so that the desired task can be performed by using this compact representation instead of the complete initial data. And the final process will be face matching that is done by correlation matching and SVM classifiers. Then the output is provided as an image along with a message box.

Related Works: Yi Sun, Xiao gang Wang and Xiao Tang (2014) propose to learn a set of high - level feature representations through deep learning (DeepID) for face verification. These features are taken from the last hidden layer neuron activations of deep convolutional networks. They gather a large number of different identities with a small number of hidden variables. If more identities are added, the performance increases. The features are extracted from various face regions. It achieved 97.45% face verification accuracy only requiring weakly aligned faces. A work reported 98.52% accuracy with Gaussian processes and multi - source training set achieving higher than human performance.

Zhenhua Chai, Zhenan sun, Heydi Mendez-Vazquez, Ran He and Tieniu Tan (2014) propose a novel facial feature extraction for face recognition, whose aim to extract feature using Gabor Ordinal Measures, to identify the related features from face image. In this proposal, the feature extraction is most important to process the face recognition in order to overcome the large intra-class face variation such as pose, illumination, expression. Here the various face ordinal measures are derived from the phase, magnitude, real and imaginary component of gabor images. The main approaches used for face feature extraction are holistic subspace analysis and local feature description. Local feature analysis can characterize the facial details which are important for person identification. In local feature analysis two methods are used for face biometrics are Gabor wavelets and Local Binary Patterns. The discriminating Gabor wavelets and robustness of ordinal measures are integrated to handle both inter-person similarity and intra-person variations in face images.

ZhenhuaChai, Heydi Mendez-Vazquez and Yoanna Martinez – Diaz (2013) introduce a new local spatiotemporal descriptor that is based on structured ordinal features for video face recognition.

The proposed method encodes jointly the local spatio and temporal information along with dynamic facial information. One - shot similarity measure for background similarity method was introduced in this paper. Though this seems to be a complex process, it reduces the

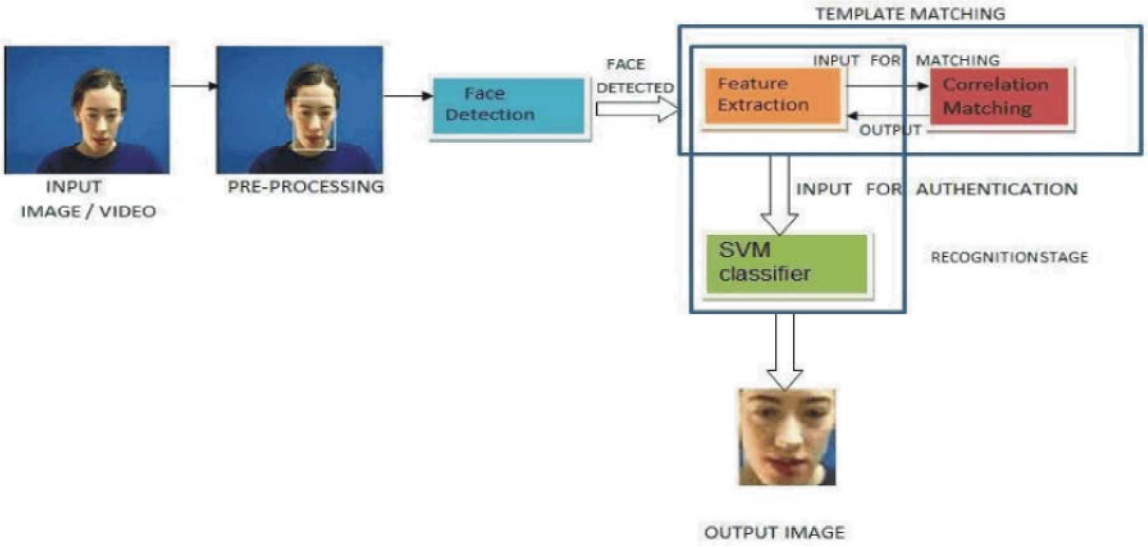

Fig. 1: Architecture Diagram for Face Recognition Syst

computational cost. The Shervin Rahimzadeh Arashloo and Josef Kittler (2013) proposedan efficient processing of MRFs for face recognition. This paper addresses a problem of pose invariant recognition of faces via an MRF matching model. Pose invariance is achievedvia dense matching of images while illustration invariant representation adopted minimizes the unwanted effects of illumination changes.

It focus on parallel processing algorithms and show how an optimization problem for image matching can be reformulated to be solved via the well-known dual decomposition approach. Further speed ups are achieved by adopting a multi resolution approach based on the re normalization group theory. The multi resolution LBP histogram were used to capture discriminative texture content of the image in different scales.

Face Detection and Featureextraction

Face Detection: Face detection is the process by which we determine where in the input image we have the faces available. We propose using Viola Jones algorithm for its efficiency over other face detection algorithms.

Pre-Processing: Pre-processing is done on all images to make it compatible for further processing. It usually evolves three processes. First, the process is to re-size the image in terms of fixed number of pixels. Next to reduce the noise in the image by using various filters. Then the mandatory one is to convert the whole image to gray-scale from any colour pattern. This reduces the complexity of the process in the further steps.

Viola Jones Algorithm: The whole process is about training the data set of how a face would be. We train the data set by providing like 1000 faces and non-faces and referring how the features in a face are. These features are stored in a file and later checked and applied to the image to defect face.

Here features which are used on the image are more or less similar to convolution kernels. Each feature results in a single value which is calculated by subtracting the sum of pixels under white rectangle from the sum of pixels under black rectangle. We continue by increasing the size of the features over the image calculating up to 160000 + features. It is very difficult to process almost 160000+ features from the image. Hence we use Adaboost algorithm to bring down the count to almost 7000 features by removing all the redundant unwanted features. Then we adopt cascading method to classify the gathered features into many classifiers. This proves as an advantage when the classifier's features do not match with the trained data set can be eliminated without further processing. Thus VIOLA-JONES algorithm is used for FACE DETECTION.

Feature Extraction: When the input data to an algorithm is too large to be process and it is suspected to be redundant. Then it can be transformed into reduced set of features. For this purpose we can use as the Gradient Boost Algorithm. This algorithm leans the features sequentially and it predicts the size of the features.

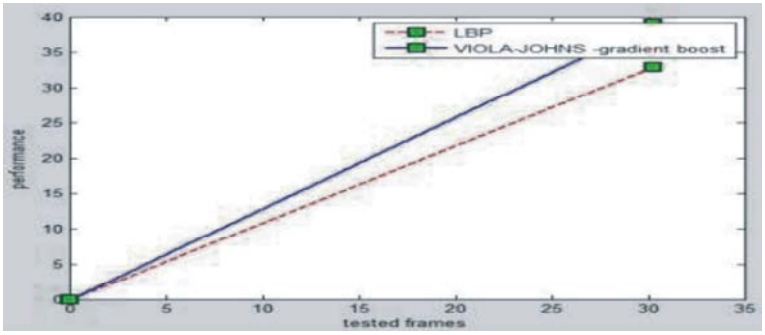

Fig. 2: Accuracy Graph

If the features are too large, it uses the Regularization. Fittings the training set too closely can lead to degradation. So the regularization reduces this over fitting effect. It takes the parameter is M. Increasing M reduces the error on training set, but setting it too high may lead to over fitting. An optimal value of M is often selected by monitoring prediction error on a separate validation data set. Thus GRADIENT BOOST ALGORITHM is used for FEATURE EXTRACTION.

Correlation Matching: Template is a small image in which it is used to find the image from source image. Here Template image size is 53*48 and source image size is 177 * 236. We can assume that the Template image is inside the source image. The template matcher object locates a template in an image. The object centers the location slightly different for template with an odd or even number of pixels. The object computes the location by shifting the template in single pixel increments throughout the interior of the image.

Support Vector Machines: In machine learning, support vector machines is a non-linear supervised learning models which is often reported as producing superior classification results compared to other methods, The idea behind the method is to non-linearly map the input data to some high dimensional space , separated , thus providing great classification (or regression)performance. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. When data are not labeled, a supervised learning is not possible and an unsupervised learning is required, that would find natural clustering of the data to groups and map new data to these formed groups. A support vector machine can be used for classification, regression or other tasks.

Experimental Results and Analysis: We can use various databases available in the internet to test the system. Experimental results have proved that face detection done using Viola Jones algorithm that gives 97% success rate in themost time consumed process. This is shown in the below graph.

Output Screen:

Fig. 3: Faces are being detected in the frame by using viola-jones algorithm. The red color square indicates the faces that are being detected

CONCLUSION

Thus we have discussed how the whole process of face recognition takes place by adopting unsupervised feature learning process that performs well even in unconstrained environments with higher accuracy in the least time that can be used in various authentication and security systems.

REFERENCES

1. Arashloo, S.R. and J. Kittler, 2013. Efficient processing of MRFs for unconstrained-pose face recognition, □ in Proc. IEEE 6th Int. Conf. BTAS, pp: 1-8.

2. Chai, Z., Z. Sun, H. Méndez-Vázquez, R. He and T. Tan, 2014. Gabor ordinal measures for face recognition, IEEE Trans. Inf. Forensics Security, 9(1): 14-26.
3. Deng, W., Y. Liu, J. Hu and J. Guo, 2012. The small sample size problem of ICA: A comparative study and analysis, □ Pattern Recognit., 45(12): 4438–4450.
4. Gui, J., W. Jia, L. Zhu, S.L. Wang and D.S. Huang, 2010. Localitypreservingdiscriminant projections for face and palmprint recognition?, Neurocomputing, 73(13-15): 2696-2707.
5. Gui, J., Z. Sun, W. Jia, R. Hu, Y. Lei and S. Ji, 2012. Discriminant sparse neighborhood preserving embedding for face recognition, Pattern Recognit., 45(8): 2884-2893.
6. Hinton, G., S. Osindero and Y. The, 2006. A fast learning algorithm fordeep belief nets, Neural Comput., 18(7): 1527-1554.
7. Le, Q.V., W.Y. Zou, S.Y. Yeung and A.Y. Ng, 2011. Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis, in Proc. IEEE CVPR, pp: 3361-3368.
8. Maturana, D., D. Mery and A. Soto, 2011. Learning discriminative local binary patterns for face recognition, in Proc. IEEE Int. Conf. FG, pp: 470-475.
9. Méndez-Vázquez, H., Y. Martinez-Diaz and Z. Chai, 2013. Volume structured ordinal features with background similarity measure for video face recognition, in Proc. ICB, pp: 1-6.