

Modular Face Recognition: A Customizable System

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Abstract: Facial Recognition is an emerging topic and has been in discussion for a long time now. It has much application in use and even more to be discovered. We propose a system where Machine Learning is used on stored extracted facial features and classifies test data into recognized classes. This requires detection of a face, normalization of detected faces, extraction of features, training on extracted features and classification as subtasks. The end result of this project is a modular and robust face recognition system, with multiple detectors, extractors, and classifiers to choose from. We are using a subset of CalTech dataset of facial images. We will be recording our results with some of the possible combinations and develop a real-time application as proof of concept.

I. INTRODUCTION

Face recognition is branch of computer vision in which faces are identified and associated with people, it has many useful applications, some including its use by Police departments in various cities of United States, Australian and Canadian Emigration departments at airports and most recently announced as a security measure against information leakage of ADHAR by government of India. A lot of applications emerged in various fields like Biometrics, Access Control, Security, Surveillance etc., this technology has evolved from laboratory experiments to various commercial applications [1]. Machine Learning is a branch of Artificial Intelligence which deals with modeling of the learning process in computers, primarily focusing on task-oriented studies, cognitive simulations and theoretical analysis[2]. It is one of the most challenging and fascinating jobs in Artificial intelligence. A machine learning can be categorized as supervised learning or unsupervised learning, regression and classification are problems under supervised learning while clustering comes under unsupervised learning. Detection of face refers to the localization of face in input frame of live feed or probe image, this tells the position of the face where the focus is needed to extract features and classify. Detection of the face might require some kind of preprocessing in accordance with the detector in use. Extraction of features is mining of useful information which will come handy when classifying. Classification requires the extracted information to train the classifier and then to make predictions using the trained model. Freedom of component selection creates ease of customizing the system and makes it more suitable for specific application for which the system is being designed. It also provides choice rather than a fixed path which enables to keep required and important pieces and discard unnecessary parts. It also helps in satisfying performance constraints as resource hungry components can be replaced with lighter counterparts. We will be using packages like Open CV and Scikit-learn for reducing the time involved in building these components.

Revised Manuscript Received on March 25, 2019.

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II. RELATED WORKS

Many traditional approaches have been successful in recognizing faces, one of these is Eigenfaces which was introduced in 1991. In this approach, information is encoded as Eigenfaces for each face and then compared with a database of models encoded similarly[3]. Another such approach is with using Fisherfaces, which is less sensitive towards variations in lighting and expression. Like Eigenfaces it also projects image space to low dimensional feature space but uses Fisher Linear Discriminant instead of Principal Components Analysis[4]. A recent approach uses Linear Binary Pattern texture features as facial representation to be used as the facial descriptor, it performs better than previously introduced holistic methods[5]. All 3 of these are readily available for use in Open CV[6]. Detection of the face is a crucial step in face recognition, it gives the local positioning of the face in an image under consideration, there have been a lot of work done in this field. One of the early examples is Viola-Jones framework for face detection, which is a frontal face detection system, faster than any of its predecessors[7]. Another example of face detection is Haar Cascade Classifiers. These features use change in contrast values among pixel groups, groups with contrast variance forms Haar-like features which are used to detect object[8]. Recently a face detection approach with Linear Binary Patterns was also introduced, facial representations were composed of micropatterns effectively detected by LBP operator and trained over a weak Gentle AdaBoost classifier[9]. Feature extraction or template formation is the next step after detection, both have their benefits. Feature extraction takes less computation and storage resources, while templates are more superior in giving results[10]. Classification is the last step, a well-trained classifier will be more accurate while making predictions. There are a number of classifiers available which use different technologies including, but not limited to artificial neural networks, support vector machines, convolutional neural networks, deep learning and tree classifiers. Ham, Lee, and Park introduced an Artificial Neural Network Architecture in their work for classifying faces[11]. They used supervised learning and backpropagation over a three-layer artificial neural network. Recently a hybrid of AdaBoost and Artificial neural networks along with active shape model and multilayer perceptron was introduced[12]. An online face recognition system was proposed which utilizes Support Vector Machines for classification, it also examines Radial Basis Function, kernel function[13]. Applications of face recognition are emerging and solving challenges in many fields. A system was simulated to help visually impaired people in identifying family and friends using Principal Component Analysis and Hidden Markov Models[14]. A system was proposed to use facial recognition to assist law enforcement agencies in identifying suspects and missing people in sensitive scenarios[16]. In our system, we will be using some of these discussed approaches along with some novel and other techniques.

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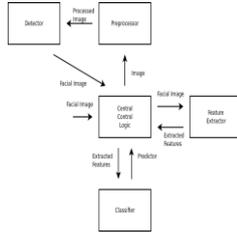


Illustration : Architecture of the system.

III. METHODOLOGY

In our system, we divided the process of face recognition into three tasks in a pipeline. The first task of these three is detection, we created a detector using Haar Cascade Classifier[8]. At this step, we gave input image from our dataset. Preprocessing was also done at this step. The second task is to extract features from detected face. We have created a series of extractors for fulfilling this purpose. We used Linear Binary Pattern[5], Grey Level Co-occurrence Matrix and a bunch of novel methods, results are discussed in later topics.

The third task is to train a classification model so that it can classify and recognize people. We used tree-based algorithms and Support Vector Machines[13] for this purpose. We also incorporated neural network based algorithms at this stage, results will be discussed in a later section. For above pipeline, different components were created serving their specific roles as detectors, feature extractors, and classifiers. For the pipeline to work at least one component is needed for each of these. We used these components in different combinations to make up our system.



MODULES

A. Detectors

Haars Cascade Classifier is one detector which we used. It works on Haar-like features, which uses change in contrast values in groups of pixels. These features are calculated from integral images, which are an intermediate representation of the actual image. Features defining the object are used to detect it. Cascading allows only sub-images with the highest probability of containing an object for analysis[8].

B. Feature Extractors

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Local Binary Pattern operator is a texture descriptor. It labels the pixel under consideration in accordance with the pixel in its neighborhood. The facial image is divided into local regions to extract texture information. Descriptors are then concatenated to

form description of the face[5] Gray Level Co-occurrence Matrix features are a set of features extracted from Gray Level Co-occurrence Matrix of an image, there are 14 such features which can be extracted among which most widely used are Contrast, Energy, and Entropy[16].

Harris Corner Detector is an interest point detector based on local auto-correlation[17]. We used Harris corner detector in combination with other feature extractors to explore new features.

C. Classifiers

Support Vector Machines are supervised learning models for classifying data. The effectiveness of an SVM model depends on kernel an kernel parameters[13].

A decision tree is another classification algorithm, based on multistage approach. Complex decisions are broken into a union of many simple decisions[18].

IV. EXPERIMENTAL RESULTS

We worked on a subset of CalTech dataset of facial images. These images were manually labeled to classes for supervised learning. We selected 5 classes with each having minimum of 18 images. All the images were distinct with variations in illumination, expressions, and background. We performed tests on different combinations of components and observed results. Our detector was a Haars Cascade Classifier for frontal face, We had 4 extractors naming Local Binary Pattern, Grey Level Co-occurrence Matrix features and Grey Level Co-occurrence matrix features at Harris Corners. We used two classifiers, a Support Vector Machine classifier, and a Decision Tree classifier

Algorithm\Classifier	SVM	Decision Tree
LBP	66.25	71.42
GLCM	63.33	91.08
GLCMHIP	70.20	69.18

Illustration : Comparing results of classifiers on with different extractors.

Apart from these extractors, we also experimented with some more along with Artificial Neural Networks. The results were extremely unsatisfactory and have not been included. Reason for this is to be explored.

V. CONCLUSION AND FUTURE WORKS

A modular facial recognition system was successfully built with acceptable accuracy. The system had 3 different extractors, 2 distinct classifiers and 1 detector with room for more. More components can be created and added to this system. As for future work, we will be adding more detectors and extractors as components. Failure of the system to comply with neural networks will be explored. We will also work out with Deep Learning and Convolutional Neural Networks for a complex system which could work better.



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