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Effective Face Detection Using DCT (Discrete Cosine Transform) Algorithm through Block Weighting Scheme

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Abstract:
Face recognition has become one of the most addressed pattern recognition problems due to its importance as a natural biometric trait and due to its role in human computer interfaces.
Face detection has wide range of applications such as automatic face recognition, human- machine interactions, surveillance, etc. In recent years there has been substantial progress on detection schemes based on appearances of faces. Holistic approaches have been dominating the face recognition research since the beginning of 1990s. On the other hand , recently, local appearance based face recognition approaches have attracted a growing interest. In salient local regions, such as the eye regions, are used to perform modular eigen-faces based face recognition.
In recent face recognition system, the face or image is considered as block of rectangular images. HaZlln Kemal Ekene1(2009), in his paper on "Block Selection in the Local Appearance-based Face Recognition Scheme, describes that the face image is divided . into rectangular smaller sub-images without considering any specific regions, and the eigen-faces approach is then performed on each of these sub-images. The local facial regions are located by a Support Vector Machine (SVM) and the combined local features are classified again with SVM. The face image is partitioned into several local regions and each local region is represented by Linear Discriminant Analysis (LOA). To combine the features extracted from each local region, another LOA is used. Along with these two techniques Discrete Cosine Transform(DCT) is also used. OCT plays the main role for face detection in this dissertation. DCT is combined with a Block Weighting Scheme. The Block Weighting Scheme measures the contribution of each block in a face image.
The basic idea is: clean blocks should impact the result more than the occluded one. For each block in one image, the probability of the block belonging to each class, rather than the classification result is computed. These probabilities are combined to obtain classification result for the whole image.

Keywords : DCT(Discrete Cosine Transform), SVM(Support Vector Machine), LBP(Local Binary Pattern), MATLAB(MATrix LABoratory).

Introduction

Face recognition is a very challenging computer vision and pattern recognition problem. Facial appearance can undergo severe variations due to changes in facial expression, illumination, occlusion, head pose, and aging. In fact, facial appearance variations caused by these factors often dominate the one caused by identity differences. Another important factor that causes difficulty in face recognition is face alignment. In order to have a proper comparison between face images, they need to be aligned precisely. This requires, in turn, precise facial feature localization, which is a challenging task. A wide range of potential applications have motivated extensive research efforts on face recognition. Many algorithms have been developed that aim at handling a single factor or combination of two factors that cause facial appearance variations.

Especially handling illumination changes has been one of the main points of interest. All these algorithms are only evaluated against the facial appearance variations that they are developed for. For example, the algorithms that are developed to handle illumination • variations are tested on data sets that contain only illumination. variations. As a result, there exist many face databases that have been collected mainly under controlled settings and that contain facial appearance variations caused by a single factor or a combination of two factors.

Keeping these facts in mind, this paper aims at developing a novel, generic face recognition algorithm appropriately modifying Discrete Cosine Transform (DCT) using Block Selection Method in which the contribution of each block will be calculated using a weighting scheme.

Block Selection Method

A generic face representation approach is introduced as a baseline for local appearance based face recognition. Discrete Cosine Transform (DCT) is utilized for representing the local regions. The input face image is partitioned into 8x8 pixel blocks, and on each block OCT is performed. The most relevant DCT features are extracted using the zigzag scan and the obtained features are fused either at the feature level or at the decision level for face recognition. The Discrete Cosine Transform (OCT) is used to represent local regions. There are several advantages of using the DCT. Its data independent bases make it very practical to use. There is no need to prepare a representative set of training data to compute a subspace. In addition, it provides frequency information, which is very useful for handling changes in facial appearance. For instance, it is known that some frequency bands are good for combating against illumination variations. Moreover, it has been found that the DCT-based local appearance representation is better than representations based on the Karhunen-Loeve ; Fourier, wavelet, and Walsh-Hadamard transforms in terms of face recognition performance .

Face Recognition Challenges

Illumination

In, "A Robust Face Recognition Algorithm for Real-World Applications", by, Hazim Kemal Ekenel(2009), one of the most addressed problems in face recognition is illumination variations. It has attracted significant attention during the last decade and there have been many solutions proposed for this problem.

These solutions can be classified as: invariant features, canonical forms, and variation modelling. In the first approach, features insensitive to illumination variations are searched for. The second approach tries to remove the illumination variation either by an image transformation or by synthesizing a new image. Finally in the third approach, illumination variation is learned and modelled in a suitable subspace.

Invariant Features

In the paper, 'A Robust Face Recognition Algorithm for Real-World Applications', by Hazim Kemal Ekenel(2009), different face representation approaches, such as edge maps, Gabor like functions, derivatives of the gray-level, and log transformations , are evaluated under lighting direction changes. In total, 107 different operators are tested, but none of them provided insensitiveness against illumination. In this study, it is concluded that the variance in appearance of one person under different lighting conditions, the inner class variance, can be

greater than the variance in appearance of different persons under the same lighting • condition, the inter class variance.

Canonical Forms

In the paper, 'A Robust Face Recognition Algorithm for Real-World Applications ', by Hazim Kemal Ekenel(2009) , the face shape is extracted from a single image using a statistical shape- from shading model in [SKOl]. After extracting the face shape, new face image samples are synthesized under different illumination conditions. In [SRRO l], the quotient image method is introduced. In this method, first •an illumination invariant signature image is obtained. Afterwards, using this image, face images with varying illumination are generated. A face normalization algorithm that transforms the lighting of one face image to that of another face image is presented. The logarithmic total variation model is proposed in. Illumination invariant facial structure is obtained from a single face image with this model

Variation Modelling

The illumination cones method is introduced in [GBKOl], in which facial appearance variations caused by different illumination conditions are modelled using a small set of face images taken under different lighting directions. The tensor faces approach is presented in. In • contrast to Eigen faces [TP91], i n which only the space of face images is spanned, in this method, multi-linear analysis is used to decompose the facial image data tensor into five different matrices , in addition to face images, the space of people parameters, viewpoint parameters, illumination parameters, and expression parameters . Light-fields theory is utilized and used in a linear discriminant analysis framework in.

Occlusion

In the paper, 'A Robust Face Recognition Algorithm for Real-World Applications', by, Hazim Kemal Ekenel(2009), partial face occlusion is one of the most challenging problems in face recognition. In this section, related work about this topic will be briefly presented . In [Mar02], face images are analysed locally in order to handle partial face occlusion. The face image is first divided into 'k' local regions and for each region an eigen-space is constructed. Ifa region is occluded, it is automatically detected. Moreover, weighting of the local regions is also proposed in order to provide robustness against expression variations. A similar approach is presented, where a Self-Organizing Map (SOM) is used to model the subspace instead of Gaussians or mixtures of Gaussians as in [Mar02]. _A face is represented by the face Attributed Relational Graph (ARG) structure. This representation contains a set of nodes • and binary relations between these nodes. In testing, first the correspondences between the ARG representations of the training and testing samples are established. According to the distance between these representations, the classification is performed. In [FSL06], robustness against occlusion is provided by combining the subspace methods that aim at best reconstruction, such as principal component analysis, with the subspace methods that aim at discrimination, such as linear discriminant analysis. The occlusion problem is handled as a reconstruction problem and the classification is done according to the obtained reconstruction error on a test image. A common point of the studies listed in this section is the use of the AR face database [MB98] for the face recognition experiments.

Face Recognition Algorithms

Viola Jones Face Detection Algorithm

The Viola-Jones object detection framework is the first object detection framework to provide competitive object detection rates in real-time proposed in 2001 by Paul Viola and Michael Jones, Even though it can be trained to detect a variety of object classes, it was motivated mainly by the problem of face detection. This face detection framework is capable of processing images extremely rapidly while achieving high detection rates.

Advantages:

- It is the most admired algorithms for face detection in real time.

- The main advantage of this approach is uncompetitive detection speed while relatively high detection accuracy, comparable to much slower algorithms.
- High accuracy. Viola Jones gives accurate face detection.

Disadvantages:

- Extremely long training time.
- Limited head poses.
- Not detect black Faces.

Local Binary Pattern (LBP)

The local binary pattern (LBP) technique is very effective to describe the image texture features. LBP has advantages such as high-speed computation and rotation invariance, which facilitates the broad usage in the fields of image retrieval , texture examination, face recognition, image segmentation, etc. Recentl y, LBP was successfully applied to the detection of moving objects via background subtraction. In LBP, every pixel is assigned a texture value, which can be naturally combined with target for tracking the1mo graphic and monochromatic video. The major uniform LBP patterns are used to recognize the key points in the target region and then form a mask for joint color-texture feature selection.

Advantages:

- Effective to describe image texture Feature.
- Used in Texture analysis, Image Retrievals, face recognition and Image segmentation. Detection of moving object via Background Subtraction. It is a Simple Approach.
- Computationally simple than Haar Like feature and fast.
- The most vital properties of LBP features are tolerance against the monotonic illumination changes and computational simplicity.

Disadvantages:

- Proposed method is not sensitive to small changes in the Face Localization.
- Using larger local regions increases the errors.
- It is insufficient for non-monotonic illumination changes.
- Not accurate.: Only used for binary and grey images

Ada-Boost Algorithm

Boosting is an approach to machine learning based on the idea of creating a highly accurate prediction rule by combining many relatively weak and incorrect rules. The Ada-Boost algorithm was the first practical boosting algorithm, and one of the most widely used and studied, with applications in numerous field. Using boosting algorithm to train a classifier which is capable of processing images rapidly while having high detection rates. Ada-Boost is a learning algorithm which produces a strong classifier by choosing visual features in a family of simple classifiers and combining them linearly.

Advantages:

- No a prior knowledge: Ada-Boost is an algorithm which only needs two inputs: a training dataset and a set of features (classification functions). There is no need to have any a priori knowledge about face structure.

- Adaptive algorithm: At each stage of the learning, the positive and negative examples are tested by the current classifier. If an example is misclassified, i.e. it cannot clearly be assign in the good class. In order to increase the discriminant power of the classifier these misclassified examples are up-weighted for the next algorithm iterations.

Disadvantages:

- The result depends on the data and weak classifiers.

- The quality of the final detection depends highly on the consistence of the training set. Both the size of the sets and the interclass variability are important factors to take in account.

- Quite slow training: At each iteration step, the algorithm tests all the features on all the examples which requires a computation time directly proportional to the size of the features and examples sets.

Discrete Cosine Transform Algorithm

Discrete Cosine Transform (DCT) is a well-known signal analysis tool used especially in compression standards due to its compact representation power. It's known that Karhunen- Loeve Transform (KLT) is the optimal transform in terms of information packing, however, its data dependent nature makes it infeasible to implement in some practical tasks. Moreover, • DCT closely approximates the compact representation ability of the KLT, which makes it a very useful tool for signal representation both in terms of information packing and in terms of computational complexity due to its data independent nature.

The obtained DCT basis functions for N = 4 are illustrated in Figure I (each base is scaled separately for illustration purposes). As one can notice from the top-left part of the basis functions and also from Eq. I , the (0,0) component represents the average intensity value of the image, which can be directly affected by illumination variations.

Block Weighting Schemes

According to Berkay Topcu and Hakan Erdogar, in their paper 'Decision Fusion for Patch- Based Face Recognition' Block Weighting Schemes are divided into following :

- Fisher Weighting

- Support Vector Machine(SVM) Weighting

- Validation Accuracy Weighting(VAW) These have been. discussed briefly below:

Fisher Weighting

The first weighting scheme, which we name as Fisher Weighting, depends on the posterior probability distribution of true and false labels. In this method, for a single sample in the validation dataset, class posterior probabilities are calculated and posterior probability of the true class (let's say true class is i) at each block, (p(Cijxb)), (16xl vector) is labeled as positive score. For a sample x in the validation data, positive score vector is shown as:

PS = [p(Ci|x1) p(Ci|x2) … p(Ci|xB)].

Support Vector Machine(SVM) Weighting

This weighting scheme has the same motivation as Fisher weighting, however, instead of employing LOA on score vectors, a linear support vector machine (SVM) is used for classifying positive and negative scores. This also yields a set of weights that can be used as weights in the weighted sum rule.

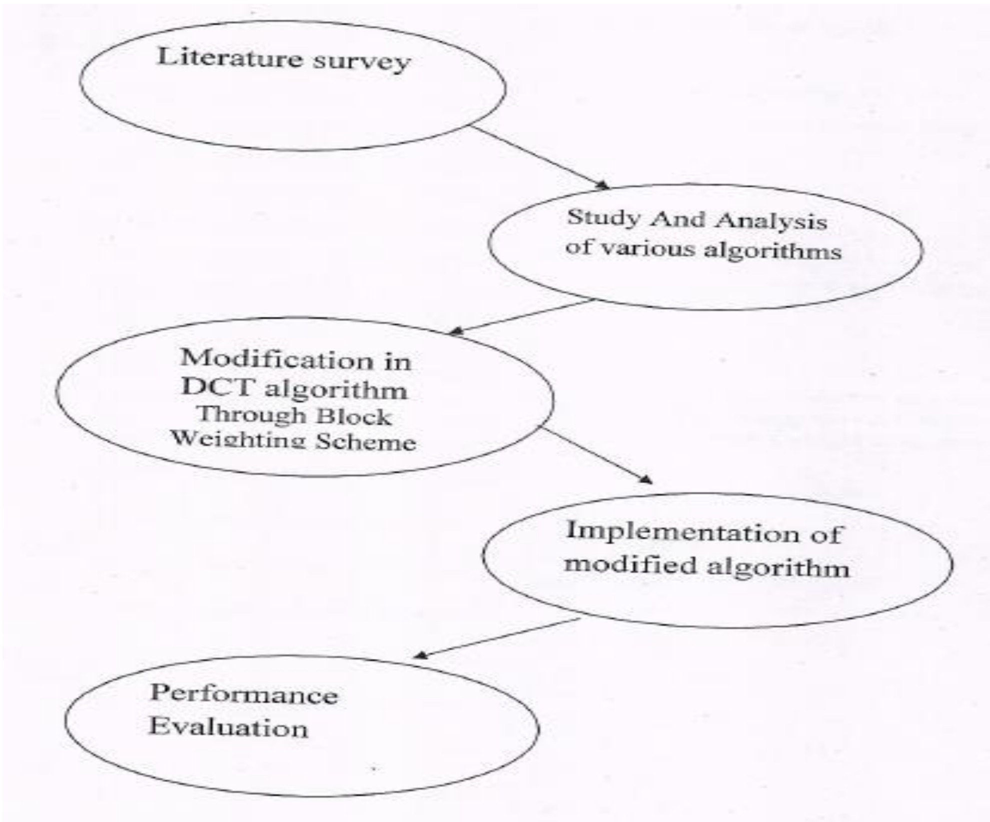
Validation Accuracy Weighting(VAW)

Another weighting scheme, which we name as Validation Accuracy, depends on individual recognition rates of each block on validation data. Using training data, a single classifier is trained for each block and each block of a sample in the validation data is classified using the classifier that corresponds to the block of interest. Individual block recognition rates for all samples in the validation data are acquired separately and weights are assigned proportional to the recognition accuracy of each block. If acc(k) denotes the recognition accuracy for the 'kth' block, weight of the 'bth' block is given as:

$$w_b = \frac{\mathrm{acc}(b)}{\sum_{k=1}^{B} \mathrm{acc}(k)}.$$

Through Block Weighting Scheme a framework is proposed for robust face recognition, which utilizes the location of local feature points to align the face images in different posses.

Proposed Work



Discrete Cosine Transform

For effective face detection each facial image is divided into a number of small area consisting of a few pixels. These areas are called Blocks. What we propose to do here is find the contribution of every single block in face detection and then by modifying each block 's weight to increase its contribution in face detection.

As one can observe, the coefficients that account for a greater degree of the representation capability are located at the top-left block of the matrix . To construct the feature vector from the 2D DCT coefficients, the coefficients are ordered using the zig-zag scanning pattern (see Figure 3.4). In this way, the coefficients containing the most information are preserved when the vector is truncated.

Block Weighting Schemes

The plan is to propose a weighing scheme for appropriately modifying the either of the three Block Weighting Schemes for effective face recognition:

- Fisher Weighting
- Support Vector Machine(SVM) Weighting
- Validation Accuracy Weighting(VAW)

Matlab Technology

MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and fourth-generation programming language. A proprietary programming language developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, C#, Java, Fortran and Python.

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing abilities. An additional package, Simulink, adds graphical multi-domain simulation and model-based design for dynamic and embedded systems

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