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Non-Uniform Motion Blur Descriptor with Applications to Face Recognition

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Abstract:

We provide a new framework in the face recognition System by the use of (ASM) Active Shape model. Initially we detect the face from the image. After that we extract the LBP feature. It is used to find the texture feature for the face image. The LBP operator assigned a label to every pixel of a gray level image. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors of the pixel. Active shape models (ASMs) are statistical model of the shape of objects which iteratively deform to fit to an example of the object in a new image. The shapes are constrained by the PDM (Point Distribution Model) Statistical Shape Model to vary only in ways seen in a training set of labeled examples. To locate a better position for each point one can look for strong edges, or a match to a statistical model of what is expected at the point. Then weighted matching will be applied between the input image and database images.

1.Introduction:

Face recognition is one of the major issues in biometric technology. It identifies and/or verifies a person by using 2D/3D physical characteristics of the face images. The baseline method of face recognition system is the eigen face by which the goal of the eigen face method is to project linearly the image space onto the feature space which has less dimensionality. One can reconstruct a face image by using only a few eigenvectors which correspond to the largest eigen values, known as eigen picture, eigen face, Karhunen-Loeve transform and principal component analysis ,Several techniques have been proposed for solving a major problem in face recognition such as fisher face , elastic bunch graph matching and support vector machine. However, there are still many challenge problems in face recognition system such as facial expressions, pose variations, occlusion and illumination change. Those variations dramatically degrade the performance of face recognition system. It is evident that illumination variation is the most impact of the changes in appearance of the face images because of its fluctuation by increasing or decreasing the intensities of face images due to shadow cast given by different light source direction. Therefore the one of key success is to increase the robustness of face representation against these variations.

In order to reduce the illumination variation, many literatures have been proposed. Belhumeur et. al.suggested that discarding the three most significant principal components can reduce the illumination variation in the face images. Nevertheless, the three most significant principal components not only contain illumination variations but also some useful information, therefore, the system was also degraded as well. Wang et. al. proposed a Self Quotient Image (SQI) by using only single image. The SQI was obtained by using the weighted Gaussian function as a smoothing kernel function. The Total Variation Quotient Image (TVQI) and Logarithmic Quotient Image (LTV) have been proposed by which the face image was decomposed into a small scale (texture) and large scale (cartoon) images. The normalized image was obtained by dividing the original image with the large scale one. The TVQI and LTV has a very high

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computational complexity due to the second order cone programming as their kernel function.

However these methods are suitable only for illumination variation but not for other variations. Whereas the face representation based method has more robustness. It is not insensitive to illumination variation but insensitive to facial expression as well, such as Local Binary Pattern (LBP) and its extension .it was originally designed for texture description. The LBP operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each surrounding pixel with the center pixel value and a decimal representation is then obtained from the binary sequence (8 bits). The LBP image is subsequently divided into *R* nonoverlapping regions of same size and the local histogram over each regions are then calculated. finally the concatenated histogram can be obtained as a face descriptor.

In existing Different types of method are implemented. Face recognition (principal component analysis (PCA), LDA, ICA, and SVMs) to assess the feasibility of real world face recognition. One of the important technique of recognition is template matching in which a template to recognize is available and is compared with already stored template. In our approach PCA method for feature extraction and matching is used. Principal Component Analysis: PCA is used to reduce the dimensionality of the image while preserving much of the information. It is the powerful tool for analyzing the data by identifying patterns in the dataset and reduces the dimensions of the dataset such that maximum variance in the original data is visible in reduced data.

PCA was invented by Karl Pearson in 1901. It works by converting set of correlated variables to linearly uncorrelated variable called principal components. Principal components are calculated by computing Eigen vectors of covariance matrix obtained from the group of hand images. The highest M eigenvectors contains the maximum variance in the original data. These principal components are orthogonal to each other and the first component is in the direction of greatest variance.

We can use PCA to compute and study the Eigenvectors of the different pictures and then to express each image with its principal components [9] (Eigenvectors). It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. First of all, we had to create the data set. The aim is to choose a good number of pictures and a good resolution of these in order to have the best recognition with the smallest database. Then, the next step is to subtract the mean from each of the data dimensions. The mean subtracted is simply the average across each dimension. The step three is to calculate the covariance matrix of the database. We could not calculate the covariance matrix of the first matrix, because it was too huge. So we had to find a way to find out the principal eigenvectors without calculating the big covariance matrix. The method consists in choosing a new covariance matrix.

The PCA approach has 2 stages: Training and Testing stage. In the training stage the Eigen space in established using training images of hand gestures and these images are mapped to the Eigen space. In the testing stage the image to be tested is mapped to same Eigen space and is classified using distance classifier.

PROPOSED SYSTEM:

We provide a new framework in the face recognition System by the use of (ASM) Active Shape model. Initially we detect the face from the image. After that we extract the LBP feature. It is used to find the texture feature for the face image. The LBP operator assigned a label to every pixel of a gray level image. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors of the pixel. Active shape models (ASMs) are statistical model of the shape of objects which iteratively deform to fit to an example of the object in a new image. The shapes are constrained by the PDM (Point Distribution Model) Statistical Shape Model to vary only in ways seen in a training set of labeled

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examples. To locate a better position for each point one can look for strong edges, or a match to a statistical model of what is expected at the point. Then weighted matching will be applied between the input image and database images.

MODULES:

- Preprocessing
- Normalization
- Active shape model
- Feature Extraction
- Recognition

Module Description:

Preprocessing:

- In noise removal process, Initially we convert the image in gray. And then we filter the noise from the image.
- In Filtering we are applying Gaussian filtering to our input image.
- Gaussian filtering is often used to remove the noise from the image.
- Here we used wiener2 function to our input image
- **Gaussian filter** is windowed filter of linear class, by its nature is weighted mean.
- Named after famous scientist Carl Gauss because weights in the filter calculated according to Gaussian distribution.

Normalization:

- Normalization is a process that changes the range of pixel intensity values.
- Illumination changes caused by light sources at arbitrary positions and intensities contribute to a significant amount of variability.
- To address this issue, we present a new method for performing image normalization.
- The method used to remove shadows and specularities from images.
- All the shadowed regions are grayed out to a uniform color, eliminating soft shadows and specularities and hence creating an illumination invariant signature of the original image.

Active Shape model:

- Active shape models (ASMs) are statistical models of the shape of objects which iteratively deform to fit to an example of the object in a new image.
- The shapes are constrained by the PDM (point distribution model) Statistical shape model to vary only in ways seen in a training set of labelled examples. The shape of an object is represented by a set of points (controlled by the shape model).
- The ASM algorithm aims to match the model to a new image. It works by alternating the following steps:
- Look in the image around each point for a better position for that point.
- Update the model parameters to best match to these new found positions.

Feature Extraction:

Initially we separate the image as patches. For each patch of image we apply the LBP(Local Binary Pattern).

The LBP operator assigned a label to every pixel of a gray level image. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors of the pixel. If we set the gray level image is I, and Z0 is one pixel in this image. So we can define the operator as a function of Z0 and its neighbors, Z1, …, Z8. And it can be written as:

$$T = t\,(Z0, Z0\text{-}Z1, Z0\text{-}Z2, \ldots, Z0\text{-}Z8).$$

However, the LBP operator is not directly affected by the gray value of Z0, so we can redefine the function as following:

$$T \fallingdotseq t\,(Z0\text{-}Z1, Z0\text{-}Z2, \ldots, Z0\text{-}Z8).$$

To simplify the function and ignore the scaling of grey level, we use only the sign of each element instead of the exact value. So the operator function will become:

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T ≒ t (s(Z0-Z1), s(Z0-Z2), …, s(Z0-Z8)).
Where the s(.) is a binary function, defined as s(x) =1,x>=0; S(x) = 0,otherwise.

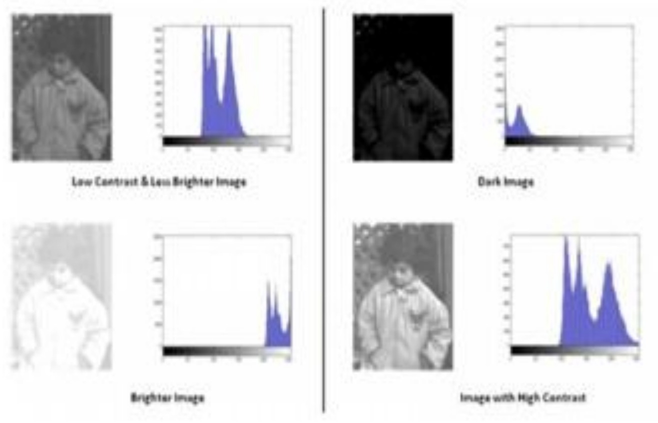


Figure 1 Different Types of Histogram Images with Different Contrasts

Adaptive Histogram Equalization

In Adaptive Histogram Equalization the image is divided into several rectangular domains, compute an equalizing histogram and modify levels so that they match across boundaries. Adaptive Histogram Equalization (AHE) computes the histogram of a local window centered at a given pixel to determine the mapping for that pixel, which provides a local contrast enhancement, Therefore regions occupying different gray scale ranges can be enhanced simultaneously. Figure 4.2 shows the effect of applying adaptive histogram equalization on a low contrast image. It is observed that adaptive histogram equalization is more suitable to bring out more detail.

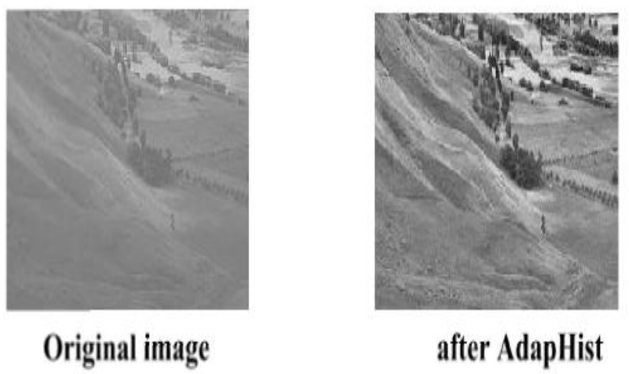


Figure 2 Effect of Adaptive Histogram Equalization

Obtain all the inputs: Image, Number of regions in row and column directions,Number of bins for the histograms used in building image transform function (dynamic range), Clip limit for contrast limiting (normalized from 0 to 1).

Pre-process the inputs: Determine real clip limit from the normalized value ifnecessary, pad the image before splitting it into regions.

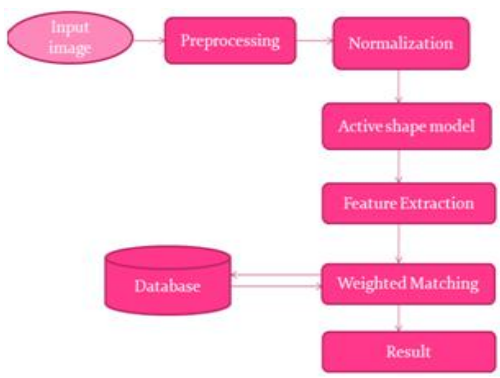
Process each contextual region (tile) thus producing gray level mappings: Extract a single image region, make a histogram for this region using the specified number of bins, clip the histogram using clip limit, and create a mapping (transformation function) for this region.

Interpolate gray level mappings in order to assemble final image, Extract cluster of four neighbouring mapping functions, process image region partly overlapping each of the mapping tiles, extract a single pixel, apply four mappings to that pixel, and interpolate between the results to obtain the output pixel; repeat over the entire image.

Recognition:

- Here the recognition process is identify by the weighted matching.
- The Euclidean distance is computed for the test feature with the database features.
- The similarity is identified between the features. Finally identified image is displayed.

System Architecture:



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Result

CONCLUSION

We proposed a methodology to perform face recognition under the combined effects of non-uniform blur, illumination, and pose. We showed that the set of all images obtained by non-uniformly blurring a given image using the TSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, we initially proposed a non-uniform motion blur-robust face recognition algorithm NU-MOB. We then showed that the set of all images obtained from a given image by non-uniform blurring and changes in illumination forms a bi-convex set, and used this result to develop our non-uniform motion blur and illumination-robust algorithmMOBIL. We then extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose. We established the superiority of this method called MOBILAP over contemporary techniques. Extensive experiments were given on synthetic as well as real face data. The limitation of our approach is that significant occlusions and large changes in facial expressions cannot be handled.

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