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Analysis of Wavelets, Brushlets and Beamlets for Feature Extraction in Face Recognition

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Abstract

Face Recognition is a very challenging area and has a wide range of applications in various fields such as video surveillance systems, crime informatics, etc. Feature extraction is the basic step in any face recognition system. It is required because the number of inputs or size of input may be too large and hence we extract only features of interest. Texture based feature extraction is preferred due to it's invariance to pose, light, reflection. Beamlets and Brushlets are used for feature extraction in Face Recognition. Beamlets follow a hierarchical approach. Brushlets use Windowed Fourier Transform to obtain local optimization. This local approach provides better accuracy than global methods. They are generally used in the field of image compression. Both provide better recognition rate than the commonly used wavelets.

Keywords: Beamlets, Beamlets dictionary, Beamlets pyramid, Beamlets graph, Brushlets, Feature Extraction, Fourier Transform, Wavelets

1. Introduction

A face recognition system is a computer application for automatically identifying a person from a digital image or video frame . One of the methods to do this is by comparing selected facial features from the image and a facial database. It is used in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems. Face recognition [1] is a very challenging area in computer vision and pattern recognition due to variations in facial expressions, poses, illumination. Face recognition is largely motivated by the need for access control, surveillance and security, telecommunication and digital library. Feature extraction[2] in face recognition refers to a special form of dimensionality reduction. When the input data for the algorithm is too large to be processed, then the input data is transformed into a reduced representation set of features. Transforming input data into a set of features is called feature extraction.

There are two kinds of features:

1. Domain specific features such as fingerprints, human face.

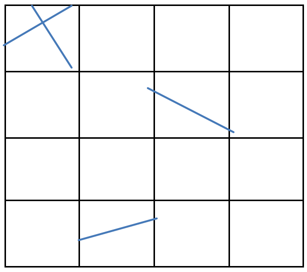
2. General features such as color, texture, shape.

Texture refers to the surface of an object. Texture can be rough, smooth, horizontal or vertical. They capture patterns in an image such as repetitiveness and granularity.

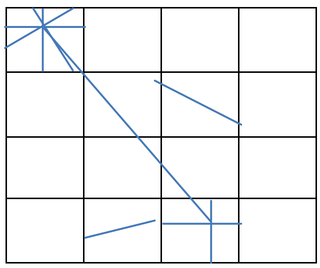
Texture based feature extraction[3] is preferred because it is pose-invariant, is not affected by light variations or illumination and hence gives more accuracy. Initially wavelets were preferred due to it's simultaneous localization in time and scale. This paper presents two techniques beamlets[4] and brushlets which are also used for feature extraction. Also the drawbacks of wavelets can be overcome by using one of these techniques. The data structure used for analyzing linear or curvilinear features in two-dimensional spaces is called beamlets. In this data structure,dyadically organized line segments are used for analysis ofmultiscale images. The key components of beamletsare beamlet dictionary , beamlet transform, beamlet pyramid, beamlet graph. There are two ways of analysis in beamlets; angular orientation and localization. This analysis is done in a hierarchical approach. The function or a toolused for directional image analysis and image compression is called brushlets[7]. It supports localization with only one peak in the frequency. Edges and texture based analysis in an image can be done at all possible locations, orientations and scales. Orthonormal or biorthogonalbrushlet bases can be considered.

Methodology for Beamlets

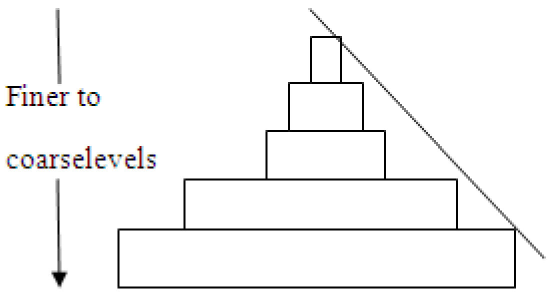
Step 1: Construct the beamletdictionary[4] which considers line segments with all possible orientations for the given test image. All possible orientations are computed and stored so that the corresponding value required can be obtained from this dictionary. A line segment can be treated as a connection between two points (x1,x2). Initially the image is divided into an arbitrary number of sub-blocks and each sub-block is of the same size to maintain uniformity. The number of sub-blocks is decided based on the accuracy level required and the application requirement. All possible orientations in each of the sub-block is computed and saved in the dictionary. Some possible orientations with 4 sub-blocks is shown below.



Step 2: Apply the beamlettransform[5],[6].
We consider three things for consideration to apply the beamlet transform,
(1) Collinearity- points or lines in the same plane
(2) Cocurvitiy-Two beamlets which belong to the same curve
(3) Simple connectivity- the second beamlet starts at the point where the first beamlet ends.

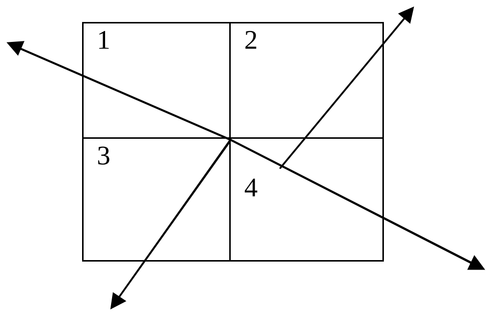


The above diagram illustrates how beamlets within different sub-blocks can be integrated. This is done by using continuous interpolation. By joining these line segments smoothly we can obtain an integrated line segment with all the points in the different sub-blocks. **Step 3:** Beamletpyramid[6] is constructed. Pyramid is a structure which grows to finer levels from the coarse levels at the bottom. Data at the coarse levels are derivable from finer levels. This pyramid contains the collection of all integrals obtained in step 2. These are multiscale features. Each continuous beamlet obtained in step 2 can be decomposed into atleast 3 finer beamlets.



Step 4: A beamlet graph is constructed(optional step). Here the nearest neighbor for a given point (x,y) is found and is connected to get a path. We use 4-neighbour graph here to obtain the cross connectivity of points. Always the neighbouring sub-blocks are examined to find the neighbours[21],[22]. Since we use line segments as parameters instead of points, they can be used to approximate curves smoothly and hence provide better performance. Global optimization can be achieved by utilizing the complete space of polygons in the given test image.

Methodology for Brushlets:
Step 1: The given image is first treated as a signal and it is divided into 'n' equally spaced intervals.
Step 2: Directional image analysis[7] can be done for feature extraction by applying selective orientation i.e by considering certain angular positions for the given test image.
Step 3: The given test image is divided into an arbitrary number of 'm' quadrants for local analysis of the image. Local approaches[8] provide better accuracy then global methods since we repeatedly apply the same procedure to each and every block of the image.
Suppose the given image is divided into 4 quadrants.
The orientations considered are :
$\pi/5 + k\pi/2$ where k=0,1,2,3
The above procedure can be pictorially illustrated as shown below:



The quadrant 1 denotes an angle of 35 degrees, quadrant 2 denotes 35+90=125 degrees, quadrant 3 denotes 35+180=215 degrees and quadrant 4 denotes 35 +270=305 degrees.
By changing the orientations we can obtain different directions for the same image. Hence used for directional image analysis. Folding operation can be done to interchange the adjacent quadrants so that 2 different orientations can be obtained by computing a single direction for a particular quadrant[23],[24]. Later unfolding can be done to restore the original orientation. Folding can be done horizontally or vertically.
Step 4: We repeat step 3 iteratively to divide into sub quadrants to obtain finer resolution. The quadrants in the outer region denote high frequency textures.
Step 5: Windowed Fourier Transform[9] is used. Bump function is used to select an appropriate window size for the Transform. Fourier Transform is applied to each quadrant locally. Then cumulatively summed to obtain the Transform for the complete image.
Step 6: Only imaginary parts(not the real parts) are considered since they are anti-symmetric with respect to the origin.
Step 7: The brushletcoefficient[10],[28] obtained are finally placed in the increasing order of their frequency. The coefficients obtained indicate the intensity of the brushlet strokes at different locations in an image.

Comparison of Beamlets and Brushlets with respect to Wavelets

Wavelets and Brushletsconsiders points in the image whereas Beamlets considers line segments for feature extraction. Wavelets cannot handle curves whereas Beamlets[25] can be used to approximate line segments to obtain smooth curves. Wavelets consider time and scale ,Beamlets consider orientation and location, Brushlets consider orientations and frequency and locations.Wavelets use Discrete Fourier Transform, Beamlets uses Beamlet Transform[29], Brushlets uses Windowed Fourier Transform. There is no unique frequency in wavelets but there is a well defined single peak for localization and hence Brushlets provide more recognition rate than wavelets.

Applications

Beamlets are used in Image analysis [11], image classification [12], detection and extraction of lines, curves & objects in a noisy image [13].

Brushlets are used for image compression along with image analysis [14].

Conclusion and Future Work:

This paper focuses mainly on the methodology used for feature extraction of images using Beamlets and Brushlets. The step by step approach is clearly indicated. A comparison of both the techniques with respect to wavelets is also done. The drawbacks of wavelets are overcome using the above techniques. The methodology is illustrated pictorially for certain selective angular orientations.

The future work includes on making a decision on which orientation is the best suited and provides maximized recognition rate.

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