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Aristotle University of Thessaloniki

School of Electrical and Computer Engineering

Department of Electronics and Computer Engineering

Feature Extraction

Nikolaos G. Giakoumoglou

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Abstract

The first step for every machine learning algorithm in a computer vision problem is to extract features from the given images. Feature extraction is a critical step in any pattern classification system. In order for the pattern recognition process to be tractable, it is necessary to convert patterns into features, which are condensed representations of the patterns, containing only salient information. Features contain the characteristics of a pattern in a comparable form making the pattern classification possible.

Feature extraction can be accomplished manually or automatically. Manual feature extraction requires identifying and describing the features that are relevant for a given problem and implementing a way to extract those features. In many situations, having a good understanding of the background or domain can help make informed decisions as to which features could be useful. Over decades of research, engineers and scientists have developed feature extraction methods for images.

The features presented in here are:

* Textural Features
* Morphological Features
* Histogram based Features
* Multi-scale Features
* Moments

Table of Contents

[Copyright 1](#_Toc84534909)

[Abstract 2](#_Toc84534910)

[Table of Contents 3](#_Toc84534911)

[List of Figures 5](#_Toc84534912)

[List of Tables 6](#_Toc84534913)

[Chapter 1: Textural Features 1](#_Toc84534914)

[1.1 First-order statistics (FOS) or Statistical Features (SF) 1](#_Toc84534915)

[1.2 Gray Level Co-occurrence Matrix (GLCM) or Spatial Gray Level Dependence Matrix (SGLDM) 2](#_Toc84534916)

[1.3 Gray Level Difference Statistics (GLDS) 6](#_Toc84534917)

[1.4 Neighbourhood Gray Tone Difference Matrix (NGTDM) method 7](#_Toc84534918)

[1.5 Statistical Feature Matrix (SFM) 8](#_Toc84534919)

[1.6 Law’s Texture Energy (LTE) Method (TEM) 9](#_Toc84534920)

[1.7 Fractal Dimension Texture Analysis (FDTA) 11](#_Toc84534921)

[1.8 Gray Level Run Length Matrix (GLRLM) 12](#_Toc84534922)

[1.9 Fourier Power Spectrum (FPS) 14](#_Toc84534923)

[1.10 Shape parameters 15](#_Toc84534924)

[1.11 High Order Spectra (HOS) on Radon Transform 16](#_Toc84534925)

[1.12 Local Binary Pattern (LPB) 17](#_Toc84534926)

[1.13 Gray Level Size Zone Matrix (GLSZM) 17](#_Toc84534927)

[Chapter 2: Morphological Features 21](#_Toc84534928)

[2.1 Multilevel Binary Morphological Analysis 21](#_Toc84534929)

[2.2 Gray Scale Morphological Analysis 24](#_Toc84534930)

[Chapter 3: Histogram Features 26](#_Toc84534931)

[3.1 Histogram 26](#_Toc84534932)

[3.2 Multi-region Histogram 26](#_Toc84534933)

[3.3 Correlogram 26](#_Toc84534934)

[Chapter 4: Multi-scale Features 27](#_Toc84534935)

[4.1 Discrete Wavelet Transform (DWT) 27](#_Toc84534936)

[4.2 Stationary Wavelet Transform (SWT) 29](#_Toc84534937)

[4.3 Wavelet Packets (WP) 29](#_Toc84534938)

[4.4 Gabor Transform (GT) 29](#_Toc84534939)

[4.5 Selection of Basis Function (DWT, SWT, WP, GT) 29](#_Toc84534940)

[4.6 Texture Feature Extraction (DWT, SWT, WP, GT) 30](#_Toc84534941)

[4.7 Amplitude Modulation-Frequency Modulation (AM-FM) 31](#_Toc84534942)

[Chapter 5: Other Features 33](#_Toc84534943)

[5.1 Image Moments 33](#_Toc84534944)

[5.2 Hu’s Moments 34](#_Toc84534945)

[5.3 Zernikes’ Moments 35](#_Toc84534946)

[Bibliography 37](#_Toc84534947)

List of Figures

[Figure D-1 Schematic diagram of the (a) 2-D DWT, (b) SWT, and (c) WP decomposition schemes for a given level of analysis. Note that, for , is the original image, whereas for , is omitted from the abbreviation of WP sub-images. , , , and are the low-pass and high-pass filters on the rows and columns of each sub-image. The symbols “2↓1” and “1↓2” denote the down-sampling procedure on the columns and rows, respectively, which is valid for DWT and WP only [19]. 28](#_Toc84534948)

[Figure D‑2 DWT decomposition [20] 29](#_Toc84534949)

[Figure D‑3 Multiresolution Feature Extraction: Red sub-image is ignored for analysis [20] 30](#_Toc84534950)

[Figure D‑4 2-D Multi-scale AM-FM demodulation. Dominant AM-FM components are selected over different image scales. The bandpass filter selector (upper left) is used to define the bandpass filters that correspond to each scale [21] 32](#_Toc84534951)

List of Tables

[Table A‑1 GLCM notation 3](#_Toc84534952)

[Table A‑2 NGTDM notation 7](#_Toc84534953)

[Table A‑3 GLRLM notation 12](#_Toc84534954)

[Table A‑4 GLSZM notation 18](#_Toc84534955)

[Table 5 Mathematical Morphology Terminology for Binary Images [17] 23](#_Toc84534956)

[Table 6 Mathematical Morphology Terminology for Grayscale Images [17] 25](#_Toc84534957)

# Textural Features

## First-order statistics (FOS) or Statistical Features (SF)

Let be a grayscale image. The first order histogram is defined as

which is the empirical probability density function for single pixels. FOS/SF consists of the following parameters:

1. Mean
2. Standard Deviation=Variance1/2
3. Median
4. Mode
5. Skewness
6. Kurtosis
7. Energy
8. Entropy
9. Minimal Gray Level
10. Maximal Grey Level
11. Coefficient of Variation

12. 13. 14. 15. Percentiles (10,25,75,90)

where . Note that 50-Percentile is the median.

16. Histogram Width

## Gray Level Co-occurrence Matrix (GLCM) or Spatial Gray Level Dependence Matrix (SGLDM)

The Spatial Gray Level Dependence Matrices (SGLDM) as proposed by Haralick [1] are based on the estimation of the second-order joint conditional probability density functions, . The is the probability that two pixels and with distance in direction specified by the angle have intensities of gray level and gray level . The estimated values for these probability density functions will be denoted by . In a image, let be the horizontal spatial domain, be the vertical spatial domain, and be the image intensity at pixel . Formally, for angles quantized at intervals, the unnormalized probability density functions are defined by

where denotes the number of elements in the set.

Table A‑ GLCM notation

|  |  |
| --- | --- |
| Notation | Meaning |
|  |  |
|  | number of gray levels |
|  |  |
|  |  |
|  |  |
|  |  |
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The following texture measures that can be extracted from the spatial gray level dependence matrices are proposed in the paper:

1. Angular Second Moment= Energy2
2. Contrast
3. Correlation
4. Sum of Squares: Variance
5. Inverse Difference Moment (1st formula)/Homogeneity (2nd formula)
6. Sum Average
7. Sum Variance
8. Sum Entropy
9. Entropy
10. Difference Variance
11. Difference Entropy
12. 13. Information Measures of Correlation

where

1. Maximal Correlation Coefficient

where

For a chosen distance we have four angular SGLDM. Hence, we obtain a set of four values for each of the preceding measures. The mean and range of each of these measures, averaged over the four values, comprise the set of features.

## Gray Level Difference Statistics (GLDS)

The Gray Level Difference Statistics (GLDS) algorithm [2] uses first order statistics of local property values based on absolute differences between pairs of gray levels or of average gray levels in order to extract texture measures. Let be the image intensity function and for any given displacement , let . Let be the probability density of . If there are gray levels, this has the form of an -dimensional vector whose th component is the probability that will have value . The probability density can be easily computed by counting the number of times each value of occurs, where and are integers. In a coarse texture, if the is small, will be small, i.e., the values of should be concentrated near . Conversely, in a fine texture, the values of should be more spread out. Thus, a good way to analyse texture coarseness would be to compute, for various magnitudes of , so memeasure of the spread of values in away from the origin. Such measures are the following:

1. Homogeneity
2. Contrast
3. Energy/ Angular Second Moment
4. Entropy
5. Mean

## Neighbourhood Gray Tone Difference Matrix (NGTDM) method

Neighbourhood Gray Tone Difference Matrix (NDTDM) [3] corresponds to visual properties of texture. Let be the gray tone of a pixel at having gray tone value . Then the average gray tone over a neighborhood centered at, but excluding , can be found

where , specifies the neighbourhood size and . Then the th entry in the NGTDM is

where is the set of all pixels having gray tone .

Table A‑ NGTDM notation

|  |  |
| --- | --- |
| Notation | Meaning |
|  | highest gray tone value present in the image |
|  | a small number |
|  | the probability of occurrence of gray tone value in a image where |
|  | total number of different gray levels present in the image |

The following textural features are defined as

1. Coarseness
2. Contrast
3. Busyness
4. Complexity
5. Strength

## Statistical Feature Matrix (SFM)

The Statistical Feature Matrix [4] measures the statistical properties of pixel pairs at several distances within an image which are used for statistical analysis. Let be the image intensity function at point , and let Δ represent the intersample spacing distance vector, where are integers. The contrast, covariance, and dissimilarity are defined as

where denotes the expectation operation and is the average gray level of the image. A statistical feature matrix, (SFM) , is an matrix whose element is the statistical feature of the image, where is an intersample spacing distance vector for , and , are the constants which determine the maximum intersample spacing distance. In a similar way, the contrast matrix , covariance matrix , and dissimilarity matrix can be defined as the matrices whose elements are the contrast, covariance, and dissimilarity, respectively. Based on the SFM, the following texture features can be computed:

1. Coarseness

where is a normalized factor, is the set of displacement vectors defined as and is the number of elements in the set.

1. Contrast
2. Periodicity

where is the mean of all elements in and is the deepest valley in the matrix

1. Roughness

where is the fractal dimension (see Fractal Dimension Texture Analysis (FDTA)) in horizontal and vertical dimensions. and where can be estimated from the dissimilarity matrix since the element of the matrix is with .

## **Law’s Texture Energy (LTE) Method (TEM)**

Law’s texture Energy Measures [5, 6], are derived from three simple vectors of length 3, , which represent the one-dimensional operations of center-weighted local averaging, symmetric first differencing for edge detection, and second differencing for spot detection. If these vectors are convolved with themselves, new vectors of length 5, are obtained. By further self-convolution, new vectors of length 7, are obtained, where again performs local averaging, acts as edge detector, and acts as spot detector. If the column vectors of length are multiplied by row vectors of the same length, Laws masks are obtained. Τhe following combinations are used to obtain the masks (for ):

In order to extract texture features from an image, these masks are convoluted with the image, and the statistics (e.g., energy) of the resulting image are used to describe texture. The following texture features were extracted:

1. LL- texture energy from LL kernel
2. EE- texture energy from EE kernel
3. SS- texture energy from SS kernel
4. LE- average texture energy from LE and EL kernels
5. ES- average texture energy from ES and SE kernels
6. LS- average texture energy from LS and SL kernels

The averaging of matched pairs of energy measures gives rotational invariance.

## **Fractal Dimension Texture Analysis (FDTA**)

Fractal Dimension Texture Analysis (FDTA) [6] is based on the Fractional Brownian Motion (FBM) Model [7]. The FBM model is used to describe the roughness of nature surfaces. It regards naturally occurring surfaces as the end result of random walks. Such random walks are basic physical processes in our universe.

One of the most important parameters to represent a fractal surface is the fractal dimension. Theoretically, the fractal dimension is estimated from the equation

where denotes the expectation operator, is the intensity variations between two pixels, is a constant, and is the spatial distance. A simpler method is to estimate the parameter (Hurst coefficient) from the relationship

where . By applying the function the following is obtained

From the above equation, we can deduce a procedure to estimate the parameter and the fractal dimension can be easily computed from the relationship

A small value of fractal dimension (large value of parameter ) means a smooth surface, and large (small ), a rough surface.

Given an image, the intensity difference vector is defined as

where is the maximum possible scale, is the average of the absolute intensity difference of all pixel pairs with vertical or horizontal distance and

The value of the parameter can be obtained by using least squares linear regression to estimate the slope of the curve of versus in log–log scales.

If the image is seen under different resolutions, then the multiresolution fractal () feature vector is defined as

where is the size of the original image, is the parameter estimated from image , and is the number of resolutions chosen. The multiresolution fractal () feature vector describes also the lacunarity of the image. It can be used for the separation of textures with the same fractal dimension by considering all but the first components of the vectors.

## Gray Level Run Length Matrix (GLRLM)

A gray level run is a set of consecutive, collinear picture points having the same gray level value. The length of the run is the number of picture points in the run [8]. For a given picture, we can compute a gray level run length matrix for runs having any given direction . Often the direction is set as . The matrix element specifies the number of times that the picture contains a run of length , in the given direction, consisting of points having gray level (or lying-in gray level range ). Computation of these matrices is very simple. The number of calculations is directly proportional to the number of points in the picture. Also, the entire picture need not reside in core. Only two rows of picture values are needed at any one time to compute the matrices. To obtain numerical texture measures from the matrices, we can compute functions analogous to those used by Haralick for gray level co-occurrence matrices.

Table A‑ GLRLM notation

|  |  |
| --- | --- |
| Notation | Meaning |
|  | The th entry in the given run length matrix for direction |
|  | Number of gray levels in the image |
|  | Number of different run length that occur (so the matrix is ) |
|  |  |
|  | The number of voxels in the image |

The RUNL features are the following:

1. Short Run Emphasis
2. Long Run Emphasis
3. Gray Level Non-Uniformity/Gray Level Distribution
4. Run Length Non-Uniformity/Run Length Distribution
5. Run Percentage
6. Low Gray Level Run Emphasis
7. High Gray Level Run Emphasis
8. Short Low Gray Level Emphasis
9. Short Run High Gray Level Emphasis
10. Long Run Low Gray Level Emphasis
11. Long Run High Gray Level Emphasis

## Fourier Power Spectrum (FPS)

The Fourier transform [2, 6] of a picture is defined by

and the Fourier power spectrum, is (where denontes the complex conjugate).

It is well known that the radial distribution of values in is sensitive to texture coarseness in . A coarse texture will have high values of concentrated near the origin while in a fine texture the values of will be more spread out. Thus, if one wishes to analyse texture coarseness, a set of features that should be useful are the averages of taken over a ring-shaped regions centred at the origin i.e. features of the form

for various values of , the ring radius.

Similarly, it is well known that the angular distribution of values in is sensitive to the directionality of the texture in . A texture with many edges or lines in a given direction will have high values of concentrated around the perpendicular direction , while in a nondirectional texture, should also be nondirectional. Thus, a good set of features for analysing texture directionality should be the averages of taken over a wedge-shaped regions entered at the origin, i.e., features of the form

for various values of , the wedge slope.

For digital pictures, instead off the continuous Fourier transform defined above, one uses the discrete transform defined by

where and . This transofrm, however treats the input picture as periodic. If, in fact, it is not, the transform is affected by the discontinuities that exist between one edge of and the opposite edge. These have the effect of introducing spurious horizontal and vertical directionalities, so that high alues are present in akibg tge and axes.

The standard set of texture features based on a ring-shaped samples of the discrete Fourier power spectrum are of the form

for various values of the inner and outer ring radii and . Similarly, the features based on a wedge-shaped samples are of the form

Note that in this last set of features, the “DC value” has been omitted, since it is common to all the wedges.

## Shape parameters

Shape parameters consists of the following parameters:

1. X-coordinate maximum length
2. Y-coordinate maximum length
3. area
4. perimeter
5. perimeter2/area

## High Order Spectra (HOS) on Radon Transform

Radon transform [9, 10] transforms two dimensional images with lines into a domain of possible line parameters, where each line in the image will give a peak positioned at the corresponding line parameters. Hence, the lines of the images are transformed into the points in the Radon domain. An equation of the line can be expressed as: , where is the small angle and is the small distance to the origin of the coordinate system. Given a function , Radon transform is defined as:

This equation describes the integral along a line through the image, where is the distance of the line from the origin and is the angle from the horizontal. So, radon transform converts 2D signal into the 1D parallel beam projections, at various angles, .

High Order Spectra (HOS) are spectral components of higher moments. The bispectrum , of a signal is the Fourier transform (FT) of the third order correlation of the signal (also known as the third order cumulant function). It is given by

where is the FT of the signal , stands for the expectation operation and denotes the complex conjugate of . The frequency may be normalized by the Nyquist frequency to be between 0 and 1. The bispectrum, is a complex-valued function of two frequencies. The bispectrum which is the product of three Fourier coefficients, exhibits symmetry and was computed in the non-redundant region. This is termed as Ω, the principal domain or the nonredundant region.

The extracted feature is [11], [12] the entropy 1 (

where

## Local Binary Pattern (LPB)

Local Binary Pattern (LBP), a robust and efficient texture descriptor, was first presented by Ojala [13, 14]. The LBP feature vector, in its simplest form, is determined using the following method: A circular neighbourhood is considered around a pixel. points are chosen on the circumference of the circle with radius such that they are all equidistant from the centre pixel. Let be the gray value of the centre pixel and , corresponds to the gray values of the points. These points are converted into a circular bit-stream of 0s and 1s according to whether the gray value of the pixel is less than or greater than the gray value of the centre pixel. Ojala et al. (2002) introduced the concept of uniformity in texture analysis. The uniform fundamental patterns have a uniform circular structure that contains very few spatial transitions (number of spatial bitwise 0/1 transitions). In this work, a rotation invariant measure called using uniformity measure was calculated. Only patterns with were assigned the LBP code i.e., if the number of bit transitions in the circular bit-stream is less than or equal to , the centre pixel was labelled as uniform.

where

Multiscale analysis of the image using LBP is done by choosing circles with various radii around the centre pixels and, thus, constructing separate LBP image for each scale. Energy and entropy of the LBP image, constructed over different scales ( with corresponding pixel count respectively) were used as feature descriptors.

## Gray Level Size Zone Matrix (GLSZM)

Gray Level Size Zone Matrix (GLSZM) [15] quantifies gray level zones in an image. A gray level zone is defined as the number of connected voxels that share the same gray level intensity. A voxel is considered connected if the distance is 1 according to the infinity norm (26-connected region in a 3D, 8-connected region in 2D). In a GLSZM , the th element equals the number of zones with gray level and size appear in image. Contrary to GLCM and GLRLM, the GLSZM is rotation independent, with only one matrix calculated for all directions in the image.

Table A‑ GLSZM notation

|  |  |
| --- | --- |
| Notation | Meaning |
|  | Number of discreet intensity values |
|  | Number of discreet zones |
|  | Number of voxels |
|  | Number of zones in the ROI where |
|  | Size zone matrix |
|  | Normalized size zone matrix |

The following features can be calculated

1. Small Zone Emphasis (SZE) or Small Area Emphasis (SAE)
2. Large Zone Emphasis (LZE) or Large Area Emphasis (LAE)
3. Gray-Level Non-Uniformity (GLN)
4. Zone-Size Non-Uniformity (ZSN)
5. Zone Percentage (ZP)
6. Low Gray-Level Zone Emphasis (LGLZE)
7. High Gray-Level Zone Emphasis (HGLZE)
8. Small Zone Low Gray-Level Emphasis (SZLGLE) or Small Area Low Gray-Level Emphasis (SALGLE)
9. Small Zone High Gray-Level Emphasis (SZHGLE) or Small Area High Gray-Level Emphasis (SAHGLE)
10. Large Zone Low Gray-Level Emphasis (LZLGLE) or Large Area Low Gray-Level Emphasis (LALGLE)
11. Large Zone High Gray-Level Emphasis (LZHGLE) or Large Area High Gray Level Emphasis (LAHGLE)
12. Gray-Level Variance (GLV)
13. Zone-Size Variance (ZSV)
14. Zone-Size Entropy (ZSE)

is an arbitrarily small positive number

# Morphological Features

## Multilevel Binary Morphological Analysis

In multilevel binary morphological analysis [16, 17, 18] different plaque components are extracted and investigated for their geometric properties. Three binary images are generated by thresholding.

Here, binary image outputs are represented as sets of image coordinates where image intensity meets the threshold criteria. Overall, this multilevel decomposition is closely related to a three-level quantization of the original image intensity. In , dark image regions representing blood, thrombus, lipid, or haemorrhage are extracted. Similarly, in , collagen and calcified components of the plaque are extracted, while in , image components that fall between the two are extracted. In the following discussion, the symbol will be used to denote any one of the three binary images .

The structural element, also known as pattern or kernel is defined as the set

The two basic operators in the area of mathematical morphology are erosion and dilation. The basic effect of the erosion on a binary image is to erode the boundaries of regions of foreground [pixels](https://homepages.inf.ed.ac.uk/rbf/HIPR2/pixel.htm) (i.e., white pixels, typically). Thus, areas of foreground pixels shrink in size, and holes within those areas become larger. Erosion is defined as

The basic effect of the dilation on a binary image is to gradually enlarge the boundaries of regions of foreground [pixels](https://homepages.inf.ed.ac.uk/rbf/HIPR2/pixel.htm) (i.e., white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller. Dilation is defined as

The -fold expansion of also known as -fold Minkowski addition of with itself is defined as

Opening and closing are two important operators from mathematical morphology. They are both derived from the fundamental operations of erosion and dilation. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. However, it is less destructive than erosion in general. The effect of the opening is to preserve foreground regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of foreground pixels. Opening is defined as an erosion followed by a dilation:

Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background colour holes in such regions), but it is less destructive of the original boundary shape. The effect of the closing is to preserve background regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of background pixels. Closing is defined as a dilation followed by an erosion:

Opening and closing are idempotent, i.e., their successive applications do not change further the previously transformed result

We define as a multiscale opening of by also known as set-processing (SP) opening at scale , the opening

A dual multiscale filter is the closing of by or set-processing (SP) closing

The SP opening can be implemented more efficiently as

Table Mathematical Morphology Terminology for Binary Images [17]

|  |  |
| --- | --- |
| Term | Mathematical Equation |
| Erosion |  |
| Dilation |  |
| -fold expansion of |  |
| Opening |  |
| Closing |  |
| Multiscale set-processing opening |  |
| Multiscale set-processing closing |  |

The pattern spectrum of is defined as the function

The set difference images can be formed as

The pattern spectrum is defined as the function

hence the discrete pattern spectrum can be obtained via a forward area difference. A probability density function (pdf) measure is considered defined as

Given the pdf-measure, the cumulative distribution function (cdf) can also be constructed using

## Gray Scale Morphological Analysis

Similarly, we henceforth represent graytone images by functions; filters whose inputs and outputs are functions (multilevel signals) are called function-processing (FP) filters. Let be a finite support graytone image function on , and let be a fixed graytone pattern. In the context of morphology, is called function structuring element.

The mathematical definition for grayscale erosion and dilation is identical except in the way in which the set of coordinates associated with the input image is derived. The erosion and the dilation of by are respectively the functions

Thus, the opening and the closing of by are respectively the functions

We define the multiscale function-processing (FP) opening of by at scale . as the function

Likewise, we define the multiscale function-processing (FP) closing of by as the function

We can implement multiscale FP opening more efficient as

Likewise, for . We define the pattern spectrum of relative to a discrete graytone pattern the function

Table Mathematical Morphology Terminology for Grayscale Images [17]

|  |  |
| --- | --- |
| Term | Mathematical Equation |
| Erosion |  |
| Dilation |  |
| -fold expansion of |  |
| Opening |  |
| Closing |  |
| Multiscale function-processing opening |  |
| Multiscale function-processing closing |  |

where and denotes the pointwise algebraic difference between functions and . is the maximum positive size such that is not all . A probability density function (pdf) measure is defined as

Given the pdf-measure, the cumulative distribution function (cdf) can also be constructed using

# Histogram Features

## Histogram

The grey level histogram of the ROI of the plaque image is computed for 32 equal width bins and used as a feature set. Histogram despite its simplicity provides a good description of the plaque structure.

## Multi-region Histogram

Three equidistant ROIs were identified by eroding the plaque image outline by a factor based on the plaque size. The histogram was computed for each one of the three regions as described above and the 96 values comprised the new feature vector. This feature was computed in order to investigate whether the distribution of the plaque structure in equidistant ROIs has a diagnostic value and more specifically if the structure of the outer region of the plaque is critical whether the plaque will rupture or not.

## Correlogram

Correlograms are histograms, which measure not only statistics about the features of the image, but also consider the spatial distribution of these features. In this work two correlograms were implemented for the ROI of the plaque image:

* based on the distance of the distribution of the pixels’ gray level values from the centre of the image, and
* based on their angle of distribution.

For each pixel the distance and the angle from the image centre was calculated and for all pixels with the same distance or angle their histograms were computed. In order to make the comparison between images of different sizes feasible, the distance correlograms were normalized into 32 possible distances from the centre by dividing the calculated distances with . The angle of the correlogram was allowed to vary among 32 possible values starting from the left middle of the image and moving clockwise. The resulting correlograms were matrices (gray level values over were set to be the white area surrounding the region of interest and were not consider for the calculation of the features).

# Multi-scale Features

## Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) of a signal x[n] is defined as its inner product with a family of functions, and , which form an orthonormal set of vectors, a combination of which can completely define the signal, and hence, allow its analysis in many resolution levels .

The functions and , consist of versions of the prototype scaling , and wavelet functions, discretized at level and at translation . However, for the implementation of the DWT, only the coefficients of two half-band filters: a low-pass and a high-pass filter, are required, which satisfy the following conditions:

Hence, the DWT is defined as follows:

where and are known as the approximation and detail coefficients, respectively, at level and location . The outputs and of the convolution are downsampled by two for every level of analysis, where the time resolution is halved, and the frequency resolution is doubled.



Figure D- Schematic diagram of the (a) 2-D DWT, (b) SWT, and (c) WP decomposition schemes for a given level of analysis. Note that, for , is the original image, whereas for , is omitted from the abbreviation of WP sub-images. , , , and are the low-pass and high-pass filters on the rows and columns of each sub-image. The symbols “2↓1” and “1↓2” denote the down-sampling procedure on the columns and rows, respectively, which is valid for DWT and WP only [19].

For images, i.e., 2-D signals, the 2-D DWT can be used. This consists of a DWT on the rows of the image and a DWT on the columns of the resulting image. The result of each DWT is followed by down sampling on the columns and rows, respectively. The decomposition of the image yields four sub-images for every level.

Figure D-1 (a) shows a schematic diagram of the 2-D DWT for a given level of analysis. Each approximation sub-image is decomposed into four sub images and named approximation, detail-horizontal, detail-vertical, and detail-diagonal sub-image respectively in Figure D-1 (a)], according to the previously described scheme. Each detail sub-image is the result of a convolution with two half-band filters: a low-pass and a high-pass for , a highpass and a low-pass for , and two high-pass filters for [19].

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Figure D‑ DWT decomposition [20]

## Stationary Wavelet Transform (SWT)

The 2-D Stationary Wavelet Transform (SWT) is similar to the 2-D DWT, but no down sampling is performed. Instead, up sampling of the low-pass and high-pass filters is carried out [see Figure D-1 (b)]. The main advantage of SWT over DWT is its shift invariance property. However, it is nonorthogonal and highly redundant, and hence, computationally expensive [19].

## Wavelet Packets (WP)

The 2-D Wavelet Packets (WP) decomposition is a simple modification of the 2-D DWT, which offers a richer space-frequency representation. The first level of analysis is the same as that of the 2-D DWT. The second, as well as all subsequent levels of analysis consist of decomposing every sub image, rather than only the approximation sub image, into four new sub images [see Figure D-1 (c)] [19].

## Gabor Transform (GT)

The Gabor Transform (GT) of an image consists in convolving that image with the Gabor function, i.e., a sinusoidal plane wave of a certain frequency and orientation modulated by a Gaussian envelope. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, rendering them appropriate for texture segmentation and classification [19].

## Selection of Basis Function (DWT, SWT, WP, GT)

Careful selection of the basis function is a critical issue in a wavelet-transform-based methodology for texture analysis. A number of basis functions from different wavelet families were used, including

* Haar (haar)
* Daubechies (db)
* symlets (sym)
* coiflets (coif)
* biorthogonal (bior)

They have compact support but differ in other properties. The Haar wavelet is orthogonal, symmetric, allows for invariant translations, but has poor frequency localization. Daubechies wavelets are orthogonal but not symmetric. Symlets and coiflets are orthogonal and near symmetric. Biorthogonal wavelets combine many of the properties of the other families. They are symmetric with optimum time/frequency localization; however, they are not shift invariant [19].

## Texture Feature Extraction (DWT, SWT, WP, GT)

The level of decomposition for each scheme was determined according to the best level of decomposition for WP. The best level algorithm based on an entropy criterion among the complete sub-images was applied, which indicated three levels of decomposition [19].

The detail sub-images contain the textural information in horizontal, vertical, and diagonal orientations. The approximation sub-images were not used for texture analysis because they are the rough estimate of the original image and capture the intensity variations induced by lighting. The total number of sub-images of three levels of decomposition, including only the detail images, was 9 in the case of DWT and SWT, 63 in the case of WP and 12 in the case of GT. For the GT, the lowest and the highest centre frequencies were set to and , respectively. The size of the Gabor filter used for texture feature extraction was . Gabor texture information was obtained at .

Table

Description automatically generated

Figure D‑ Multiresolution Feature Extraction: Red sub-image is ignored for analysis [20]

The texture features that were estimated from each detail sub-image were the mean and standard deviation of the absolute value of detail sub-images, both commonly used as texture descriptors:

where are the detail sub-images of dimension in every orientation at level .

## Amplitude Modulation-Frequency Modulation (AM-FM)

We consider multi-scale Amplitude Modulation – Frequency Modulation (AM-FM) representations, under least-square approximations, for images given by

where denote different scales, denotes the instantaneous amplitude (IA) for the n-th AM component, and denotes the instantaneous phase (IP) for the n-th FM component. In addition, the gradient of the phase defined as

represents the instantaneous frequency (IF) for the n-th FM component.

Given the input discrete image , we first apply the Hilbert transform to form a extension of the analytic signal: . is processed through a collection of bandpass filters with the desired scale. Each processing block will produce the instantaneous amplitude, the instantaneous phase, and the instantaneous frequencies in both and directions. Figure below depicts the basic AM-FM demodulation method approach.

As feature vector, the histogram of the low, medium, high and dc reconstructed images is used with 32 bins as a probability density function of the image.

Diagram

Description automatically generated

Figure D‑ 2-D Multi-scale AM-FM demodulation. Dominant AM-FM components are selected over different image scales. The bandpass filter selector (upper left) is used to define the bandpass filters that correspond to each scale [21]

# Other Features

## Image Moments

### Raw Moments

In image processing, computer vision and related fields, an image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of such moments, usually chosen to have some attractive property or interpretation.

For a 2-D continuous function the moment (sometimes called "raw moment") of order is defined as

For . For a grayscale image with pixel intensities , raw image moments are calculated by

In some cases, this may be calculated by considering the image as a probability density function, i.e., by dividing the above by

### Central Moments

Central moments are defined as

where and are the components of centroid. If is a digital image, then the previous equation becomes

It can be shown that:

[22].

### Moment Invariants

Moments are well-known for their application in image analysis since they can be used to derive invariants with respect to specific transformation classes.

The term invariant moments is often abused in this context. However, while moment invariants are invariants that are formed from moments, the only moments that are invariants themselves are the central moments.

Note that the invariants detailed below are exactly invariant only in the continuous domain. In a discrete domain, neither scaling nor rotation are well defined: a discrete image transformed in such a way is generally an approximation, and the transformation is not reversible. These invariants therefore are only approximately invariant when describing a shape in a discrete image [22].

#### Translation Invariants

The central moments of any order are, by construction, invariant with respect to translations.

#### Scale Invariants

Invariants with respect to both translation and scale can be constructed from central moments by dividing through a properly scaled zero-th central moment:

where . Note that translational invariance directly follows by only using central moments.

#### Rotation Invariants

See Hu’s Moments 5.2

## Hu’s Moments

As shown by the work of [23], invariants with respect to translation, scale, and rotation can be constructed:

These are well-known as Hu moment invariants. The first one, , is analogous to the moment of inertia around the image's centroid, where the pixels' intensities are analogous to physical density. The first six, , are reflection symmetric, i.e., they are unchanged if the image is changed to a mirror image. The last one, , is reflection antisymmetric (changes sign under reflection), which enables it to distinguish mirror images of otherwise identical images [22].

## Zernikes’ Moments

Zernikes’ moment [24] is a kind of orthogonal complex moments and its kernel is a set of Zernike complete orthogonal polynomials defined over the interior of the unit disc in the polar coordinates space. Let be the image intensity function, and the 2-D Zernike moment of order with repetition is defined as:

where is the complex conjugate of Zernike polynomial and and both are integer and the relation between and can be described as:

where and the orthogonal radial polynomial is given by

From the formula mentioned above and the Euler’s complex number formula, the equations listed as follows are available.

For the computer digital image, let be the intensity of the image pixel, and the 2-D Zernike moment can be represented as:

[25]

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