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# Texture Feature Extraction Methods: A Survey

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**ABSTRACT** Texture analysis is used in a very broad range of fields and applications going from texture classification (e.g., for remote sensing), to segmentation (e.g., in biomedical imaging), passing through image synthesis or pattern recognition (e.g., for image in-painting). For each of these image processing procedures, it is first necessary to extract – from raw images – meaningful features that describe the texture properties. Various feature extraction methods have been proposed in the last decades. Each of them has its advantages and limitations: performances of some of them are not modified by translation, rotation, affine and perspective transform; others have a low computational complexity; others again are easy to implement,... This article provides a comprehensive survey of texture feature extraction methods. The latter are categorized into seven classes: statistical approaches, structural approaches, transform-based approaches, model-based approaches, graph-based approaches, learning-based approaches, and entropy-based approaches. For each method in these seven classes, we present the concept, the advantages and drawbacks, and give examples of application. This survey allows us to identify two classes of methods that particularly deserve attention in the future as their performances seem interesting but their thorough study not performed yet.

**INDEX TERMS** Classification, feature extraction, image processing, image synthesis, segmentation, shape from texture, texture.

## I. INTRODUCTION

TEXTURE is a key element of human visual perception and is used in many computer vision systems. For the eyes, distinguishing different textures is an easy task. Nevertheless, no precise definition of texture has been adopted yet. Some authors proposed to define it as a measure of coarseness, contrast, directionality, line-likeness, regularity, and roughness [1]. The texture can also be seen as a similarity grouping in an image [2] or as natural scenes containing semi-repetitive arrangements of pixels [3]. In spite of the difficulty to give a precise definition of this notion, the analysis of texture is used in many applications: biomedical field (see, e.g., [4]–[7]), industrial automation (see, e.g., [8]–[10]), document image analysis (see, e.g., [11]–[13]), remote sensing (see, e.g., [14]–[16]), face recognition (see, e.g., [17]) to cite only a few. These applications use texture parameters for classification, segmentation, or synthesis of images. For this purpose, the extraction of features characterizing the texture is necessary. This can only be performed by proposing mathematical definitions for image textures [18].

A large number of texture feature extraction methods are now proposed for engineers and researchers. Moreover, new methods are still proposed, often based on the recent advances of scientific areas.

This survey presents the main texture feature extraction methods to help engineers, students, researchers in choosing the best algorithms for their applications. We will focus here on static texture analysis only (dynamic textures – temporal textures – are not studied in this survey). Moreover, in this work we do not intend to compare the methods presented nor to give all their specific characteristics or application domains. Our goal is more to try to be exhaustive on the methods listed and to focus on their basic principles than to give a full and in-depth development of each method. Nevertheless, we give references where details can be found.

Texture feature extraction methods have already been the focus of some survey papers in the last 25 years. Thus, Materka and Strzelecki proposed a review of texture analysis methods but is was published more than 20 years ago [19].

Since then, many improvements in the methods have been proposed. In 2002 Zhang *et al.* proposed a brief review of texture analyses for which the performances are not modified by translation, rotation, affine, and perspective transform [20]. This review is therefore restricted to a small number of methods and is now out of date. In 2004, Castellano *et al.* made a review of the principles of the main texture analysis methods and their applications to the medical field [21]. However, this review is short as only the main ideas are presented. Moreover, since 2004, many improvements have been proposed in the methods. There are therefore new trends and developments that are not presented in the previous surveys.

In our work, the texture feature extraction methods are divided into seven classes: statistical approaches, structural approaches, transform-based approaches, model-based approaches, graph-based approaches, learning-based approaches, and entropy-based approaches. Different methods, see Table 1, are detailed in each class. Thus, for each method, we first focus on the presentation of the concept, then we expose advantages and drawbacks for each of them. We finally cite examples of applications.

## II. STATISTICAL APPROACHES

For statistical approaches, the statistical properties of the spatial distribution of grey levels are used as texture descriptors.

### A. GREY LEVEL CO-OCCURRENCE MATRIX OR SPATIAL GREY LEVEL DEPENDENCE MATRIX

#### 1) Concept

The grey level co-occurrence matrix approach (GLCM), also called spatial grey level dependence matrix (SGLDM) approach, consists in considering second order statistics: pairs of pixels in certain spatial relations to each other are studied. For this purpose, co-occurrence matrices are used. They relate the relative frequencies $P(i,j|d,\theta)$ that two pixels at a constant vector distance $(d,\theta)$ from each other have intensity $(i,j)$: in the GLCM $P(i,j|d,\theta)$, the $(i,j)$th entry of the matrix, represents the number of occurrences of a pixel having the intensity value $i$ that is separated from another pixel with intensity value $j$ at a distance $d$ in the direction $\theta$. Two forms of co-occurrence matrix exist. In the first case, the matrix is symmetric where pairs separated by $d$ and $-d$ (for a direction $\theta$) are counted. In the second case, the matrix is not symmetric and only pairs separated by a distance $d$ are counted. This leads to a square matrix that has a dimension equal to the number of intensity levels in the image, for each distance $d$ and orientation $\theta$. If pixel pairs in the image are highly correlated, the entries in the GLCM are gathered along the diagonal of the matrix. Note that the computation of the matrices (for each distance $d$ and direction $\theta$) may be time consuming. This is why the distance and the number of orientations are often limited to a small number of sets. The computation time can be reduced by using a reduced number of intensity levels (performed through the quantization of the image). The classification of fine textures necessitates the use of small values for $d$ whereas the classification of coarse textures requires to use large values for $d$. Once the matrices computed, each one has to be condensed to a few numbers to classify texture. For this purpose, Haralick *et al.* proposed 14 measures [22]. Later, authors mentioned that only 5 of these 14 measures are sufficient [23] (in what follows, the image has $G$ discrete intensity levels):

1) **energy**: it provides information on image homogeneity; it has low values when the probabilities of the grey level pairs are rather similar and high values otherwise. It is computed as $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j|d,\theta)^2$.
2) **entropy**: it measures the disorder of the GLCM. It is computed as
$$-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j|d,\theta)\log_2(P(i,j|d,\theta)). \quad (1)$$
3) **correlation**: it measures the grey level linear dependence between pixels (relative to each other) at the specified positions; it has high values when the values are uniformly distributed in the GLCM and low values otherwise.
4) **local homogeneity (also called inverse difference moment)**: it is high when the same pairs of pixels are found (e.g., in the case of a spatial periodicity). It is computed as $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{P(i,j|d,\theta)}{1+(i-j)^2}$.
5) **inertia (also called contrast)**: it quantifies local variations present in the image. It is computed as $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2 P(i,j|d,\theta)$.

As mentioned above, the GLCM approach consists in considering second order statistics. The GLCM method studies the grey level distribution of pairs of pixels. This is why it is also known as the second-order histogram method. In the same way, higher-order statistics analyze the joint distribution of more than two pixels. Thus, with the grey level run-length matrix (GLRLM), the occurrence of runs of pixels is studied (see below): the occurrence of a given grey value in a given direction is analyzed. Then, higher-order statistical features can be extracted from the GLRLM, as explained below.

#### 2) Advantages and limitations

One of the drawbacks of the GLCM approach is the high dimensionality of the matrix and the high correlation of the Haralick features. Maillard compared the performance of the semi-variogram, the Fourier spectra, and the GLCM methods in various classification contexts [24]. The results showed that the GLCM method shows better results for simple situations where the textures are visually easily separable [24]. Furthermore, the GLCM algorithm is easy to implement and has been shown to give very good results in a large fields of applications (see, e.g., [25]). However, due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples that are processed. This is

TABLE 1: Classes and corresponding methods presented in the survey.

| Classes | Methods | Section |
|---|---|---|
| Statistical approaches | - Grey level co-occurrence matrix | Section II-A |
| | - Grey level run-length matrix | Section II-B |
| | - Autocorrelation-based approaches | Section II-C |
| | - Histogram of gradient magnitudes | Section II-D |
| | - Local mapped patterns-based approaches | Section II-E |
| | - Local energy pattern | Section II-F |
| | - Variogram | Section II-G |
| | - Tamura features | Section II-H |
| | - Local binary pattern and variants | Section II-I |
| | - Shape index histograms | Section II-J |
| | - Weber local descriptor | Section II-K |
| | - Deterministic walk | Section II-L |
| Structural approaches | | Section III |
| Transform-based approaches | - Filter banks: Law's texture features | Section IV-A |
| | - Fourier transform-based approaches | Section IV-B |
| | - Gabor decomposition-based approaches | Section IV-C |
| | - Wavelet-based approaches | Section IV-D |
| | - Shearlet-based approaches | Section IV-E |
| | - Contourlet-based approaches | Section IV-F |
| | - Locally encoded transform feature histogram (LETRIST) | Section IV-G |
| Model-based approaches | - Complex network-based approach | Section V-A |
| | - Mosaic models | Section V-B |
| | - Random field models | Section V-C |
| | - Fractal-based measures | Section V-D |
| | - Gravitational models | Section V-E |
| | - Wold decomposition | Section V-F |
| Graph-based approaches | - Local graph structures | Section VI-A |
| | - Graph of tourist walk approach | Section VI-B |
| | - Shortest paths in graphs | Section VI-C |
| Learning-based approaches | - Vocabulary learning methods | Section VII-A |
| | - Extreme learning machine-based methods | Section VII-B |
| | - Deep learning methods | Section VII-C |
| Entropy-based approaches | - Two-dimensional sample entropy | Section VIII-A |
| | - Two-dimensional distribution entropy | Section VIII-B |
| | - Two-dimensional multiscale entropy | Section VIII-C |

why the number of grey levels is often reduced. Moreover, it has been shown that, when processing document images, the GLCM-based approach has good performance in terms of processing time and complexity [11] but consumes a high amount of memory. Furthermore, for historical document images with a large amount of noise, the GLCM features are not appropriate [11]. However, for historical document images, containing graphics and single text font, the features given by the GLCM method should be a good choice because the method is fast and easy to use. Nevertheless, the method is not adapted for separating different text fonts [11]. Finally, for image classification purposes, selecting the distance $d$ may be crucial. The value of $d$ must be large enough to include the texture pattern but also small enough to keep the local character of spatial dependence.

#### 3) Examples of applications

Recently, Seul and Okarma proposed to use the GLCM method as a texture classification approach for cleaning robots [26]. Nouri *et al.* used GLCM texture features as indices for non-destructively assessing bread staling progress [27]. The method has also been used for the detection of channel by seismic texture analysis [28]. In the biomedical field, the technique has been used to distinguish benign and malignant breast lesions [29]. Other biomedical applications can be found in [21].

### B. GREY LEVEL RUN-LENGTH MATRIX (PRIMITIVE LENGTH TEXTURE FEATURES)

#### 1) Concept

With GLRLM, the principle relies on the fact that coarse textures are characterized by many neighbouring pixels having the same grey level. By opposition, fine textures are characterized by a low number of neighbouring pixels having the same grey level [30]. The so-called primitive (run) is a set of maximum number of pixels having the same grey level, in the same direction. Thus, a primitive is defined by its grey level $g$, its length $l$, and its direction. For an image, an element of the GLRLM $e(g, l)$ is defined as the number of runs with pixels of grey level $g$ and run-length $l$. Thus, e.g., given the vertical direction, GLRLM is computed by searching – for each allowed grey level value – how many times there are runs of, e.g., 2 consecutive pixels having the same value. The same is performed for 3 consecutive pixels, then for 4 consecutive pixels, etc. Many different GLRLM can be computed for an image, one for each chosen direction. Usually, 4 matrices are computed: one for the horizontal direction, one for the vertical direction, and two for the diagonal directions. Then, a 2D run-length histogram ($H_{g,l}$) is computed for each direction.

For this, one axis represents the run-length $l$ and the other corresponds to the grey level value $g$. For each histogram $H_{g,l}$, a feature vector of GLRLM indices is computed. Thus, by denoting $P(g,l)$ the probability of a specific run-length, several image texture features can be defined, among which we can find (with $H_{g,l}$ being normalized)

- **Short primitive emphasis (short run emphasis)**: it characterizes fine-grained textures. It is computed as $\sum_{g=0}^{n_G-1} \sum_{l=1}^{L} \frac{P(g,l)}{l^2}$,
- **Long primitive emphasis (long run emphasis)**: it characterizes coarse textures. It is computed as $\sum_{g=0}^{n_G-1} \sum_{l=1}^{L} P(g,l) \times l^2$,
- **Primitive length uniformity**: it is an indicator of few run-length outliers dominating the histogram. It is computed as $\sum_{g=0}^{n_G-1} [\sum_{l=1}^{L} P(g,l)]^2$,

where $n_G$ is the number of grey level bins (number of bins used for the quantization of the image) and $L$ is the maximum run-length.

#### 2) Advantages and limitations

Several studies compared the GLRLM features with other traditional texture features [23], [31]. These studies have shown that the run-length features are the least efficient texture features compared with other methods. This is why Tang designed several new run-length matrices using a multilevel dominant eigenvector estimation algorithm [32]. Moreover, Venkateswarlu *et al.* proposed the run-length matrix on fuzzy local binary pattern [33].

#### 3) Examples of applications

Biomedical applications of the GLRLM method can be found in [21]. Recently, Vamvakas *et al.* used GLRLM for the differentiation of glioblastoma multiform from solitary metastasis [34]. In other fields of applications, GLRLM has been used for the automated recognition of drill core textures [10] and to classify different varieties of maize seeds [35].

### C. AUTOCORRELATION-BASED APPROACHES

#### 1) Concept

In this approach, the dot product of the image with shifted copies of this image is computed. This gives features that are used to obtain information on periodic and similar patterns [36]. Thus, if the sub-patterns (primitives) inside the image are large, the autocorrelation function decreases slowly with increasing distance. On the other hand, if the primitives are small, the autocorrelation will decrease rapidly [18]. If the primitives are periodic, the autocorrelation function decreases and increases periodically with distance. Therefore, coarseness can be detected with autocorrelation. The directionality of the sub-pattern can also be determined with the shift orientations. Thus, for the horizontal and vertical axes and for an image $I$, the autocorrelation function is computed as

$$R_{I,\alpha,\beta}(x,y) = \sum_{\alpha\in\Omega} \sum_{\beta\in\Omega} I(x,y) I(x+\alpha, y+\beta), \quad (2)$$

where $\alpha$ and $\beta$ correspond, respectively, to the pixels in the horizontal and vertical axes on the plane $\Omega$ with which the image is translated. From these results, a polar diagram – the so-called rose of directions – can be obtained [18]. It is computed for each orientation through the summation of the different values of the autocorrelation function

$$R_{I,x,y}(\theta_i) = \sum_{L_i} R_{I,\alpha,\beta}(x,y), \quad (3)$$

where $\theta_i \in [0,\pi]$ is the orientation of the set of possible orientations $L_i$ which is represented by a straight line passing through $(x,y)$ and the angle $\theta_i$. The rose of directions gives information on the significant orientations and periodicities of the texture.

#### 2) Advantages and limitations

It has been reported that autocorrelation is not a good measure of coarseness [37]. Moreover, it seems that – in natural textures – the method is not a very good discriminator of isotropy.

#### 3) Examples of applications

Unser and Coulon used correlation and grey level difference measure in an automatic visual inspection system of texture [38]. Moreover, the method has been used to extract features for synthetic aperture sonar image seabed segmentation [39].

### D. HISTOGRAM OF GRADIENT MAGNITUDES

#### 1) Concept

In 2015, Sharma and Ghosh proposed a new rotation invariant local texture descriptor, the so-called histogram of gradient magnitudes [40]. In the latter method, a histogram of magnitudes of the gradients is computed and the orientation of the local gradients of pixel intensities is ignored [40]. The gradient of magnitude gives the strength of the edge through the amount of the difference between pixels in the neighborhood: it gives an information on how quickly the image is changing. The histogram over the gradient-magnitudes of pixels is computed and does not take into account the gradient orientation. This is why the method is rotation-invariant. The full algorithm of the method is given in [40]. Moreover, using a different approach but still with histogram of gradients, Li *et al.* proposed in 2016 the histogram of oriented gradient based gist (HOG-gist) for building recognition [41]. This latter method individually computes the normalized histograms of multi-orientation gradients for the same image with four different scales. These normalized histograms of oriented gradients are orientation gist feature vectors of an image.

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#### 2) Advantages and limitations

The two main advantages of the histogram of gradient magnitudes are its rotation invariance and its low computational complexity: the computation time linearly varies with the number of pixels in the image under study [40]. Moreover, the method has shown to outperform other texture descriptors, as LBP and rotation invariant LBP, in texture classification and image segmentation [40].

#### 3) Examples of applications

Sharma and Ghosh used the histogram of gradient magnitudes on several datasets (Outex texture database, Mirflickr 25000 image-collection, and a satellite-imagery dataset) [40]. Their results show that the histogram of gradient magnitudes gives very good performances compared to other existing methods.

### E. LOCAL MAPPED PATTERNS-BASED APPROACHES

#### 1) Concept

Local mapped pattern-based methods are an evolution of the local fuzzy pattern method [42]. In the latter, the grey level values of a neighborhood is interpreted as a fuzzy set and each grey level of a pixel as a fuzzy number [42]. Moreover, a membership degree of the central pixel in a neighborhood is given by a membership function (fuzzy membership function). For local mapped pattern, any mapping function can be used. Thus, in the local mapped pattern descriptor, each pattern is defined by a neighborhood $p = W \times W$ that can be mapped to a histogram bin $h_b$ as:

$$h_b = \text{round}\left(\frac{\sum_{i=1}^{v-1} f_{g_i} M(i)}{\sum_{i=1}^{v-1} M(i)}(B-1)\right), i = 1, \ldots, (v-1), \tag{4}$$

where $f_g$ is the mapping function, $M(i)$ is a weighting matrix containing predefined values for each pixel position in the neighborhood, and $B$ is the number of bins in the histogram. Several approaches based on local mapped patterns have been proposed as feature descriptor [43]–[45]. The local mapped pattern approach has also been extended for circular neighborhoods: the method, called sampled local mapped pattern [46], considers the neighborhood of a center pixel as a set of values within a circular symmetry radius. In 2016, Vieira *et al.* proposed a new texture descriptor for classification of rotated textures, the so-called sampled local mapped pattern magnitude, based on the local mapped patterns approach [46]. This method combines the sampled local mapped pattern descriptor and a histogram with magnitude information. It therefore considers the magnitude between neighboring pixels and extract rotation invariant features. Very recently, the completed local mapped pattern descriptor has been proposed as an improvement of the sampled local mapped pattern magnitude descriptor [47].

#### 2) Advantages and limitations

The sampled local mapped pattern magnitude descriptor and the completed local mapped pattern descriptor have the advantage of being robust to image rotation variation.

#### 3) Examples of applications

The sampled local mapped pattern magnitude method has successfully been used for human epithelial type 2 cell classification [48].

### F. LOCAL ENERGY PATTERN

#### 1) Concept

In 2013, Zhang *et al.* proposed a statistical histogram-based representation, the local energy pattern, for texture classification [49]. The procedure leads to a local descriptor which models texture image as histogram over statistical local feature vectors. The algorithm relies on three steps: first, normalized local-oriented energies are used to generate local feature vectors. For this purpose, the input image $I$ is convolved with the oriented Gaussian-like second derivative filters. This leads to image $I_{\theta_p}$ where $\theta_p$ $(p = 0 \ldots P-1)$ are the orientations and $P$ is the number of oriented filters. Then, for an image the oriented energy is defined as $e_{\theta_p} = I_{\theta_p}^2$. Afterwards, the energies are locally summed over a Gaussian weighted region with the corresponding pixel at the center. This leads to the local oriented energy computed as $E_{\theta_p} = G_w \star e_{\theta_p}$, where $G_w$ is the Gaussian window used for smoothing. The local feature vector $V$ is defined as $V = \{E_{\theta_0}, E_{\theta_1}, \ldots, E_{\theta_{P-1}}\}$. The local feature is then normalized as described in [49]. In the second step, each local feature vector is quantized and transformed to a number by N-nary coding. Finally, the frequency histogram is a global representation of the texture.

#### 2) Advantages and limitations

The local feature vectors that are generated in the local energy pattern approach are relatively invariant to the imaging conditions [49]. Moreover, the N-nary coding reduces the quantization loss and thus preserves more local structure information.

#### 3) Examples of applications

The local energy pattern approach has been used in material categorization [49].

### G. VARIOGRAM

#### 1) Concept

For the grey levels $I(x, y)$ positioned at row $x$ and column $y$ in an image having $N$ pairs of pixel values $[I(x, y)$ and $I(x', y')]$ separated by a distance $h$, the variogram is computed as [50]

$$2\gamma(h) = \int_x \int_y [I(x, y) - I(x', y')]^2 dydx, \tag{5}$$

where $h$ is the Euclidean distance between the pixel value at row $x$ and column $y$ and the pixel value at row $x'$

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and column $y'$. In practice the above-mentioned equation is approximated by

$$2\gamma(h) = \frac{1}{N}\sum_{i=1}^{N}[I(x,y) - I(x',y')]^2. \quad (6)$$

In practice, the semi-variogram is computed instead of the variogram

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}[I(x,y) - I(x',y')]^2. \quad (7)$$

Spatial directions can be chosen in the computation. For instance, the E-W direction gives

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}[I(x,y) - I(x+h,y)]^2. \quad (8)$$

The semi-variogram is computed by starting at $h = 1$ (a one-pixel offset), then incrementing by one through a maximum value for $h$. For the plot, the variogram corresponds to the plot of $\gamma(h)$ as a function of distance $h$. From this plot, three quantities are often computed [51]

- the $y$-intercept, also called nugget. This quantity reflects the variability at distances smaller than the sample spacing,
- the limiting value of the variogram over large scales, also called sill. This quantity corresponds to the maximum variance reached by the variogram,
- the distance at which the limiting value is obtained, also called range. It corresponds to the distance at which the sill is reached.

#### 2) Advantages and limitations

The variogram approach is computationally simple and easy to interpret as a graph. However, the estimator given in Eq. 8 is not robust with respect to outliers or severe skewness [52]. This drawback led to the development of robust semi-variograms [53].

#### 3) Examples of applications

St-Onge *et al.* proposed the variogram to estimate forest stand structure [54]. Atkinson used the variogram in the field of airborne multispectral scanner imagery [55]. The variogram has also been used in the biomedical field [56] and in urban area extraction [57].

### H. TAMURA FEATURES

#### 1) Concept

In what follows an image of width $W$ and height $H$ will be noted as $I$ and the pixel at location $x$ and $y$ as $I(x,y)$. Tamura *et al.* proposed texture features that correspond to human visual perception [1]. They proposed six basic texture descriptors (see below) where the three first outperform others for global descriptions of textures for image segmentation and classification:

1) **Coarseness** corresponds to the scale and repetition rates of texture. As Tamura *et al.* mentioned [1], for patterns with different structures, the bigger its element size, the coarser it is. Coarseness can be computed as

$$Coarseness(I) = \frac{1}{W \times H}\sum_{x=0}^{W-1}\sum_{y=0}^{H-1} S_{best}(x,y), \quad (9)$$

where $S_{best}(x,y) = 2^k$. $k$ is the value that maximizes $\max_{1\leq k\leq L}(E_{k,h}(x,y), E_{k,\nu}(x,y))$ in the horizontal or vertical direction, $k \in [1,L]$ where $2^L \leq \min(W,H)$. $E_{k,h}(x,y)$ and $E_{k,\nu}(x,y)$ are computed from $A_k(x,y)$ which is the average at each pixel $I(x,y)$ of the neighborhood of size $2^k \times 2^k$:

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1}\sum_{j=y-2^{k-1}}^{y+2^{k-1}-1}\frac{I(i,j)}{2^{2k}}. \quad (10)$$

From $A_k(x,y)$, $E_{k,h}(x,y)$ and $E_{k,\nu}(x,y)$ are computed as

$$E_{k,h}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)| \quad (11)$$

and

$$E_{k,\nu}(x,y) = |A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1},y)|. \quad (12)$$

2) **Contrast** takes into account the distribution polarization of black and white pixels and describes the dynamic range of grey levels. It is computed as

$$Contrast(I) = \frac{\sigma}{\sqrt[4]{\alpha_4}}, \quad (13)$$

where $\sigma$ is the standard deviation and $\alpha_4 = \frac{\mu_4}{\sigma^4}$. $\mu_4$ corresponds to the fourth moment about the mean.

3) **Directionality** measures the total degree of directionality. It is computed from an histogram of local edge probabilities against their directional angle. With the quantification of the sharpness of the histogram peaks, we measure the texture directionality by summing the second moments around each peak.
4) **Line-likeness** is concerned only with the shape of a texture element. It is defined as an average coincidence of the edge directions in the grey levels.
5) **Regularity** is a property for variations of a placement rule. When there is no variation in the placement rule in the texture, it is observed as regular. By opposition, when a texture presents large variations in the placement rule, it is observed as irregular.
6) **Roughness** is related to the standard deviation of the normalized grey levels.

A Tamura image is an image computed from the value of the three features "coarseness-contrast-directionality" (CND) at each pixel. This image can be seen as done for a joint RGB distribution.

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#### 2) Advantages and limitations

In the context of texture features extraction, Tamura properties are very meaningful. Tamura features are derived from a psychophysical context. Therefore, they are visually meaningful to humans. This is the great advantage of the Tamura features. Howarth *et al.* performed an evaluation of texture features between the GLCM, the Tamura features, and the Gabor filters [58]. In the same way, Zhao *et al.* showed that – when the criterion of Human Vision System is used for the performance – Tamura texture model performance for the description of coarseness is better than grey level co-occurrence texture coarseness and fractal dimension textural coarseness [59].

#### 3) Examples of applications

The Tamura features have been used to analyze historical document images [11], [60], [61]. They also have been used to facilitate the similarity measurement and improve the retrieval accuracy in the biomedical field [62]. Moreover, Tamura features have also been used for analyzing and describing textures in linguistic terms [63]. In the latter work, three steps were proposed: texture analysis (to extract Tamura features), fuzzy clustering, and texture description.

### I. LOCAL BINARY PATTERN AND VARIANTS

#### 1) Concept

Local binary pattern (LBP) was first suggested by Ojala *et al.* in 1996 [64]. LBP associates the analysis of local structures (as in structural methods) and the analysis of occurrences (as in statistical methods). The LBP method represents each image pixel $q_c$ with a binary pattern. The latter is based on the difference between the grey level value of the pixel $q_c$ and its circular neighborhood with specified radius $R$ centered at $q_c$. Thus, the LBP codes are computed as

$$LBP_{P,R}(q_c) = \sum_{p=0}^{P-1} s(x)2^p, \tag{14}$$

where $x = q_p - q_c$ is the difference between the intensity levels of the neighboring pixels ($q_p$) and the central pixel ($q_c$) within the circular neighborhood of radius $R$ and $P$ neighboring pixels. In addition, $s(x)$ is

$$s(x) = \begin{cases} 1 & \text{x} \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

In practice, the neighboring pixels is on a circle. Therefore, we use interpolation for neighbors that are not exactly in the center of pixels. The binary number is formed by arranging each bit in a clockwise or anti-clockwise sequence and assigned to the center pixel. As each digit of a LBP code is 0 or 1, the codes are ranging from 0 to $2^P - 1$. Due to the sign function $s()$, the LBP code is invariant against any monotonic transformation of image brightness. The histogram of these different labels can then be used as a texture descriptor. Thus, a texture image can be characterized by the distribution of LBP patterns, representing an image by a LBP histogram vector h

$$\text{h} = \sum_{i=1}^{W} \sum_{j=1}^{H} \delta(LBP_{P,R}(i,j) - k), \tag{15}$$

where $0 \leq k < d = 2^P$ is the number of LBP patterns, $\delta$ is the Heaviside function, and $W$ and $H$ are the dimensions of the image. In 2011, Fernandez *et al.* proposed a variant of LBP: the binary gradient contours (BGC) that are a family of descriptors relying on pairwise comparison of adjacent pixels where the latter belong to one or more closed paths traced along the periphery of the $3 \times 3$ neighbourhood [65]. An improved version of BGC has also been proposed [66]. In 2013, Wang *et al.* proposed the local neighboring intensity relationship pattern (LNIRP) descriptor to extract texture feature [67]. The LNIRP descriptor relies on the neighboring intensity relationship (NIR) operator and applies the same binary encoding strategy as LBP. The LNIRP descriptor is complementary to the LBP descriptor. In 2015, the phase congruency-based binary pattern (PCBP) has been proposed by Cai *et al.* as a texture descriptor for classification of breast ultrasound images [68]. PCBP is an integration of the phase congruency approach and the LBP-based method. In 2016, Nguyen *et al.* extended the binary patterns from the pixel level to the local distribution level [69]. In 2016 also, Qi *et al.* proposed the local orientation adaptive descriptor (LOAD) to capture *regional* texture in an image [70]. For this, point description is defined on an adaptive coordinate system (ACS). A binary sequence descriptor is used to obtain relationships between a point and its neighbors. A multi-scale description is also proposed to capture multi-scale texture information [70]. In 2017, based upon LBP, Zhang *et al.* proposed the completed discriminative local features (CDLF) that improves the LBP features in two main points [71]: (i) in the pattern encoding stage, a transformation matrix using labeled data is learnt; (ii) in the histogram accumulation step, an adaptive weight strategy is used to consider the contributions of pixels in different regions. Other improvements have also been proposed very recently (see, e.g., [72]–[77]).

#### 2) Advantages and limitations

The advantage of LBP-like approaches is that they combine structural and statistical methods leading to an increase in performance for texture analysis. Moreover, the implementation of the method is easy and the computational cost is low. Furthermore, it is invariant to monotonic illumination changes. Nevertheless, the original method has some drawbacks: it is sensitive to image rotation; it produces rather long histograms leading to decreased distinctiveness and also the need to large storage; the textural information extracted is limited if the spatial support (e.g., $3 \times 3$ neighbourhood) is small; it loses local textural information (e.g., contrast) because it considers only the signs of differences of neighbouring pixels; and it is highly sensitive to noise and blurring. This is why several variants of the original LBP method have been proposed, as reviewed in [78]. Thus, in 2000, a rotation invariant version has been proposed [79]. It consists in grouping rotated versions of the same binary code. However, this version still has some drawbacks and this is why other extensions of the LBP descriptors have been proposed then, as described in [80]. Other rotation invariant versions have also been proposed [81]–[84]. Furthermore, other variants have been developed to improve the discriminative power of the method [85]–[87], including multiscale approaches [88], [89].

The sensitivity to noise has also been the subject of several works such as [17], [90] where, among others, the local ternary patterns (LTP) is proposed to overcome the high sensitivity to noise in near-uniform regions that is present in LBP, and to introduce a higher level of granularity. A local combination adaptive ternary pattern (LCATP) descriptor has also recently been proposed to encode both colour and local information [91]. A variant of LBP to obtain texture descriptors insensitive to blur is also available [92].

In [78], the authors proposed six classes of a taxonomy for the LBP variants to classify them according to their roles in feature extraction [78]:

1) Traditional LBP
2) Neighborhood topology and sampling
3) Thresholding and quantization
4) Encoding and regrouping
5) Combining complementary features
6) Methods inspired by LBP.

The reader is invited to refer to this paper and [93] to obtain more details on existing LBP variants.

#### 3) Examples of applications

Heikkila *et al.* used an LBP-based method for interest region description [94]. LBP-based features have also been used for medical image analysis [93]. Authors *et al.* used LBP-based features in face recognition problems [95]- [96] whereas Satpathy *et al.* used them in object recognition tasks [97].

### J. SHAPE INDEX HISTOGRAMS

#### 1) Concept

The shape index histograms method proposed by Larsen *et al.* in 2014 consists of a texture descriptor based on second-order image structure captured by the shape index [98]. The shape index is an image geometry measure that captures second-order image structure in a continuous interval, as described in detail in [99]. From this, the distribution of curvatures in a histogram can be summarized. A rotation-invariant spatial pooling scheme for the shape index histograms has also been proposed [98].

#### 2) Advantages and limitations

The second-order structure captured by the shape index is well suited for blob-like structures. Moreover, the parameters (shape scale and pooling scale) of shape index histograms are intuitive. Nevertheless, the number of bins is determined in an *ad hoc*-manner [98].

#### 3) Examples of applications

The method has been used for an automatic classification of indirect immunofluorescence images of HEp-2 cells into different staining pattern classes [98].

### K. WEBER LOCAL DESCRIPTOR

#### 1) Concept

The Weber local descriptor (WLD) is based on the Weber's law (a psychological law) [100]. This descriptor is made of two components. Thus, for each pixel of the image under study, two components of the WLD feature are computed: differential excitation and gradient orientation. The differential excitation component is a function of the ratio between the relative intensity differences of a current pixel against its neighbors and the intensity of the current pixel. The orientation component is the gradient orientation of the current pixel [100]. Therefore, the descriptor depends on both the local intensity variation and the magnitude of the center pixel's intensity. With the combination of the WLD feature per pixel, a histogram of the input image is obtained. Texture classification with the WLD is performed using the 2D WLD histogram. In 2018, some authors used the Weber's law methods and proposed a multi-scale counting and difference representation (CDR) [101]. Thus, the single scale CDR feature is composed of two components: the local counting vector (LCV) and the differential excitation vector (DEV). The LCV captures local texture structures using the local counting projection. The DEV is constructed to represent the difference information of textures based on the outputs of Weber's law. The multiscale CDR improves the discrimination of the extracted single-scale CDR [101].

#### 2) Advantages and limitations

The advantage of the WLD is that it is based on the Weber's law that is a law developed according to the perception of human beings.

#### 3) Examples of applications

Ullah *et al.* proposed an approach based on WLD for gender recognition from face images [102].

### L. DETERMINISTIC WALK

#### 1) Concept

In 2010, Backes *et al.* proposed a texture feature extraction method based on the analysis of the transient time and cycle period joint probability distribution calculated by the deterministic tourist walk [103]: the method uses a "tourist" to explore the input image on a given scale considering a deterministic rule. Thus, for an image two pixels are considered as neighbors if the geometrical distance (Euclidian distance) between them is smaller than 2. For two pixels considered as geometric neighbors, the module of the difference of their intensities is the real distance between these two pixels. Therefore, a traveler walking through neighboring pixels can only walk to the following rule: move to the nearest or furthest neighbor if it has not been visited in the last $\mu$ previous steps [103]. The tourist trajectory depends on the walking rule and the image context. Each walk is composed of two parts: (i) the transient for which the agent walks freely to exploit texture characteristics; (ii) the attractor which is a sequence of pixels which repeats along the walk and from which the agent cannot escape. The tourist's movements are performed based on a neighborhood table that represents the tourist graph. A histogram is used to extract information from the joint probability distribution of transient times and attractor periods from which it is possible to quantify and compare textures [103]. As suggested by the authors, a relation exists between the histogram and texture behavior [103]. Thus, for textures with well defined and constant patterns, there are many near attractors. Therefore, the histogram contains a higher peak in the beginning of the curves. It then decreases rapidly (there are few long walks). By opposition, for textures with sparse and not constant patterns, the histogram is more uniform [103]. In 2010 also, Backes *et al.* proposed another approach to compute the direction during the deterministic tourist walk to explore an image [104]. In 2013, the deterministic partially self-avoiding walk (tourist walk) has been associated with fractal dimension theory [105].

#### 2) Advantages and limitations

The method proposed by Backes *et al.* has the advantage of exploring the image on all scales simultaneously.

#### 3) Examples of applications

The deterministic tourist walk-based approach has been used to build a system for the identification of wear particles [106]. Wear particles give information on the wear processes taking place between mechanical components.

## III. STRUCTURAL APPROACHES

### A. CONCEPT

Structural approaches decompose textures into elements, the primitives or texels. The primitives and their spatial arrangements are used to characterize textures. Thus, for the structural approaches, texture is considered as the replication – in a more or less regular manner – of a basic textural element or primitive. The structural approaches aim at determining the textural primitive and at defining the placement rules.

The difference between structural approaches is the choice of primitives. Texture primitives are often considered as regions with uniform grey levels [107], pixels [108], grey level peaks [109], line segments [110], average edge separation in different orientations [111], repetition of edges in different orientations [112], etc. Indeed, periodic structures can also be seen as a regular arrangement of lines, or line segments, of different orientations. In 2005, Lazebnik *et al.* proposed a method that uses a set of affine Harris and Laplacian regions as texture elements [113]. The latter are characterized by spin image and the rotation-invariant feature transform (RIFT) descriptors. Different methods have been proposed to identify the texture primitives: boundaries detection such as Laplacian of Gaussian (LoG) or difference of Gaussian (DoG) filters [114]–[116], mathematical morphology [117]–[120].

The placement rule step consists in inferring placement rules that define the spatial relationships between the primitives. Measures and statistics of homogeneous primitives can also be computed: intensity, orientation, elongation, and compactness [121]–[125]. Matsuyama *et al.* evaluated the energy distribution in the Fourier power spectrum to extract the two spatial vectors representing the placement rule [126]. Some used the diagonality of the co-occurrence matrix to extract periodicity vectors [127]. Other approaches have also been proposed, see, e.g., [128], [129]. Eichmann *et al.* based their work on the fact that regular textures are an arrangement primarily of line structures appearing periodically in the texture [130]. This is why they proposed a structural line detection approach. For this purpose, the line detection was performed using the Hough technique. Texture features proposed were computed from the Hough domain: principal directions of lines in the texture, periodicity and line separation in each direction, among others.

For structural approaches, two ways of analysis are possible: the bottom-up analysis procedure in which texture primitives are determined and, afterwards, the spatial arrangement of the extracted elements is chosen, and the top-down methods in which the spatial structure of texture is first computed and, then, the element extraction is performed. The combination of the two approaches can also be used [131].

### B. ADVANTAGES AND LIMITATIONS

The structural approaches are usually used for regular textures because structural approaches are based on regularity. A primitive is periodically repeated in the texture with some placement rules. These approaches are therefore not appropriated for textures with a high degree of randomness. The advantage of the structural approaches is that they give a good symbolic description of the image. Moreover, the feature extraction algorithm proposed by Eichmann *et al.* has the advantage of being independent of geometrical transformations such as translation, rotation, and scaling [130]. However, the structural approaches are better for synthesis than for analysis purposes.

### C. EXAMPLES OF APPLICATIONS

A structural approach has been used to quantitatively characterize nuclear chromatin texture in light microscope images of Pap smears [132]. For this purpose, the chromatin was segmented into blob-like primitives and their properties and arrangement were then characterized [132].

## IV. TRANSFORM-BASED APPROACHES

Transform methods represent an image in a space (such as the frequency or the scale space) whose coordinate system has an interpretation closely related to the characteristics of a texture.

### A. FILTER BANKS: LAW'S TEXTURE FEATURES, A TEXTURE ENERGY APPROACH

#### 1) Concept

This feature extraction method involves the application of simple filters to digital images. It is based on two steps. First, several 1D arrays (see below) convolved together in a combinatorial way are used to generate twenty-five $3 \times 3$ or $5 \times 5$ masks [133]. The latter are then convolved with a texture field to stress its *microstructure*. This leads to an image from which the energy (and other statistics) of the microstructure is measured. Second, *macrostatistic* features are obtained over large windows. The five 1D arrays (size of 5) identified by Laws are:

- Level L5 = [1 4 6 4 1]
- Edge E5 = [-1 -2 0 2 1]
- Spot S5 = [-1 0 2 0 -1]
- Wave W5 = [-1 2 0 -2 1]
- Ripple R5 = [1 -4 6 -4 1].

For oriented textures, steerable filters have also been proposed [134]. They correspond to a set of orientation-selective filters, computed from a linear combination of basis filters. Unser and Eden also proposed an equivalent filter bank from a nonlinear transformation and an iterative Gaussian smoothing algorithm [135]. The local statistics (texture energy measures) are computed at the output of this equivalent filter bank. In 2008, Mellor *et al.* proposed a method based on invariant combinations of linear filters [136]. This method is composed of two steps: the first step consists in computing two descriptors at each point in the image. Thus, the Hessian matrix is constructed by the polar-separable filters and then the eigenvectors (principal directions) and eigenvalues (principal curvatures) of the matrix are computed. These eigenvectors and eigenvalues are rectified to the local phases and local energies. These descriptors are locally invariant to contrast changes, intensity shifts, rotations, and scaling. They are also robust to skew. Then, the texture is represented with first-order statistics of these descriptors.

#### 2) Advantages and limitations

Law's measures have the drawback of not being rotationally invariant. However, the method proposed by Mellor *et al.* leads to a texture description invariant to local changes in orientation, contrast, and scale [136].

#### 3) Examples of applications

Law's features have been used to describe texture of soil images [137]. They also have been used in the biomedical field [138]–[140]. The filter-based approach has also been used in a framework to identify fibrotic regions, in ultrasound images, with minimal user interaction [141].

### B. FOURIER TRANSFORM-BASED APPROACHES

#### 1) Concept

In the Fourier transform-based approaches, a 2D discrete Fourier transform (called $\mathscr{F}$ in what follows) is used to decompose the image $I$ of size $H \times W$ under study into its frequency components (sum of orthogonal basis functions)

$$\mathscr{F}(u, v) = \sum_{n=1}^{W} \sum_{m=1}^{H} I(n, m) \exp(-j2\pi(\frac{un}{W} + \frac{vm}{H})), \quad (16)$$

where $u$ and $v$ are, respectively, the horizontal and vertical frequencies. The real and imaginary parts can be extracted, as well as the magnitude and phase. For feature extraction, the principle is that spatial edges exhibit a low frequency in one direction, whereas in the orthogonal direction there are multiple frequencies. In the Fourier domain, this is shown by straight lines. For the zero frequencies ($u = v = 0$), the Fourier transform computes the mean of the image (colour measure information rather than texture information). Usually, the result of the Fourier transform is plotted as an amplitude spectrum corresponding to the modulus of the complex values. The farest we are from the center of the spectrum, the highest the frequency observed. Thus, a smooth texture will show high values around the center (low frequencies) whereas a rough texture will show values that are spread over the spectrum (high frequencies). The idea for the texture feature extraction is therefore to consider the Fourier transform as a way to represent the image as a weighted combination of vertical and horizontal sinusoids, each one having its own frequency $(u, v)$: a sum of sinusoidal plane waves of varying frequencies is used to approximate the image. In 2013, Maani *et al.* proposed an approach that first considers a neighboring function defined on a circle of radius $R$ at each pixel of the input image. Then, the magnitude of the 1D Fourier transform coefficients of this neighboring function is defined as local frequency components. Afterwards, the 2D Fourier transform is applied on the local frequency components and bandpass filters are applied on the result. This leads to local frequency descriptors that are noise robust rotation invariant texture features [142]. In 2015, Zhang *et al.* used the combination of wedge filters in the frequency domain and gradient orientation for texture representation [143]. More precisely, Zhang *et al.* proposed the computation of the 2D joint distribution of two descriptors; the first descriptor is based on frequency decomposition by using scale invariant wedge filters; the second descriptor is based on the gradient orientation [143].

#### 2) Advantages and limitations

The Fourier spectrum may be used when one wants translation invariance. However, one of the drawbacks of the Fourier transform is that it cannot describe local variations of textures. Moreover, the Fourier transform contains information localized in the frequency domain, not in the space. Analyzing the spectrum does not allow to conclude directly on the spatial localization of the texture whose frequency response is observed in the spectrum. This is why other methods as Gabor decomposition-based approaches or wavelet-based approaches are proposed.

#### 3) Examples of applications

The Fourier transform has been used in fingerprint identification [144]. Moreover, Ojansivu *et al.* proposed a new descriptor for texture classification that is robust to image blurring [92]. Their texture analysis method operates on the Fourier phase [92].

### C. GABOR DECOMPOSITION-BASED APPROACHES

#### 1) Concept

To extract the Gabor features, the multi-channel Gabor filtering technique is used [145]. A Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. It can be seen as a bandpass filter with tunable central frequency, orientation, and bandwidth. A 2D Gabor filter can be computed as

$$G_{\sigma,f_0,\phi}(x,y) = \exp\Big(-\frac{1}{2}\Big[\frac{x'^2}{\sigma_x^2}+\frac{y'^2}{\sigma_y^2}\Big]\Big)\cos(2\pi f_0 x' + \phi), \tag{17}$$

where $\sigma_x$ and $\sigma_y$ are the scales of the Gaussian envelop (standard deviations) in the $x$ and $y$ directions, respectively. $f_0$ and $\phi$ are respectively the frequency and phase of the sine wave. $x'$ and $y'$ are

$$x' = x\cos(\theta) + y\sin(\theta), \tag{18}$$

$$y' = -x\sin(\theta) + y\cos(\theta). \tag{19}$$

Daugman modeled the visual information processing from the 2D multi-channel Gabor functions [146]. The approach enables filtering in the frequency and spatial domains. The general principle of the Gabor decomposition-based approaches relies on the decomposition of the original image into several filtered images, each one having a limited spectral information. Thus, the multichannel filtering of the original image is performed through a bank of filters at different scales and orientations. Filtering an image $I(x,y)$ with Gabor filters results in its Gabor wavelet transform [147]. The Gabor features are then extracted from the magnitudes of the Gabor-filtered images. They represent the statistical distribution of the Gabor magnitude response. The directions 0, $\pi/4$, $\pi/2$, and $3\pi/4$ and the spatial frequencies $2\sqrt{2}$, $4\sqrt{2}$, $8\sqrt{2}$, $16\sqrt{2}$, $32\sqrt{2}$, and $64\sqrt{2}$ are widely used.

#### 2) Advantages and limitations

Because of its localization both in the spatial and frequency domain, a Gabor filter bank is able to perform a robust multiresolution decomposition. The multiresolutional aspect of the approach, as for the wavelet transform, allows the extraction of frequency and orientation information. Small scales extract high frequency content and large scales extract low-frequency content. However, Gabor filters have the drawback of being non-orthogonal which leads to redundant features at different scales [148]. Gabor filters provide means for better spatial localization than the Fourier transform. However, most of the time there is no single filter resolution at which one can localize a spatial structure in natural textures [19]. In 2013, Riaz *et al.* proposed texture features using Gabor filters which are invariant to scale and rotation changes in the image [149].

#### 3) Examples of applications

Gabor decomposition-based approaches have been used in the biomedical field [150]. They also have been used for unsupervised texture segmentation in a deterministic annealing framework [151].

### D. WAVELET-BASED APPROACHES

#### 1) Concept

Gabor filters and wavelet transforms analyze the content of texture both in frequency and spatial domains. A 2D wavelet transform allows the localization in the scale domain (i.e. frequency) from dilations, but also in the spatial domain via translations of a mother wavelet: a wavelet transform approximates the image by dilated and translated local wavelets. 1D (child) wavelets are computed by dilation (by a power of two) and translation of a mother wavelet $\psi$:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k2^j}{2^j}\right), \tag{20}$$

where $j$ and $k$ are, respectively, the scale and shift parameters. A discrete wavelet transform consists in applying a series of scaled filters: high-pass and low-pass decompositions followed by down-sampling. The coefficients obtained contain vertical (rows low-pass and columns high-pass), horizontal (rows high-pass and columns low-pass), and diagonal (high-pass on both rows and columns) details. Thus, the HH sub-image corresponds to the diagonal details (high frequencies in the two directions, the corners), HL gives horizontal high frequencies (vertical edges), LH represents the vertical high frequencies (horizontal edges), and the image LL gives the lowest frequencies. At the next scale, the image LL undergoes the decomposition using the same filters. At each stage of the analysis, 4 sub-images are produced whose size is reduced twice compared to the previous scale. Thus, the 2D $j$-level wavelet transform decomposes an input image $I(x,y)$ into 4 sub-bands and produces $3j+1$ sub-images. The sub-images obtained are then used to extract scale dependent texture features such as energy, entropy, variance, refined histogram, etc (see Ref. [152] for examples of wavelet-based signatures). In 2017, based on the wavelet transform, Dong *et al.* proposed a multiscale rotation-invariant representation of textures by using multiscale sampling [153]. In 2018, Yang *et al.* proposed the association of the dual-tree complex wavelet transform and LBP for rotation, illumination, and scale invariant texture classification [154].

#### 2) Advantages and limitations

The wavelet transform has the advantage of minimizing the Heisenberg uncertainty, capturing localised frequency and spatial information. However, the wavelet transform directly uses wavelet basis, which is considered as a type of fixed dictionary: they are therefore dataset independent. By opposition, vocabulary learning methods (see below) are dataset dependent. Dictionary learning uses all the samples to train the dictionary. The features are then extracted based on the dictionary. The wavelet transform therefore achieves lower flexibility than dictionary learning. Nevertheless, the wavelet transform has the advantage of needing less complex computation. Compared with the Gabor transform, the wavelet transform has the advantage of providing variation of the spatial resolution. This allows to represent textures at different scales. Moreover, the choice of the wavelet function can be an advantage for specific applications. However, the wavelet transform is not translation-invariant [19] nor rotation-invariant [155]. However, several papers proposed attempts towards rotation invariant texture analysis using wavelet transform (see, e.g., [156] and a short survey mentioned in [156]).

#### 3) Examples of applications

Wavelet features have been used to analyze historical document images [11]. They also have been used in the biomedical field: some authors used wavelet-based texture features to differentiate healthy from pathological hippocampal tissue [157]. The results could help physicians in the determination of candidates for epilepsy surgery. Wavelet features have also been used in a vegetation and land cover classification based on a Quickbird image of subantarctic Macquarie Island [158]. Fukuda *et al.* used the wavelet features in the classification of multifrequency polarimetric SAR images [159]. The wavelet features have also been used in the automatic vine detection from airborne infrared color image [160].

### E. SHEARLET-BASED APPROACHES

#### 1) Concept

In 2013, He *et al.* proposed a rotation invariant texture descriptor based on the shearlet transform [161]. The procedure proposed by the authors relies on four steps: (i) the input image is first decomposed by the shearlet transform; (ii) the local shearlet-based energy features are computed; (iii) the latter features are quantized and encoded to be rotation invariant; (iv) from all the decomposition levels, the energy histograms are concatenated into one histogram and used to describe texture images. Later, in 2015, Dong *et al.* proposed another method based on shearlet for texture retrieval [162]. In the latter work, shearlet subband dependences are modeled with linear regression. Then, energy features from shearlet subbands are extracted and their dependences are modeled using linear regression. The regression residuals are finally used to compute the distance from a test texture to a texture class [162].

#### 2) Advantages and limitations

The shearlet-based method proposed by He *et al.* has the advantage of being robust with respect to noise and rotation invariant [161].

#### 3) Examples of applications

The shearlet-based method has recently been used for face recognition [163].

### F. CONTOURLET-BASED APPROACHES

#### 1) Concept

In 2015, Zhang *et al.* proposed a contourlet-based texture feature extraction method for shear-wave elastography [164]. Thus, the contourlet transform was applied to decompose shear-wave elastography images. The framework of the authors then performs a subband reconstruction, initial feature derivation and feature averaging to obtain the final features [164].

#### 2) Advantages and limitations

The contourlet-based texture feature yields good quantification of the elastic properties of breast tumors and thus increases diagnostic performance [164].

#### 3) Examples of applications

The contourlet-based texture features were used in shear-wave elastography for breast tumor classification [164].

### G. LOCALLY ENCODED TRANSFORM FEATURE HISTOGRAM (LETRIST)

#### 1) Concept

In 2018, Song *et al.* proposed the Locally Encoded TRansform feature hISTogram (LETRIST) for texture feature extraction [165]. The procedure is based on the following steps: (i) the extremum responses of the first and second directional Gaussian derivative filters at multiple scales are computed; (ii) a set of transform features is constructed by performing linear and non-linear operators on previous responses. This allows to capture discriminative texture information; (iii) these transform features are quantized into discrete texture codes via simple binary or multi-level thresholding; (iv) these texture codes are encoded across scales to build feature histograms, which are further concatenated to form the image descriptor, i.e., LETRIST.

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#### 2) Advantages and limitations

LETRIST is training-free and efficient to implement. It is also robust for texture description, robust to Gaussian noise, robust to rotation, illumination, scale and viewpoint changes [165].

#### 3) Examples of applications

LETRIST has been used in problems as face recognition [166].

## V. MODEL-BASED APPROACHES

Model-based approaches aim at representing texture using mathematical models (such as fractal or stochastic).

### A. COMPLEX NETWORK-BASED APPROACH

#### 1) Concept

A complex network is represented by a matrix (the adjacency matrix, $W$) [167]. The latter has a dimension of $N \times N$ when the complex network has $N$ nodes (or vertex). The weight of the connection from each note $j$ to each node $i$ is represented by $W(i, j)$. When no connection exists between two nodes, a null value is assigned. Another matrix, binary this one, is also computed ($W_T$). It contains only the most significant connections: only elements of the matrix $W$ that are greater than or equal to a threshold $T$ are kept [167]. From this, in 2008 – for texture characterization – Chalumeau *et al.* suggested to represent the image pixels as nodes and similarities between such pixels were mapped as links between the network nodes [167]. More precisely, weights of edges are defined with the grey level of pixels and the connection between nodes $i$ and $j$ defined by [167]

$$W(i,j) = \frac{255 - |I(i) - I(j)|}{255}, \tag{21}$$

where $I(i)$ represents the grey level of node $i \in [0, 255]$. We thus have $W(i, j) \in [0, 1]$ where 0 corresponds to no connection and 1 corresponds to the maximum connection between two nodes.

Later, Backes *et al.* used this approach and focused on pattern recognition of texture [168]. Thus, the complex network-based approach uses the complex network theory to analyze texture [168]: degree measurements are used to compose a set of texture descriptors. More precisely, a graph $G = (V, E)$ ($V$ is the set ot vertices and $E$ the set of edges) is built by considering each pixel $I(x, y)$ of the image $I$ as a vertice $v_{x,y} \in V$ of the graph $G$. A non-directed edge $e \in E$ is used to connect the vertices associated to two pixels $I(x, y)$ and $I(x', y')$, where $e = (v_{x,y}, v_{x',y'})$, when the Euclidean distance between them is no longer than a value $r$. Then, for each non-directed edge $e$, a weight $w(e)$ is associated. This weight is defined by the square of the Euclidian distance between the two connected vertices and the difference of pixel intensity (between $I(x, y)$ and $I(x', y')$), normalized according to the square of the radius $r$ [168]. The histogram degree can then be computed to determine features. For this, the degree (or connectivity) of a node represents the number of edges connected to this node. By computing the degree for each network vertice $v \in V$, the histogram degree is determined. Local and global characteristics of the network can be determined from features computed from the degree histogram. To extract additional information about the structure and dynamic of a complex network, a transformation to the original network is applied: a threshold $t$ to the original set of edges $E$ is applied, thus selecting a subset $E_t$, $E_t \in E$, where each edge of $e \in E_t$ has weight $w(e)$ equal to or smaller than $t$. Thus, by applying a set of thresholds $T$, $t \in T$, to the original network $G$, the behavior of its histogram features can be obtained (computation of the mean, energy, entropy and contrast).

In 2015, Scabini *et al.* also proposed to analyze texture with complex network theory [169]. For this, they constructed a vocabulary of visual words with bag-of-visual-words method. The vocabulary was built by extracting, from the networks, the degree and strength of each vertex. The feature vector was composed by the visual word occurrence.

More recently, another approach has been proposed because some informative properties such as spatial information are not analyzed in texture analysis based on a complex network mode [170]. In the latter work, a local spatial pattern mapping (LSPM) method was presented for manipulating the spatial information in an image texture with multi-radial distance analysis to capture the texture pattern. The LSPM method was thus proposed to describe the spatial arrangement of neighbors in a network. More precisely, it was proposed to describe the uniformity of texture primitives when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1 in the same way as uniformity in LBP theory [170]. In practice, LSPM is implemented by using a look-up table.

#### 2) Advantages and limitations

It has been shown that the computational complexity of the original network-based approach can be considered as $O(N^2)$ [168]. Backes *et al.* have shown that the complex network-based approach presents a higher success rate of classification for several databases when compared with traditional texture analysis methods (first order method, Fourier, Gabor, GLCM, discrete cosine transform, wavelets,...) [168]. Moreover, the method is *relatively* invariant to rotation [168]: the network model is derived from the Euclidean distance between pixels. In discrete space, as the Euclidian distance is not constant at all rotation angles, a small error is added [168]. One of the drawbacks of the complex network-based approach is that, to compute the features, the texture has first to be modeled by a complex network using radius $r$. Then, a set of thresholds $T$ has to be applied to this network to compute different samples of the network during its life [168]. Therefore, several parameter values have to be set, which may be a tricky task. Moreover, the presence of noise affects the way the edges are built in

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the network.

#### 3) Examples of applications

Xu *et al.* used a complex networks-based texture extraction and classification method to describe the froth image texture and also to classify the different production states [171].

### B. MOSAIC MODELS

#### 1) Concept

Mosaic models correspond to a class of generative models where random pattern generation processes are used in the plane to provide image structure [172]. Mosaic models therefore describe images by specifying geometrical processes that may have generated the visual pattern under study. Then, geometric properties of components in mosaics can be investigated. In mosaic models, two classes can be derived: cell structure and coverage models.

##### a: Cell structure models

For this class, a random geometric process is first used to tessellate the plane into “cells” and colors or grey levels are then assigned randomly to the cells. The set of colors may correspond to a set of values of any property, not necessarily grey level. Different types of tessellations lead to different types of mosaics. The possible tessellations include Poisson line model, Delaunay model, and occupancy model.

##### b: Coverage (or “bombing”) models

In this case, figures are randomly dropped on the plane, and colors are then assigned randomly to the figures. Therefore, from a random arrangement of a set of geometric figures (“bombs”) in the plane, a coverage mosaic is obtained [172], [173].

#### 2) Advantages and limitations

The large number of possible models enables a means of controlling or matching many texture features.

#### 3) Examples of applications

Ahuja *et al.* proposed to fit the mosaic image models to real images to obtain insights into the structure of the data [174].

### C. RANDOM FIELD MODELS

#### 1) Autoregressive models

##### a: Concept

The autoregressive (AR) models rely on the assumption that a local interaction exists between image pixels. Thus, we assume that pixel intensity is a weighted sum of neighboring pixel intensities as (assuming $I_s$ is the intensity of the pixel at site $s$ in an image)

$$I_s = \sum_{r \in N_s} \theta_r I_{s+r} + e_s, \tag{22}$$

where $e_s$ is an independent and identically distributed noise with standard deviation $\sigma$, $N_s$ is a neighborhood of $s$, and $\theta$ is a vector of model parameters. Over non-causal spatial interaction models, causal AR models are more simple and efficient for the parameter estimation. In AR models, the parameters (the standard deviation $\sigma$ of the driving noise $e_s$ and the model parameter vector $\theta$) have to be determined for a given image region and these parameters are then used for texture discrimination. For the parameter determination, the sum of the squared error

$$\sum_s e_s^2 = \sum_s (I_s - \hat{\theta}\mathbf{w_s})^2, \tag{23}$$

has to be minimized and then the parameters can be estimated with

$$\hat{\theta} = (\sum_s w_s {w_s}^T)^{-1} (\sum_s w_s I_s), \tag{24}$$

and

$$\sigma^2 = \frac{\sum_s (I_s - \hat{\theta} w_s)^2}{N^2}, \tag{25}$$

where $w_s$ = col$[I_i,\ i \in N_s]$.

Kashyap and Khotanzad [175] also developed a circular symmetric autoregressive model for invariant texture analysis. The latter model is based on circular neighborhoods.

##### b: Advantages and limitations

Compared to non-causal spatial interaction models, causal AR models have an advantage of simplicity and efficiency in parameter estimation.

##### c: Examples of applications

AR model-based features have been used in many applications, see, e.g. [176]–[179].

#### 2) Moving average models

##### a: Concept

For the 2D moving average model, an image is considered as a circular convolution of a stationary input process and a point spread function. The latter is assumed as a linear geometric transform of an isotropic function [180]. The input process is either a white Gaussian process (for stochastic textures) or a summation of white Gaussian process and a deterministic trend function (for structured textures). The parameters of the 2D moving average model (estimated by a maximum likelihood method in the frequency domain) are able to discriminate different kinds of textures. Spatial autoregressive and moving average (ARMA) models have also been used to represent texture images [181].

##### b: Advantages and limitations

The 2D moving average model is flexible and is able to model isotropic and anisotropic textures [180].

##### c: Examples of applications

Chanyagorn *et al.* used the moving average models for texture segmentation [182]. Moreover, Eom proposed the segmentation of monochrome and color textures using a moving average modeling approach [180]. Andrews and Eom used moving average models to synthesize color textures where the estimation of model parameters were done by the maximum-likelihood method [183].

#### 3) Markov random field models of texture

##### a: Concept

Markov models rely on the Markov property which assumes that – in a system – the future state depends only on the current stage. Thus, in the field of texture analysis and synthesis, a Markov random field (MRF) assumes that the intensity of a pixel (whatever the pixel) depends only on the intensity of the previous pixel in a chain and on a transition probability matrix [184]. A MRF is therefore a graphical model. The parameters of the model are chosen to best fit the image. For this purpose, an optimization method is used. The latter minimizes an energy function. Then, the model parameters are used as texture features.

##### b: Advantages and limitations

Cohen *et al.* used Gaussian MRF to model texture [185]. They used the maximum likelihood to estimate coefficients and rotation angles. The drawback here is that the likelihood function is highly nonlinear and local maxima may exist. Moreover, the algorithm is computationally intensive because it uses an iterative method. This is why some authors used multichannel subband decomposition and hidden Markov model to obtain rotation invariant texture features [186], [187]. However, in the work of Chen and Kundu, feature vectors computed from the original texture and those computed from the rotated version are different [20]. Therefore, Wu and Wei proposed another method [188]. However, other improvements can still be performed, as mentioned in, e.g., [20].

##### c: Examples of applications

The texture features obtained with a MRF approach have been used for glaucoma detection [189]. They also have proven to give interesting results for hyper-spectral image analysis for plant classification [190] and for image classification [191].

#### 4) Generalized long correlation model

##### a: Concept

Long correlation models are a general class of random field models. Bennett and Khotanzad have suggested that the long correlation models can be considered as a generalization of the simultaneous autoregressive and Markov random field models [192]. With long-correlation models it is possible to model correlations that extend over large image regions with few model parameters. Indeed, one of the drawbacks of simultaneous autoregressive models and Markov random field models is that they are not able to model correctly low frequency power in an image because the autocorrelation function decays rapidly beyond the span of the defined neighbor set. Therefore, they are not able to model correlations with large spatial extent. Long correlation models have an autocorrelation function that decays more slowly. More details on the theory can be found in [192]. Long-correlation models have also been generalized to represent isotropic and elliptical long-correlation characteristics as well as short-correlation characteristics [193]. A "narrow band" long correlation model has also been proposed as an extension of the isotropic long-correlation model, to generate random images with periodicity [194]. A general method for estimating the parameters of a generalized long correlation model, without restrictions on its form, is developed in [192].

##### b: Advantages and limitations

The advantage of the generalized long correlation models is that they are able to characterize textured images having correlations which extend over substantial distances with small-order models [192].

##### c: Examples of applications

Kashyap and Eom used the long correlation texture model with a small number of parameters to characterize texture [195]. Moreover, Kashyap and Lapsa generated natural textures such as images by the long correlation model [196].

### D. FRACTAL-BASED MEASURES OF TEXTURE

#### 1) Concept

One of the parameters defining complex or chaotic systems is the self-similarity or fractal behavior. Fractal "objects" are self-similar under magnifications: they have identical statistics of characteristics of shape at different scales of examination. In this case, the frequency spectrum shows an inverse power-law ($1/f^n$-like) scaling pattern, and thus a linear log power spectrum. Some natural textures have a linear log power spectrum and it has been shown that the human visual system is well suited to characterize such textures. This is why the fractal dimension can be well suited to characterize such textures. The fractal geometry relies on self-similarity across scales (repeated patterns at multiple scales) and is measured with the fractal dimension $D$. The latter has been found to correspond to the human judgment of roughness of a texture [197]. It is computed as

$$D = \frac{\log(N)}{\log(1/r)}, \tag{26}$$

where $N$ is the number of repeated patterns down-sampled by a ratio $r$. The fractal dimension can be determined by several methods such as box-counting method [198] or fractional Brownian motion with spectral analysis [197].

In 2011, the fast fractal stack has also been proposed as a feature extraction method [199]. It consists in computing fractal measurements from a set of binary images computed from the grey scale image under study with the binary stack decomposition algorithm [199].

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In 2012, Costa *et al.* proposed the segmentation-based fractal texture analysis that consists, first, in decomposing the image under study into a set of binary images [200]. This is performed by the two-threshold binary decomposition algorithm proposed by the same authors [200]. For each binary image, the fractal dimensions of the regions' borders are then calculated. Moreover, the regions' mean grey level and size are also determined. From this, the segmentation-based fractal texture analysis feature vector is constructed as the resulting binary images' size, mean grey level, and boundaries' fractal dimension. The fractal measurements allow to describe the boundary complexity of objects and structures segmented in the image under study.

#### 2) Advantages and limitations

The segmentation-based fractal texture analysis has the advantage of having a low computation time compared to other texture feature extraction methods. However, some authors have shown that the fractal dimension does not allow to distinguish all textures [198], [201]: texture having different appearances can have the same fractal dimension. This is why other measures have been proposed such as lacunarity [198], [202]–[205]. Lacunarity is related to the distribution of gap sizes: low lacunarity geometric objects are homogeneous as all gap sizes are the same. By opposition, high lacunarity objects are heterogeneous.

#### 3) Examples of applications

The fractal-based measures of texture have been used in a computer-aided diagnosis system for mass detection and classification in breast ultrasound images based on the fuzzy support vector machines [206]. They also have been used for classification of breast tumors as benign or malignant [207]

### E. GRAVITATIONAL MODELS

#### 1) Concept

In 2012, some authors proposed a texture analysis approach based on the gravitational model. Thus, the input image is transformed in a dynamic system in the gravitational collapse process to obtain different states and each one represents a texture pattern [208]. Thus, the model proposes a gradual "gravitational collapse process", i.e. all the particles – that are pixels here – are attracted to the center of the image. This generates different texture patterns as the process occurs. The Bouligand-Minkowski fractal dimension method is used to quantify each state in order to obtain a feature vector [208]. In 2013, an extension to color images has been published, using the Bouligand-Minkowski and the lacunarity methods [209].

#### 2) Advantages and limitations

The method based on the gravitational model has the drawback of having a higher computational cost than methods as Gabor filters or co-occurrence matrices.

#### 3) Examples of applications

The gravitational model has been used for plant classification using adaxial epidermis texture [210] and for plant leaf identification [211].

### F. WOLD DECOMPOSITION

#### 1) Concept

The Wold decomposition measures randomness, directionality, and periodicity [212]. Thus, in the Wold decomposition, the texture of the image is decomposed into three mutually orthogonal components, assuming that texture images are homogeneous random fields. Thus, a texture image $I(m,n)$ is decomposed as [213]

$$I(m,n) = w(m,n) + p(m,n) + g(m,n), \tag{27}$$

where $w(m,n)$ is the purely indeterministic component, $p(m,n)$ is the half-plane deterministic component, and $g(m,n)$ is the generalized evanescent component. By choosing the parameters of the 3 components, we can obtain the modeling of a large number of textures, going from periodical macrotextures to random microtextures. The decomposition of the spatial field can also be performed by decomposing their spectral density function [213], [214].

#### 2) Advantages and limitations

The key problem of this method is the estimation of the coefficients and the choice of the correct model. Let's note that some authors proposed a method using the Wold model for invariant texture analysis [215].

#### 3) Examples of applications

The Wold decomposition has been used for indexing and retrieving multimedia data through texture segmentation [216]. It also has been of interest for unsupervised texture segmentation [217] and in edge detection for remote sensing image [218].

## VI. GRAPH-BASED APPROACHES

The methods of this class are those where the extraction of the texture features relies on graphs obtained from the input image [219].

### A. LOCAL GRAPH STRUCTURES

#### 1) Concept

The features of local graph structures are computed from the texture in a local graph neighborhood [220]. The image is represented by a graph of points. More precisely, local graph structures work with the 6 neighbors of a pixel. The target pixel $I(x,y)$ is chosen as a threshold. The neighbors pixels of $I(x,y)$ are "visited" by moving anticlockwise at the left region of $I(x,y)$. If the neighbor pixel has a higher (or same) grey value than (as) $I(x,y)$, then a binary value 1 is assigned on the edge connecting the two vertices, else a binary value 0 is assigned. When the left region is finished, then the same process is applied

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in a horizontal way (clockwise) to the right region of the graph [220]. Then, the decimal value is computed from the generated string. In 2016, the extended local graph structure has been proposed [221]. The latter takes into account both the vertical graph and the horizontal graph in order to capture wider spatial information. Thus, two descriptors are obtained. A histogram is computed for ech descriptor independently. Then, the two histograms features are concatenated to form a global descriptor [221].

#### 2) Advantages and limitations

Local graph structures contain information on the distribution of local micropatterns (edges, spots, flat areas). Moreover, local graph structures are rather insensitive to illumination intensities, and invariant to shifting and scaling [220]. The computation time is also fast.

#### 3) Examples of applications

The local graph structure has been used for face recognition tasks [220], [222]. Another graph-based approach has been used for clothing classification [223].

### B. GRAPH OF TOURIST WALK APPROACH

#### 1) Concept

In 2011, authors suggested to generate graphs out of the trajectories produced by the tourist walks described in Section II-L [224]. Thus, instead of focusing on attractor and transient length histograms, the generated trajectories are used to build a graph. The motion from one pixel to another is interpreted as a connection between these two pixels. Therefore, a graph is built from the trajectories. This graph describes the tourist transitivity. The statistical position and dispersion calculated from the graphs were proposed as texture descriptors [224]. In 2012, Goncalves *et al.* suggested to use graph theory to model the connections among neighbor pixels: this led to a new approach that uses graph modeling with posterior use of the deterministic tourist walk [225].

#### 2) Advantages and limitations

From experimental results on plant leaves image database involving textures that have similar appearance, Goncalves *et al.* have shown that their method is robust in terms of micro-texture recognition and that it gives good results using rotated and noised images [225].

#### 3) Examples of applications

Based on the work from Backes *et al.* [224], some authors proposed to extract froth image texture features [226].

### C. SHORTEST PATHS IN GRAPHS

#### 1) Concept

In 2013, another method based on graph theory has been proposed to analyze texture [227]. In this approach, the texture is explored as it if were a landscape: the texture is described by statistical moments computed from shortest paths in the landscape between pairs of points. For this purpose, the pixels of the input image are converted into vertices of an undirected weighted graph whose weights are defined by the image grey levels. Then, the shortest paths between different square regions of the graph/image are computed using the Dijkstra's algorithm. This approach is performed for different scales and orientations of the image [227]. An extension for color images has also been proposed [228].

#### 2) Advantages and limitations

The shortest paths are computed between different square regions, starting with large square and diminishing its size in a multiscale approach. Therefore, both micro and macro texture information can be retrieved.

#### 3) Examples of applications

The shortest paths in graph approach has been used in medical image analysis [229].

## VII. LEARNING-BASED APPROACHES

In the last few years, new texture feature extraction methods have been proposed based on learning-based approaches. We propose to gather these methods in a new class that can be divided into three subsections: the vocabulary learning methods, the extreme learning machine-based methods, and the deep learning methods. These two latter families (the extreme learning machine-based methods and the deep learning methods) are very recent and have brought a new start in the texture feature extraction studies due to their high capacities in a large number of applications. This new class of approaches (learning-based approaches) surely deserves attention in the future.

### A. VOCABULARY LEARNING METHODS

#### 1) Concept

In image analysis, vocabulary learning methods – also called visual dictionary methods – imply the learning of a visual dictionary. In vocabulary learning, the patterns are learnt from a training set by clustering (using, e.g., K-means or Gaussian mixture models) local descriptors into clusters in the feature space. The cluster centers constitute the words in a visual dictionary. Words are therefore visual patterns: the dictionary is composed of representative patterns. A repeated pattern or *texton* is described by descriptors that are clustered in the same visual word, in the feature space. Dictionary learning generally involves the detection of keypoints, the extraction of local descriptors, clustering to learn the dictionary (e.g., K-means), and pooling into a global image descriptor (e.g., occurrence count histogram) [230]. Thus, the descriptors of training images are aggregated together to form, by clustering, the texton dictionary (the codebook). The feature encoding step may use vector of locally aggregated descriptors (VLAD) [232], [233], Fisher vector and improved Fisher vector [234]–[236].

In 2005, Varma and Zisserman proposed a statistical learning approach (VZ-MR8) : textures were modelled by the joint distribution of filter responses [237]. The distribution was represented by the histogram of the frequency of filter response cluster centres (textons). VZ-MR8 uses the MR8 filter bank. The latter consists of 36 directional filters, a Gaussian filter and a Laplacian of Gaussian filter to retrieve the features. Textons and texture models were learnt from training images. Later, the same authors proposed another texton dictionary-based algorithm (VZ-Joint): instead of applying filter banks, the authors proposed an alternative image patch representation based on the joint distribution of pixel intensities in a neighborhood [238]. In 2010, Crosier and Griffin proposed a statistical texture representation that models images as histograms over a dictionary of features [239]. The latter is based on basic image features (BIFs) and does not rely on a dictionary based on clustering. The authors show that the features are invariant to rotation and reflection [239]. They also have proposed a framework that is invariant to changes in scale [239]. In 2013, Zhang *et al.* proposed two local descriptors that both have the property of continuous rotation invariance [240]. These local descriptors are based on Gaussian derivatives filters. The first descriptor uses the maximum of the filter responses named continuous maximum responses (CMR), while the second descriptor rectifies the responses of Gaussian derivatives filters to determine the principal curvatures of the image surface [240]. In 2016, Mehta and Egiazarian proposed the dense micro-block difference (DMD) that densely captures the granularities at multiple scales and orientations [241]. DMD is fast to compute, low in dimensionality and easy to implement. In 2018, Dong *et al.* extended this approach and proposed the multiscale symmetric DMD [242].

#### 2) Advantages and limitations

As mentioned above, vocabulary learning methods are dataset-dependent. Dictionary learning achieves therefore higher flexibility than the wavelet transform. However, dictionary learning requires more complex computation.

#### 3) Examples of applications

In 2001, Leung and Malik built a small, finite vocabulary of micro-structures [231]. The latter were called 3D textons. The textons in the vocabulary encode the appearances of local geometric and photometric features. Then, the surface of material is represented as a spatial arrangement of symbols from this vocabulary [231]. More precisely, they used images from a set of training materials to learn a vocabulary which can characterize all natural materials.

In 2014, Cimpoi *et al.* proposed a vocabulary of 47 terms as texture descriptors and introduced a describable texture dataset containing 5640 texture images jointly annotated with these 47 attributes [233]. Their results show that this annotated dataset provides a good basis for learning to recognize describable texture attributes in images [233].

### B. EXTREME LEARNING MACHINE-BASED METHODS

#### 1) Concept

Texture signature has also been extracted with extreme learning machine (ELM) [243]. An ELM is a single-hidden layer feedforward neural network with a very fast learning algorithm. Thus, Sa Junior and Backes proposed to first divide the input image into $K \times K$ joint windows ($K$ is odd) [243]. The central pixel of each window is considered as a label and its neighboring pixels as input vector in the ELM. The set of output weights is used as a feature vector.

#### 2) Advantages and limitations

ELM has a fast computation speed and good generalization performance.

#### 3) Examples of applications

The method has shown good results in texture classification [243].

### C. DEEP LEARNING METHODS

#### 1) Concept

Deep learning – and in particular convolutional neural networks (CNNs) – have recently significantly been used in the field of computer vision. These networks are biologically inspired and trained with powerful algorithms. The CNN model is a supervised learning method that has recently been successfully used in a large number of applications because of its excellent capability of feature representation. CNNs consist of multiple locally connected layers (the most important are convolutional layers). Convolutional layers convolve kernels with a small span over the entire area of the input image [244]. Andrearczyk proposed to explore the use of CNNs in texture analysis (among others) [230], [245], [246]. For this purpose, the CNN architecture uses an orderless pooling of intermediate layers to exclude the overall shape analysis [230]. Lin *et al.* recently performed a study of CNN-based texture representations [247]. They reported that the studied models are a good approach for texture synthesis and manipulation of content of images using texture attributes [247]. In the same way, Li *et al.* proposed deep decomposition of circularly symmetric Gabor wavelet (DD-CSGW) for rotation-invariant texture image classification [155]. The energies of DD-CSGW and the parameters of copula model based on DD-CSGW were used as the features of texture [155]. In 2016, Cimpoi *et al.* have shown that deep learning can be used in many domains of texture analysis [248].

#### 2) Advantages and limitations

Due to hierarchical architecture, deep learning models have the capacity of learning high-level features from raw data automatically. However, CNN performance depends on the amount of the training sample marked. Moreover, the approach is computationally expensive. In 2016, Liu *et al.* evaluated several deep texture descriptors and compared

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them to several variants of LBP descriptors [90]. Their results showed that the deep convolutional descriptors obtain the best results. However, they have a much higher computational complexity than LBP variants [90].

#### 3) Examples of applications

Recently, Han *et al.* used a deep learning model to extract multiple haptic features and to recognize objects from multi-modal haptic images [249]. Deep-learning has also been used for ground texture classification [250]. Andrearczyk used the CNN approach for the recognition of malignant lymphomas and the classification of mouse liver tissue based on age, gender, and diet [230].

## VIII. ENTROPY-BASED APPROACHES

Entropy-based measures have been proposed since the 1990's, and especially since the 2000's, to process time series (unidimensional data). These measures have proven to give very interesting results in domains as the biomedical field, the financial time series, and the engineering aspects. Many papers have been published on the use of these entropy measures [251]. However, before 2011 (and even before 2016) they were restricted to the processing of time series. No extension to images had been suggested. Very recently, new texture feature extraction methods have been proposed based on the bi-dimensional approaches of 1D entropy measures. Moreover, multiscale approaches of these measures are now available. These new texture feature extraction methods are simple to implement, based on strong theoretical aspects because they are extensions of already well-known 1D measures, and give very interesting results. This new class, the entropy-based approaches, gathers the texture feature extraction methods where an entropy measure is *directly* computed on the image. They are therefore directly related to the irregularity / complexity of the image. Methods where entropy is computed to quantify the disorder of a matrix obtained from a processing step applied to the image (as in, e.g., GLCM) do not belong to this entropy-based class: in methods as GLCM the entropy measure does not represent the irregularity of the image but the disorder of the intermediate matrix.

The entropy-based approaches surely deserve attention in the future and need to be developed based on their performances for time series.

### A. TWO-DIMENSIONAL SAMPLE ENTROPY

#### 1) Concept

In 2011, Yeh *et al.* and later in 2016 Silva *et al.* proposed the bi-dimensional sample entropy ($\mathrm{SampEn}_{2D}$) as a measure of irregularity in pixel patterns [252], [253]. Thus, it has been shown that $\mathrm{SampEn}_{2D}$ can be applied as a texture feature quantifier [253]. The algorithm to compute $\mathrm{SampEn}_{2D}$ is composed of the following steps for an image $I$ with width $W$ and height $H$ [253]

1) Let $x_m(i,j)$ be the $m$-length square window with origin at $I(i,j)$. Let $N_m$ be the total number of square windows within $I$ that are generated for $m$ and $m+1$ size: $N_m = (W-m)\times(H-m)$. For a similarity threshold $r$, compute $U^m(r)$ as

$$U^m(r) = \frac{1}{N_m}\sum_{i=1,j=1}^{i=H-m,j=W-m} U^m_{ij}(r), \tag{28}$$

where $U^m_{ij}(r) = \frac{1}{N_m-1}\times$ number of $x_m(a,b)$ such that $\mathrm{d}[x_m(i,j),x_m(a,b)] \le r$ and where $a$ and $b$ range from 1 to $H-m$ and from 1 to $W-m$, respectively. The origin points $(i,j)$ and $(a,b)$ must be different to exclude self-matches. The distance d is computed as

$$\mathrm{d}[x_m(i,j),x_m(a,b)] = \max_{0\le k\le m-1,0\le l\le m-1}(|u(i+k,j+l)-u(a+k,b+l)|). \tag{29}$$

2) Compute $V^m(r)$ as

$$V^m(r) = \frac{1}{N_m}\sum_{i=1,j=1}^{i=H-m,j=W-m} V^m_{ij}(r), \tag{30}$$

where $V^m_{ij}(r) = \frac{1}{N_m-1}\times$ number of $x_{m+1}(a,b)$ such that $\mathrm{d}[x_{m+1}(i,j),x_{m+1}(a,b)] \le r$ and where $a$ and $b$ range from 1 to $H-m$ and from 1 to $W-m$, respectively. As above, the origin points $(i,j)$ and $(a,b)$ must be different to exclude self-matches.

3) Compute the bi-dimensional sample entropy as

$$\mathrm{SampEn}_{2D}(m,r,N) = -\ln\left(\frac{V^m(r)}{U^m(r)}\right). \tag{31}$$

#### 2) Advantages and limitations

For the computation of $\mathrm{SampEn}_{2D}$, two parameters have to be set: $m$ and $r$. Their choice is not an easy task. The greater the $m$ value, the greater the chance of no pattern matches. The latter case leads to an undefined value for $\mathrm{SampEn}_{2D}$. Moreover, for low image sizes, $\mathrm{SampEn}_{2D}$ can give undefined values or unreliable results. Furthermore, $\mathrm{SampEn}_{2D}$ has the drawback of being very slow in terms of computation time. However, $\mathrm{SampEn}_{2D}$ has the advantage of being a completely automated method. Moreover, it is rotation-invariant [253].

#### 3) Examples of applications

$\mathrm{SampEn}_{2D}$ has been applied to histological images [253]. The results have shown that $\mathrm{SampEn}_{2D}$ is able to discriminate rat sural nerve images by age groups [253].

### B. TWO-DIMENSIONAL DISTRIBUTION ENTROPY

#### 1) Concept

In order to overcome the drawbacks of $\mathrm{SampEn}_{2D}$ (undefined values or unreliable values for small-sized textures, long computation time), Azami *et al.* recently proposed the bi-dimensional distribution entropy ($\mathrm{DistEn}_{2D}$) [254]. Its algorithm for an image $I$ with width $W$ and height $H$ is the following [254]

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1) Normalize $I$ between 0 and 1. Create all two-dimensional matrices (template matrices) $X^m_{kl}$, ($k = 1, 2, \ldots, H - (m_h - 1)$ and $l = 1, 2, \ldots, W - (m_w - 1)$) with size $m_h \times m_w$ as described in [254]. The embedding dimension vector is denoted $m = [m_h, m_w]$.
2) Compute the distance matrix $D = \{d_{kl}\}^{l=1,\ldots,W-(m_w-1)}_{k=1,\ldots,H-(m_h-1)}$ as the greatest element of the absolute difference of $X^m_{kl}$ and $X^m_{ab}$ where $a$ goes from 1 to $H - (m_h - 1)$ and $b$ goes from 1 to $W - (m_w - 1)$. Elements $(a, b) = (k, l)$ are not taken into account.
3) Estimate the empirical probability density function of $D$ with the histogram approach using $M$ bins. Denote $p_t (t = 1, \ldots, M)$ the probability of each bin.
4) Compute $\text{DistEn}_{\text{2D}}$ as

$$\text{DistEn}_{\text{2D}}(U, m, M) = -\sum_{t=1}^{M} p_t \times \log_2(p_t). \quad (32)$$

### 2) Advantages and limitations

It has been shown that $\text{DistEn}_{\text{2D}}$ is not very sensitive to its parameter values [254] and gives values even for low image sizes, by opposition to $\text{SampEn}_{\text{2D}}$ [254]. Moreover, $\text{DistEn}_{\text{2D}}$ is more rapid than $\text{SampEn}_{\text{2D}}$ [254]. $\text{DistEn}_{\text{2D}}$ is also rotation-invariant [253], [254].

### 3) Examples of applications

$\text{DistEn}_{\text{2D}}$ is able to detect different amounts of noise, and distinguish periodic from synthetized textures [254].

## C. TWO-DIMENSIONAL MULTISCALE ENTROPY

### 1) Concept

The bi-dimensional multiscale entropy ($\text{MSE}_{\text{2D}}$) is an extension, over spatial scales $\tau$, of $\text{SampEn}_{\text{2D}}$ [252], [255]. For an image $I$ with width $W$ and height $H$, $\text{MSE}_{\text{2D}}$ consists of two steps [255]

1) Construct the coarse-grained images $\{I^{(\tau)}\}$ as

$$I^{(\tau)}_{ij} = \frac{1}{\tau^2} \sum_{\substack{k=(i-1)\tau+1 \\ l=(j-1)\tau+1}}^{\substack{k=i\tau \\ l=j\tau}} I_{kl}, \quad (33)$$

where $1 \leq i \leq \lfloor \frac{H}{\tau} \rfloor$ and $1 \leq j \leq \lfloor \frac{W}{\tau} \rfloor$.
2) Compute $\text{SampEn}_{\text{2D}}$ of each coarse-grained image.

A variant of $\text{MSE}_{\text{2D}}$ ($\text{ModMSE}_{\text{2D}}$) has also been proposed [255]. $\text{ModMSE}_{\text{2D}}$ is $\text{SampEn}_{\text{2D}}(I^{(\tau)}, m, r)$ where $I^{(\tau)}$ is, in this case, computed as

$$I^{(\tau)}_{ij} = \frac{1}{\tau^2} \sum_{\substack{k=i \\ l=j}}^{\substack{k=i+\tau-1 \\ l=j+\tau-1}} I_{kl}. \quad (34)$$

It has recently been revealed that the profile of $\text{MSE}_{\text{2D}}$ is sensitive to the amplitude and phase of the discrete Fourier transform [256].

### 2) Advantages and limitations

$\text{MSE}_{\text{2D}}$ has the advantage, over $\text{SampEn}_{\text{2D}}$ and $\text{DistEn}_{\text{2D}}$, of giving information over spatial scales. Moreover, the computation time of $\text{MSE}_{\text{2D}}$ is faster than the one of $\text{ModMSE}_{\text{2D}}$, while $\text{ModMSE}_{\text{2D}}$ is more robust to small image sizes [255]: $\text{MSE}_{\text{2D}}$ can generate undefined entropy values due to the absence of template matches. This is even more obvious with scales: the larger the scale value, the higher the probability of obtaining an undefined entropy value.

### 3) Examples of applications

$\text{ModMSE}_{\text{2D}}$ and $\text{MSE}_{\text{2D}}$ have been applied to synthetic and real data and have proven to be suitable and powerful tools for image classification according to texture patterns [255]. $\text{MSE}_{\text{2D}}$ has also been used in the biomedical field [252], [256].

## IX. DATABASES FOR EXPERIMENTS

To test and compare the above-mentioned algorithms of texture feature extraction, a large number of texture datasets have been developed. Hossain *et al.* [257] as well as Bianconi *et al.* [258] proposed comprehensive surveys of these databases. In the latter papers, the datasets are categorized into four areas:

1) texture databases in medical images, including among others a MRI brain database, a digital database for screening mammography, a computed-tomography emphysema database, the Epistroma database, the IICBU biological image repository, the mammographic patches, the MESSIDOR database,
2) natural texture image databases, including the Brodatz texture database, the vision texture database (VisTex), the USC-SIPI texture mosaic, the texture library, the Mayang's texture database, the Salzburg texture image database (STex), the USPTex dataset,
3) texture of materials databases, including the Meastex database, the PhoTex database, the PhoTex 3D database, the Amsterdam library of textures (ALOT) database, the university of Maryland (UMD) dataset, the OUTex database, the Columbia-Utrecht reflectance and texture (CUReT) database, the textile database, the UIUC database, the CMU near-regular texture database, the Rutgers skin texture database, the KTH-TIPS database, the KTH-TIPS2 material database, the PerTex database, the building texture database, the grain mixtures dataset, the Kylberg texture dataset, the BTF database Bonn, the drexel texture database, the forest species database, the Jerry Wu photometric image database, the Kylberg sintorn rotation dataset, the MondialMarmi database, the parquet image database, the VxC TSG image database for surface grading,
4) the dynamic texture databases dedicated to dynamic texture datasets where the temporal textures are variable and changing with time.

The readers are encouraged to read these two surveys [257], [258] to obtain more information on existing databases.

## X. CLOSING REMARKS

### A. SUMMARY

We have reviewed different texture feature extraction methods and classified them into seven different classes: statistical approaches, structural approaches, transform-based approaches, model-based approaches, graph-based approaches, learning-based approaches, and entropy-based approaches. For each method, the concept, an emphasis on the advantages and drawbacks, and examples of applications have been given. Among the seven classes, four classes (statistical approaches, structural approaches, transform-based approaches, and model-based approaches) are now well-known. The corresponding methods are therefore largely used: GLCM or LBP and variants, to cite only a few. However, in these four classes, some methods become "out-of-date" because more recent algorithms lead to better performances. Even if it is difficult to advise on the use of a method for a particular case, we have seen that some methods lead to interesting results for only some particular cases (for instance, structural approaches may be appropriated for regular textures only). Moreover, if the application requires invariant features to rotation/translation/scaling, the number of possible methods decreases.

In this survey, methods that have been proposed for very specific cases have not been mentioned. Thus, for very high resolution remote sensing images, Demir *et al.* proposed histogram-based attribute profiles that allow the modeling of texture information from attribute profiles [259]. The latter paper also contains a literature survey of the methods that model spatial information in the context of very high resolution remote sensing image classification. We invite the readers to refer to this paper and others as Ref. [260] for the specific case of such data.

### B. FUTURE DIRECTIONS

The two most recent classes are undoubtedly the learning-based approaches and the entropy-based approaches. Methods based on deep learning are recent and their use is growing due to their high performances. For sure, they are not yet exploited to their full potential and deserve attention for the future. Moreover, the entropy-based measures for texture analysis are also very recent ones. Their performances seem promising but need to be studied deeply. Their great advantage is that the corresponding methods for the unidimensional case are now well-known in the information-theory field and have proven to give very interesting results in a large field of applications. For these two recent classes, one of the challenges will be to reduce the computation time so that the applications can come from large domains.

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