Survey for Image Feature Extraction Method

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Abstract: Feature extraction methods play a crucial role in computer vision and pattern recognition applications. This survey paper provides an overview of various feature extraction techniques, including Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrix (GLCM), Oriented FAST and Rotated BRIEF (ORB), Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Features from Accelerated Segment Test (FAST), Binary Robust Independent Elementary Features (BRIEF), Low-complexity coding and decoding, variogram, correlation-based approaches, Hough Transform, Wavelet-based methods, and Deep Learning-based techniques. For each method, we discuss its concept, advantages, limitations, and provide examples of their applications in various domains, such as object recognition, image classification, and texture analysis. The conclusion summarizes the key findings and highlights the importance of selecting appropriate feature extraction methods based on the specific requirements of the application.

Keywords: Feature Extraction, Texture, image processing, object detection, object recognition

I. Introduction

Feature extraction is a fundamental process in data analysis and pattern recognition that involves identifying and selecting relevant characteristics, or features, from raw data. It aims to transform high-dimensional data into a lower-dimensional representation that retains essential information for subsequent analysis or classification tasks.

In various fields, including computer vision, natural language processing, signal processing, and machine learning, feature extraction plays a crucial role in understanding and interpreting complex data. By extracting meaningful features, it becomes possible to capture the underlying patterns, structures, and discriminative information present in the data, enabling more efficient and accurate analysis.

The process of feature extraction involves a combination of domain knowledge, statistical techniques, and mathematical transformations. It seeks to identify the most informative aspects of the data that are relevant to the specific problem at hand. These features should possess the following characteristics: they should be discriminative, capturing the differences between different classes or categories; they should be robust to noise and irrelevant variations; and they should be compact, representing the essential information in a concise manner.

Feature extraction techniques can vary depending on the nature of the data and the specific problem. They may include methods such as principal component analysis (PCA)[26], linear discriminant analysis (LDA) [26], wavelet transforms[32], Fourier transforms[29], histogram-based features[7][8][9], and many others. These techniques allow for the extraction of features in various domains, such as spatial, temporal, frequency, or semantic.

The extracted features serve as input for subsequent analysis, classification, or machine learning algorithms, where they are used to make predictions, perform clustering, or gain insights into the underlying data. Effective feature extraction is critical for achieving accurate and efficient data analysis, as it reduces dimensionality, removes noise and irrelevant information, and enhances the interpretability of the data.

In conclusion, feature extraction is a crucial step in data analysis and pattern recognition, enabling the identification and selection of relevant characteristics from raw data. It serves as a means to reduce dimensionality, capture essential information, and facilitate subsequent analysis and interpretation. By effectively extracting features, it becomes possible to gain insights, make predictions, and solve complex problems in various domains.

II. Feature Extraction Method

This paragraph will introduce multiple feature extraction methods and provide an overview of its "concept", "advantages and limitations", and an "example of application".

A. Gray-Level Co-occurrence Matrix(GLCM)

a) Concept:

GLCM is a statistical method used in image processing and texture analysis to quantify the spatial relationships between pixels in an image. The GLCM captures the frequency of pixel pairs with specific intensity values occurring in different spatial relationships, such as distance and direction. To create a GLCM, an image is divided into a grid of cells, and for each cell, the co-occurrence of pixel intensity values is computed. The co-occurrence is determined by counting the occurrences of pixel pairs with specific intensity values and their spatial relationship within the cell. In figure 1, an example is shown for calculating the GLCM by determining the frequency of each value at four angles: 0 degrees, 45 degrees, 90 degrees, and 135 degrees. Taking horizontal 0 degrees as an example, for the light blue line in image M, the pixel pair (2, 1) that are horizontally adjacent has a count of two. Therefore, G1(2, 1) = 2 indicates that there are only two pairs of pixels with a grayscale value of (2, 1) that are horizontally adjacent. Similarly, for the adjacent pixel pairs in directions 45 degrees, 90 degrees, and 135 degrees in M, they are computed and represented as G2, G3, and G4, respectively. Compute a feature of a GLCM to serve as a compact summary of the matrix. The properties are computed as follows:

- **Contrast:** The contrast between a pixel and its neighbor pixels in terms of brightness.

$$\sum_{i,j=0}^{level-1} P_{i,j}(i-j)^2 \qquad (1)$$

- **Correlation:** It measures the similarity of GLCM elements in row or column direction. The value reflects the GLCM correlation in the image

$$\sum_{i,j=0}^{level-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \qquad (2)$$

- **Dissimilarity:** Calculating the difference between pixels in a designated region, allowing for quantification of dissimilarity between pairs of objects based on their pixel values.

$$\sum_{i,j=0}^{level-1} P_{i,j}|i-j| \qquad (3)$$

- **Homogeneity:** Calculating the level of change or variability in pixel values within the matrix.

$$\sum_{i,j=0}^{level-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{4}$$

- **Angular Second Moment (ASM):** It quantifies how evenly the different gray levels are distributed, indicating the texture's overall uniformity.

$$\sum_{i,j=0}^{level-1} P_{i,j}^2 \tag{5}$$

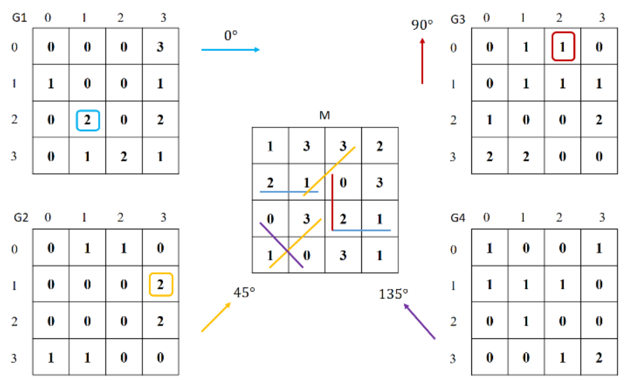

Figure1 GLCM calculation. M is original image matrix, G1, G2, G3, G4 are GLCM.

b) Advantages and Limitations

- Advantages:
  1. **Texture characterization:** GLCM provides a quantitative measure of texture properties in an image, allowing for the analysis and comparison of texture patterns.
  2. **Spatial relationships:** GLCM considers the spatial relationships between pixels, capturing information about the arrangement and distribution of different pixel values.
  3. **Rotation and scale invariance:** GLCM can be computed for different orientations and scales, allowing for the extraction of texture features that are invariant to rotation and scaling transformations.
- Limitations:
  1. **Sensitivity to image properties:** GLCM is sensitive to variations in image properties such as lighting conditions, noise, and resolution, which can affect the accuracy and reliability of texture analysis results.
  2. **Dependency on parameters:** GLCM requires the selection of appropriate parameters such as the distance and angle of pixel pairs, which can impact the extracted texture features and their interpretation.
  3. **Limited to second-order statistics:** GLCM captures second-order statistical information, which may not fully capture higher-order or more complex texture patterns.
  4. **Difficulty with non-uniform textures:** GLCM may struggle to accurately characterize textures that exhibit non-uniform or non-homogeneous patterns, as it assumes a stationary and homogeneous texture model

c) Example of Applications

GLCM is texture analysis. GLCM can be used to extract texture features from images, which can be useful in various computer vision tasks, including rock texture retrieval [1], detection of discrete structural changes in cell nuclei [2]. By computing the GLCM and comparing texture features, differences between images can be detected, allowing for applications such as image comparison and identifying different regions.

B. Local Binary Patterns (LBP)

a) Concept:

LBP is a texture descriptor used in computer vision and image processing. It was introduced by Ojala et al. in 1996 [3] as a method to represent local texture patterns in an image. The concept of LBP involves comparing each pixel (be a central pixel) with its neighboring pixels and stores the results as binary numbers. It quantifies the texture pattern by comparing the intensity values of each pixel with its neighboring pixels. The LBP operator works as follows:

1. Select a pixel in the image.
2. Define a local neighborhood around the selected pixel, typically using a circular or rectangular region.
3. Compare the intensity value of each neighboring pixel with the central pixel.
4. If the neighboring pixel's intensity is greater than or equal to the central pixel's intensity, assign it a value of 1; otherwise, assign it a value of 0.
5. Form a binary number by concatenating the binary values of all the neighboring pixels in a clockwise or counterclockwise order.
6. Convert the binary number to decimal to obtain the LBP value for the central pixel.

The resulting LBP value represents the local texture pattern around the central pixel. We can see original image at figure 2 and the image after LBP calculation at figure 3[4].

Figure 2 original image

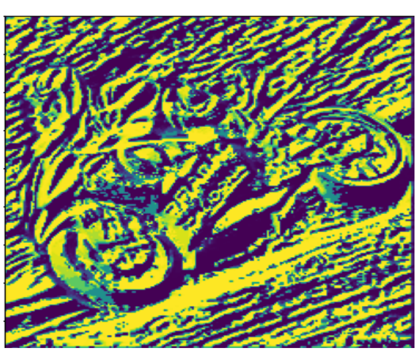

Figure 3 LPB image

Most importance attribute of LBP is its strength to grayscale variations caused by factors such as lighting changes. So it can do object detection well.

b) Advantages and Limitations:

- Advantages:
  1. Robustness to illumination changes: LBP is known for its robustness to changes in illumination, making it suitable for analyzing images under varying lighting conditions.
  2. Simple and intuitive: LBP is a simple and intuitive texture descriptor that does not require complex mathematical operations, making it easy to understand and implement.
  3. Discriminative power: LBP captures local texture patterns by comparing pixel intensities with their neighbors, enabling it to effectively discriminate between different texture classes or regions.
- Limitations:
  1. Sensitivity to noise: LBP is sensitive to noise, which can affect the accuracy of texture analysis results, especially in images with high levels of noise.
  2. Limited spatial information: LBP considers only local pixel neighborhoods and does not capture global spatial information, which may limit its ability to analyze texture patterns that rely on larger context.
  3. Dependency on parameter settings: LBP requires the selection of appropriate parameters such as the neighborhood size and the number of sampling points, and different parameter choices can lead to variations in the extracted texture features.

4. Difficulty with rotation and scale invariance: LBP is not inherently rotation or scale invariant, meaning that the same texture pattern in a rotated or scaled image may result in different LBP codes, making direct comparisons challenging.

c) Example of Applications:

LBP has proven to be effective in various applications, including texture classification, face recognition, and object detection, due to its simplicity and robustness to image transformations. [4] mention a lot of Facial Image Analysis, like Local-Binary-Pattern-Based Face Description, Face Detection, Face Recognition. There are others object recognition application, including currency recognition [5], HE-p2 Cell classification [6].

C. Histogram of Oriented Gradients (HOG)

a) Concept:

HOG is inspired by SIFT descriptor. It aims to capture the local gradient information in an image to represent its shape and texture.

In the HOG algorithm, the image is divided into small cells, typically square regions. Within each cell, the gradients (direction and magnitude of intensity changes) are computed using edge detection techniques, such as the Sobel operator. The gradient orientations indicate the direction of the intensity changes in the image, which can be indicative of important image features. For each cell, a histogram of gradient orientations is created. This histogram represents the distribution of gradient orientations within that cell. The histogram bins correspond to different orientation ranges, and the values in the bins indicate the frequency or magnitude of gradients with those orientations. Figure 4 shows the original image and the corresponding HOG image[8].

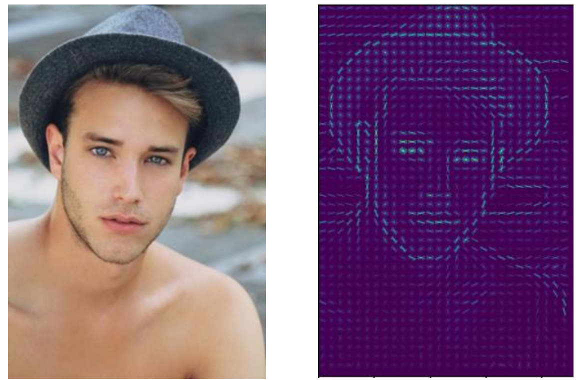

Figure 4 left: original image; right: HOG image

b) Advantages and Limitations:

- Advantages:
  1. **Robustness:** HOG features are robust to changes in illumination and contrast, making them effective in varying lighting conditions.
  2. **Localized information:** HOG captures local image gradients, enabling it to focus on specific object parts or regions of interest.
  3. **Invariant to geometric transformations:** HOG features are invariant to translation, rotation, and scale changes, making them suitable for object detection and recognition tasks.
- Limitations:
  1. **Lack of fine details:** HOG features focus on local gradient patterns and may not capture fine texture or shape details present in the image.
  2. **Sensitivity to noise:** HOG features can be sensitive to noise or clutter in the image, affecting their accuracy in complex scenes.
  3. **Limited viewpoint variations:** HOG may struggle to handle significant changes in object viewpoint, as it relies on local gradient information that can vary greatly with viewpoint changes.
  4. **Difficulty with occlusion:** HOG may have difficulties detecting partially occluded

objects, as occlusions can disrupt the local gradient patterns used for feature extraction.

c) Example of Applications:

HOG has found various applications. It has been widely used for tasks such as human detection [7] and face recognition [8]. Moreover, HOG has also shown its effectiveness in the field of Ground Penetrating Radar (GPR) [9]. The versatility and versatility of HOG make it a valuable tool in a wide range of applications, including both computer vision and GPR-based systems.

D. Scale Invariant Feature Transform(SIFT)

a) Concept:

SIFT is a computer vision algorithm that extracts distinctive and robust features from images. It identifies key points in an image and computes their descriptors based on their local gradients and orientations. SIFT is designed to be invariant to scale changes, rotation, and affine transformations. This is achieved through the scale-space representation and the use of orientation histograms in the descriptors. By considering multiple scales, SIFT can detect keypoints at different scales, allowing it to handle objects at various sizes. The use of orientation histograms captures the local image structure, making SIFT robust to changes in rotation and affine transformations. This invariance makes SIFT suitable for tasks such as object recognition and image matching, where objects may undergo different transformations in different images.

b) Advantages and Limitations:

- Advantages:
  1. **Scale Invariance:** SIFT features are robust to changes in scale, allowing for accurate matching and recognition across different image resolutions.
  2. **Distinctiveness:** SIFT features are highly distinctive and can accurately represent the local structure and texture of an object, enabling reliable matching and recognition.
  3. **Robustness to Illumination Changes:** SIFT features are less affected by changes in lighting conditions, making them suitable for applications in varying lighting environments.
- Limitations:
  1. **Computational Complexity:** The computation of SIFT features can be computationally expensive, especially when dealing with large-scale images or real-time applications.
  2. **Sensitivity to Affine Transformations:** While SIFT is robust to scale and rotation changes, it is sensitive to other affine transformations such as shearing and perspective distortions.
  3. **Limited Robustness to Extreme Scale Changes:** SIFT features may struggle to handle extremely large or small scale changes, resulting in decreased matching accuracy.

c) Example of Applications

SIFT is a versatile algorithm that finds applications in diverse fields. It has proven effective in tasks such as face recognition [10], [11], object detection [12], object recognition [18], and has even found utility in the field of biology [13]. The versatility and effectiveness of SIFT make it a valuable tool in diverse applications that require robust feature detection and matching capabilities.

E. Oriented FAST and Rotated BRIEF(ORB)

a) Concept:

ORB is a feature detection and description algorithm commonly used in computer vision applications. It combines the efficiency of the FAST (Features from Accelerated Segment Test) keypoint detector with the robustness of the BRIEF (Binary Robust Independent Elementary Features) descriptor. The ORB algorithm starts by identifying keypoints in an image using the FAST algorithm, which detects corner-like structures. These keypoints are then refined by calculating the intensity centroid and selecting the most prominent ones. Next, ORB computes a binary feature vector for each keypoint using the BRIEF descriptor. The BRIEF descriptor compares pairs of pixels within a local neighborhood around the keypoint and encodes their relative intensity comparisons into a binary string. This binary representation makes the descriptor fast to compute and efficient to store. To improve rotation invariance, ORB applies a rotation test during the keypoint detection stage. This test determines the orientation of the keypoint by analyzing the local intensity distribution and assigns an orientation to the keypoint. This allows ORB to handle image rotations and improves the matching performance.

b) Advantages and Limitations:

- Advantages:
  1. **Efficiency:** ORB is a fast algorithm, making it suitable for real-time applications and scenarios where computational resources are limited.
  2. **Robustness:** ORB performs well in varying lighting conditions and viewpoint changes, making it reliable in different environments.
  3. **Rotation Invariance:** ORB includes a rotation test, allowing it to handle image rotations and improving its matching performance.
  4. **Real-valued Features:** ORB utilizes real-valued features in combination with binary descriptors, which can enhance its distinctiveness.
- Limitations:
  1. **Scale Variation:** ORB may not perform as effectively in scenarios with significant scale changes, where other algorithms designed specifically for scale invariance may be more suitable.
  2. **Occlusion:** ORB may struggle to handle occlusions, where objects of interest are partially or fully obscured from view.
  3. **Descriptor Distinctiveness:** The binary nature of the BRIEF descriptor used in ORB can result in reduced distinctiveness compared to descriptors that use real-valued features. This can impact the accuracy and discriminative power of feature matching.

c) Example of Applications:

ORB has found wide-ranging applications in different fields. One notable application of ORB is in object detection [12], where it is employed to accurately detect and identify objects of interest in images or videos. Moreover, ORB has demonstrated its effectiveness in the field of 3D surface reconstruction [14], particularly in the domain of electron microscopy. Additionally, ORB finds application in object recognition [18], aiding in the precise identification and classification of objects in various contexts. By extracting and matching ORB features, it aids in reconstructing detailed 3D models of microscopic structures. Furthermore, ORB has been applied to the classification of plants [15], enabling the identification and categorization of different plant species based on their visual characteristics. These examples highlight the versatility and usefulness of ORB in various domains, showcasing its potential in tasks such as object detection, image reconstruction, and plant classification. These applications demonstrate the versatility and effectiveness of ORB in various domains, highlighting its usefulness in tasks such as object detection, image reconstruction, and plant classification.

F. SURF (Speeded-Up Robust Features)

a) Concept

SURF [16] is a feature extraction and description algorithm used in computer vision and image processing tasks. It is designed to efficiently detect and describe local image features that are robust to changes in scale, rotation, and illumination. SURF operates by identifying interest points in an image based on the detection of local intensity variations. These interest points are then described using a set of orientation-invariant descriptors that capture the distribution of gradient information in their vicinity. The key advantage of SURF is its computational efficiency, achieved through the use of integral images and fast approximations. SURF has found applications in various tasks such as object recognition, image matching, and image registration.

b) Advantages and Limitations

- Advantages:
  1. **Efficiency:** SURF utilizes a fast algorithm for feature extraction, making it computationally efficient compared to other feature detection methods like SIFT.
  2. **Scale and Rotation Invariance:** SURF features are inherently invariant to scale and rotation changes in an image, allowing for robust matching across different viewpoints and image resolutions.
  3. **Robustness to Affine Transformations:** SURF features can handle affine transformations, such as changes in perspective, tilt, and skew, making it suitable for applications involving geometric changes.
  4. **Descriptor Dimensionality:** SURF descriptors are compact, represented by a vector of fixed dimensionality, which facilitates efficient storage and matching of features.
  5. **Robustness to Noise and Illumination Changes:** SURF features exhibit good robustness to noise and moderate changes in lighting conditions, enabling reliable feature matching even in challenging environments.
- Limitations:
  1. **Sensitivity to Large Viewpoint Changes:** While SURF is robust to moderate viewpoint changes, it may struggle to match features when there are significant changes in viewpoint, such as extreme rotations or extreme changes in camera angle.
  2. **Limited Robustness to Occlusions and Clutter:** SURF features may not handle occlusions or cluttered scenes well, as the descriptors may be influenced by surrounding features or obscured by other objects.
  3. **Limited Discrimination Power:** In certain complex scenes, SURF features may not provide sufficient discrimination power to differentiate between similar objects or textures, resulting in potential matching ambiguities.
  4. **Limited Localization Accuracy:** SURF may not always provide highly accurate localization of feature points, particularly in regions with low contrast or repetitive

patterns.

c) Example of applications

SURF finds applications in various domains, including face anti-spoofing [17], 2D human face recognition [11], and 2D object recognition [18]. In the field of face anti-spoofing, SURF contributes to detecting and preventing fraudulent attempts to deceive face recognition systems. For face recognition, SURF provides robust and efficient features for accurate identification of individuals in 2D images. Similarly, in 2D object recognition, SURF aids in recognizing and classifying objects of interest in different visual scenes. Furthermore, SURF demonstrates its potential in the medical field, specifically in the detection of calcaneus fractures in Computed Tomography (CT) images [19]. By extracting distinctive features from the fractured regions, SURF can assist in the automated detection and diagnosis of fractures, aiding medical professionals in providing timely and accurate treatment.

G. Features from Accelerated Segment Test (FAST)

a) Concept

Features from Accelerated Segment Test (FAST) [20] is a popular feature detection and extraction algorithm widely used in computer vision and image processing tasks. It was introduced by Edward Rosten and Tom Drummond in 2006. FAST is designed to efficiently and robustly identify interest points or keypoints in an image that possess unique and distinguishable visual characteristics. The concept of FAST revolves around the idea of corner detection. Corners are significant features in an image as they typically represent distinct changes in intensity or color. FAST algorithm aims to identify these corners by examining a set of contiguous pixels in a circular pattern around a central pixel. The key idea behind FAST is to compare the intensity values of pixels in a circular neighborhood around the central pixel. If a sufficient number of consecutive pixels have intensities higher or lower than the central pixel, then it is classified as a corner. This comparison process is accelerated by using a set of predetermined threshold values and a binary decision tree structure.

b) Advantages and Limitations

- Advantages:
  1. **Computational Efficiency:** FAST is designed to be computationally efficient, making it suitable for real-time applications.
  2. **Rotation and Scale Invariance:** FAST features are invariant to image rotation and scaling, allowing robust feature matching across different orientations and scales.
  3. **Corner Localization:** FAST is particularly effective in detecting corners or key points in images, which are important for tasks such as image registration and object tracking.
  4. **Minimal Memory Requirements:** FAST requires minimal memory resources, making it suitable for implementation in resource-constrained environments.
- Limitations:
  1. **Sensitivity to Noise:** FAST is sensitive to noise and can produce false positives in noisy image regions, affecting the accuracy of feature detection.
  2. **Limited Feature Description:** FAST primarily focuses on feature detection and does not provide a detailed feature descriptor. This limitation can impact the performance of tasks that require robust feature matching

and recognition.

3. **Lack of Scale Adaptation:** While FAST is rotation and scale invariant, it does not adapt well to variations in feature size. This can lead to difficulties in matching features across different scales.

c) Example of applications

FAST has demonstrated its effectiveness in various medical image analysis applications, including cell segmentation and tracking [21], as well as brain tumor segmentation and classification [22].

H. Binary Robust Independent Elementary Features (BRIEF)

a) Concept

BRIEF [23] is a feature descriptor used in computer vision for image matching and object recognition tasks. It is designed to capture distinctive local image features by encoding the intensity comparisons between pairs of pixels in a binary format.

The main idea behind BRIEF is to select a set of pixel pairs from an image patch and compare their intensities. These pixel pairs are chosen based on a predefined pattern or distribution. The intensity comparisons between the pairs are then quantized into binary values, creating a compact binary descriptor for the image patch.

Unlike other feature descriptors that use floating-point values, BRIEF relies on binary comparisons, which makes it computationally efficient and memory-friendly. It can operate on low-resolution images and handle real-time applications with limited computational resources.

b) Advantages and Limitations

- Advantages:
  1. **Fast computation:** BRIEF is known for its computational efficiency, making it suitable for real-time applications and scenarios where speed is crucial.
  2. **Memory-efficient:** BRIEF requires minimal memory resources, enabling it to be implemented on resource-constrained devices.
  3. **Rotation invariance:** BRIEF can be designed to be rotation-invariant, allowing it to handle variations in object orientation.
- Limitations:
  1. **Sensitivity to scale changes:** BRIEF is sensitive to changes in the scale of the image or object being analyzed. It may not perform well when confronted with significant scale variations.
  2. **Limited discriminative power:** BRIEF relies on binary comparisons and may not capture complex and discriminative image features as effectively as other methods.
  3. **Lack of robustness to image noise:** BRIEF may be susceptible to noise in the image, which can affect the accuracy and reliability of feature extraction.
  4. **Limited invariance to affine transformations:** BRIEF is not inherently invariant to affine transformations such as shearing and non-uniform scaling, which can limit its performance in certain scenarios.

To overcome some of limitations, variations of BRIEF, such as ORB (Oriented FAST and Rotated BRIEF), have been introduced. These extensions incorporate additional steps, such as feature orientation estimation and descriptor rotation, to enhance the robustness and invariance of the descriptor.

c) Example of applications

BRIEF, an important feature extraction method, finds application in the medical field, such as medical image classification for disease diagnosis [24]. Additionally, it is used in Hybrid Indoor Localization utilizing IMU Sensors and Smartphone Camera [25].

I. Low-complexity coding and decoding (LOCOCODE)

a) Concept

LOCOCODE (Low-complexity coding and decoding) is a novel approach to sensory coding and unsupervised learning. It is designed to explicitly consider the information-theoretic complexity of the code generator. LOCOCODE computes loco codes that convey information about the input data and can be computed and decoded using low-complexity mappings. This method involves training auto associators with flat minimum search to discover low-complexity neural networks.

b) Advantages and Limitations

The advantages of LOCOCODE include its ability to extract a minimal number of low-complexity features needed to represent the data, enabling the separation of unknown independent data sources. Unlike standard autoencoders, lococodes are based on feature detectors and exhibit desirable properties such as sparsity and locality. LOCOCODE performs well on benchmark problems and real-world images, providing feature detectors with fewer bits per pixel compared to other techniques like independent component analysis (ICA) and principal component analysis (PCA). Another advantage is that LOCOCODE does not require prior knowledge of the number of independent sources.

However, LOCOCODE has some limitations. It is not explicitly designed to enforce sparse or factorial codes, although it can produce such codes depending on the statistical properties of the data. Additionally, while it shows promise in the vowel recognition benchmark problem, further research is needed to explore its application in other classification tasks.

c) Example of applications

Examples of applications for LOCOCODE include unmixing independent data sources, extracting optimal codes for challenging benchmark problems like the "bars" problem, and preprocessing for vowel recognition tasks. It also establishes a connection between regularizer research and ICA-related research, potentially leading to a unification of regularization and unsupervised learning[26].

J. Variogram

a) Concept

Variogram is a geostatistical technique used in remote sensing and image analysis. It captures the covariance structure of a spatial process by measuring the variation of gray tones in a local neighborhood. Variogram parameters, such as range, sill, and nugget, describe the characteristics of the spatial process and can be used for texture classification in remote sensing imagery. There are two main approaches to using variograms: using semi-variances directly and deriving parameters from experimental variograms.

b) Advantages and Limitations

- Advantages:
    1. **Statistical measure of texture:** Variograms provide a statistical measure of texture in an image, allowing for the quantification and

characterization of textural patterns present.

2. **Automated image classification:** Variograms can be used in automated image classification processes, as they capture the spatial dependency and variability of pixel values, providing valuable information for distinguishing different classes or objects within an image.

- Limitations:

1. **Variability of variogram models:** Variogram models may vary depending on the underlying spatial process. This means that different datasets or areas within an image may require different variogram models, limiting the generalizability of a single model.
2. **Misleading model fitting:** Fitting the variogram model to local variograms can be misleading, as local patterns and fluctuations may not accurately represent the overall spatial structure of the image. Care should be taken when interpreting variogram fits at small scales.
3. **Challenges in obtaining meaningful parameters:** Extracting meaningful variogram parameters, such as range, sill, and nugget, can be challenging. This difficulty is particularly pronounced when the assumptions of the model are not met or when outliers are present in the data.
4. **Assumption violations:** Variogram models often assume stationarity, isotropy, and normality of the data. Violations of these assumptions can lead to unreliable variogram estimates and inaccurate interpretations of the image's textural properties.
5. **Impact of outliers:** Outliers in the data can significantly influence the variogram estimation and model fitting process, potentially distorting the resulting variogram and affecting subsequent analysis or classification tasks. Proper data preprocessing techniques may be required to address outliers before utilizing variograms.

c) Example of applications

Variograms have been applied in various remote sensing applications, including mineral mapping, cloud pixel replacement, noise estimation, sampling strategy design, and evaluation of spatial resolution effects. In texture classification, variograms have been used to classify different land cover types based on the semi-variogram signature. For example, in one study, a semi-variogram based texture measure provided higher classification accuracy for microwave images compared to optical images. Another study proposed an algorithm to extract variogram parameters for seafloor classification in remote sensing imagery. The development of algorithms that can automatically extract important variogram parameters, independent of the underlying models, is desirable for improved texture classification in remote sensing imagery[27].

K. Correlation-based

a) Concept

The paper[28] introduces the concept of correlation-based feature extraction in computer-aided design (CAD) for regression-based machine learning algorithms. It addresses the challenges of dimensionality and parameterization in engineering design by proposing a method to extract compact and relevant features from CAD models. The method involves ranking features based on correlation matrices and utilizing geometric entities to define new parameters as performance indicators.

b) Advantages and Limitations

- Advantages:
  1. **Improved prediction efficiency and accuracy:** The method selects the most relevant features, enhancing the performance of prediction models by focusing on the most informative aspects of the data.
  2. **Feature reduction:** The method reduces the number of features, addressing the curse of dimensionality. This can improve computational efficiency and prevent overfitting by eliminating irrelevant or redundant features.
  3. **Reduced model parameterization:** Unlike some feature extraction methods, the correlation-based approach does not require extensive parameterization of the model. This offers designers more flexibility and freedom in the design process.
- Limitations:
  1. **Dependence on data availability and quality:** The effectiveness of the method relies heavily on the availability and quality of the CAD (Computer-Aided Design) data. Insufficient or low-quality data may hinder the accuracy and reliability of the extracted features.
  2. **Suitability for supervised learning methods:** The correlation-based feature extraction method is best suited for supervised learning approaches, where labeled data is available for training. Unsupervised or semi-supervised learning methods may not be as compatible with this approach.

c) Examples of Applications

The paper presents a case study using finite element simulations and parametric studies in CAD. It demonstrates the effect of CAD parameters on volume prediction and introduces new parameters (sleeping parameters) derived from geometric entities to improve prediction accuracy. The extracted parameters are shown to have better correlations with the volume and can be obtained without extensive model parameterization. The study validates the performance of the extracted parameters in regression models and highlights their ability to reduce prediction error margins. The application of correlation-based feature extraction in CAD enables designers to build simple and accurate regression models with a small training set[28].

L. Fast Fourier Transform

a) Concept

The concept of applying Fourier Transform on feature extraction of electrocardiogram (ECG) signals involves using the Fourier Transform to analyze the frequency content of the ECG signal and extract relevant features for the detection and classification of cardiac abnormalities. Fourier Transform is a mathematical technique that decomposes a signal into its constituent frequencies, allowing for the identification of specific frequency components present in the signal.

By applying Fourier Transform on ECG signals, the time-domain signal is transformed into the frequency domain representation. This transformation enables the identification of characteristic frequency components associated with different cardiac events, such as the QRS complex duration, heart rate, and arrhythmias. By extracting these features from the frequency domain representation, it becomes possible to analyze and classify cardiac conditions more accurately using computer-based devices.

b) Advantages and Limitations

- Advantages:
  1. **Frequency analysis:** Fourier Transform enables the identification of specific frequency components in the ECG signal, providing insights into the underlying cardiac activity.
  2. **Feature extraction:** Fourier Transform allows for the extraction of important features, such as heart rate, QRS complex duration, and frequency characteristics associated with different arrhythmias.
  3. **Enhanced accuracy:** By analyzing the frequency content of the ECG signal, Fourier Transform-based feature extraction can contribute to more accurate detection and classification of cardiac abnormalities.
  4. **Non-invasive:** The method is non-invasive, as it relies on analyzing the recorded ECG signals, making it a safe and widely applicable technique in medical environments.
- Limitations:
  1. **Signal interpretation:** While Fourier Transform provides frequency information, interpreting the extracted features requires domain knowledge and expertise in cardiac physiology.
  2. **Signal artifacts:** ECG signals can be affected by noise, artifacts, and interference, which may impact the accuracy of feature extraction using Fourier Transform.
  3. **Time-frequency trade-off:** Fourier Transform provides frequency information but does not capture temporal changes in the signal. This limitation may affect the ability to detect transient abnormalities or variations in the ECG signal over time.
  4. **Complex arrhythmias:** Some complex arrhythmias may have frequency components that are challenging to detect using Fourier Transform alone, requiring additional analysis techniques.

c) **Examples of Applications**

Fourier Transform finds diverse applications in the analysis of electrocardiogram (ECG) signals for feature extraction and cardiac health assessment. One application is Heart Rate Variability (HRV) Analysis, where Fourier Transform is employed to extract frequency-domain features from HRV signals, providing insights into the autonomic control of the heart and aiding in cardiac health assessment. Another application is Arrhythmia Classification, where Fourier Transform-based feature extraction helps classify different types of arrhythmias by analyzing the frequency characteristics of the ECG signal, facilitating early detection and management of cardiac disorders. Additionally, Fourier Transform is used for Signal Denoising, selectively removing noise and artifacts from the ECG signal to enhance its quality and reliability for further analysis. In Ischemia Detection, Fourier Transform assists in identifying ischemic episodes by analyzing frequency content changes associated with reduced blood flow to the heart, aiding in diagnosing and monitoring coronary artery disease. Lastly, Signal Compression techniques based on Fourier Transform, such as Discrete Fourier Transform (DFT) or Fast Fourier Transform (FFT), reduce storage requirements of ECG data while preserving important frequency components for subsequent analysis[29].

M. Hough Transform

a) Concept

The Hough transform is a computer vision technique used for feature extraction, particularly in image analysis. It is commonly used to identify simple geometric shapes, such as lines or circles, within an image. The fundamental idea behind the Hough transform is to represent these shapes in a parameter space, where each point corresponds to a specific shape instance. By transforming the image's coordinate space into this parameter space, the Hough transform allows for robust detection and extraction of features based on their characteristic shapes.

b) Advantages and Limitations

- Advantages:
  1. **Robustness to noise:** The Hough transform can effectively detect and extract features even in the presence of noise or partial occlusions. It achieves this by considering global shape information rather than relying solely on local image gradients.
  2. **Parameterization:** The Hough transform provides a parameterized representation of features, making it easier to describe and manipulate them. This parameterization allows for straightforward interpretation and analysis of the extracted features.
  3. **Flexibility:** The Hough transform can be adapted to detect various geometric shapes, such as lines, circles, ellipses, or even custom shapes. Its versatility makes it suitable for a wide range of applications.
- Limitations:
  1. **Computationally expensive:** The Hough transform can be computationally intensive, especially for complex shapes or high-resolution images. The transformation process involves scanning through a parameter space, which can result in increased computational requirements.
  2. **Limited to explicit shapes:** The Hough transform is primarily designed for detecting explicit geometric shapes. It may struggle with detecting more complex or abstract features that do not conform to a predefined shape model.
  3. **Sensitivity to parameter tuning:** The performance of the Hough transform heavily depends on the correct selection of parameters. Determining the appropriate parameter values can be challenging and may require manual tuning or optimization algorithms.

c) Examples of Applications

The Hough transform finds versatile applications in computer vision. One prominent use is line detection in images, where it can identify straight lines, facilitating tasks like lane detection in autonomous driving or quality control in industrial settings for inspecting printed circuit boards. In the field of medical imaging, the Hough transform proves valuable for circle detection, aiding in the identification of circular structures such as tumors or blood vessels. This automated analysis and feature extraction contribute to the diagnosis and treatment of various medical conditions. Additionally, the Hough transform plays a role in object recognition and tracking by extracting distinctive geometric features. For instance, it enables the identification and tracking of specific shapes or contours in video surveillance systems, facilitating efficient monitoring and analysis of moving objects[30].

N. Wavelet-based

a) Concept

Wavelet-based[32] approaches on feature extraction refer to the utilization of wavelet transform techniques in extracting relevant features from signals or images. Specifically, in the context of magnetic resonance imaging (MRI), wavelet-based approaches aim to extract informative features from MRI images to aid in analysis, diagnosis, and research.

b) Advantages and limitations:

- Advantages:
  1. **Localization:** Wavelet transform provides good localization in both spatial and spectral domains. This means that it can capture fine details of the image at different scales, allowing for a more comprehensive representation of the underlying features.
  2. **Multiresolution analysis:** Wavelet-based approaches enable the analysis of images at multiple resolutions. By decomposing an image into different frequency bands, it becomes possible to extract features at various levels of detail, thereby capturing both global and local characteristics.
  3. **Feature extraction:** Wavelet-based methods can effectively extract relevant features from complex images, such as MRI scans, by focusing on regions of interest while suppressing noise and irrelevant information. This can enhance the accuracy and efficiency of subsequent analysis tasks.
- Limitations:
  1. **Translation variance:** The discrete wavelet transform (DWT) is translation variant, meaning that the wavelet coefficients behave unpredictably under signal translation. This can result in significant changes in the extracted features when the image is slightly shifted, which can lead to misinterpretation or erroneous classification.
  2. **Sensitivity to positioning:** Wavelet-based feature extraction methods may be sensitive to the positioning of image centers. In the case of brain MR images, even slight differences in the position of image centers can cause significant variations in the extracted features. This can potentially lead to misclassification, particularly when distinguishing between images from the same subject and those from different subjects.
  3. **Complex implementation:** Implementing wavelet-based approaches for feature extraction can be computationally intensive and require careful parameter selection. Additionally, the interpretation and analysis of the extracted features may require domain expertise to ensure their relevance and meaningfulness.

c) Examples of applications:

1. **Brain tumor detection:** Wavelet-based feature extraction techniques can be applied to MRI scans to identify and characterize abnormalities associated with brain tumors. By analyzing the frequency and spatial information extracted using wavelet transforms, specific features indicative of tumor presence or characteristics can be identified.
2. **Image denoising:** Wavelet-based approaches can be used to remove noise from MRI images while preserving important details. By decomposing the image into different frequency bands, noise can be selectively filtered out, resulting in improved image quality and clarity.
3. **Texture analysis:** Wavelet-based feature extraction can be employed to analyze the texture properties of MRI images. By

examining the variations in texture at different scales and orientations, it is possible to quantify and characterize specific tissue properties or pathologies, aiding in the diagnosis and monitoring of diseases such as multiple sclerosis or Alzheimer's disease. Figure 5 is the example of Wavelet-based transform[32].

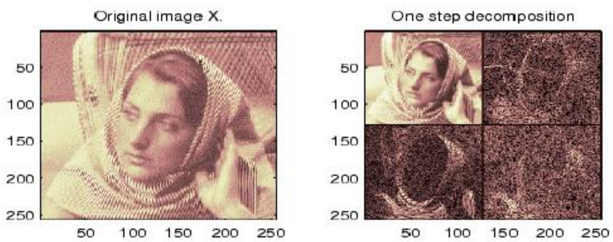

Figure 5 Example of Wavelet-based transform.

O. Deep Learning

a) Concept

Deep Learning on Feature Extraction refers to the application of deep learning techniques to extract meaningful and representative features from raw data. It involves utilizing deep neural networks to automatically learn and identify relevant features that capture the underlying patterns and structures within the data. This approach enables the extraction of high-level features that can enhance the performance of various machine learning tasks, such as classification, recognition, and pattern detection.

b) Advantages and Limitations

- Advantages:

1. **Automatic feature learning:** Deep learning models can learn and extract features directly from raw data, eliminating the need for manual feature engineering. This automated process reduces human effort and potential biases in feature selection.
2. **Hierarchical representation:** Deep neural networks can learn hierarchical representations of features, where lower layers capture simple and local patterns, while higher layers capture complex and global patterns. This hierarchical representation enables the model to capture intricate relationships and dependencies in the data.
3. **End-to-end learning:** Deep learning on feature extraction allows for end-to-end learning, where the entire model, including feature extraction and subsequent tasks (e.g., classification), can be trained simultaneously. This end-to-end approach improves performance and reduces the need for intermediate processing steps.

- Limitations

1. **Data dependency:** Deep learning models heavily rely on large amounts of labeled data for training. Insufficient or biased training data can lead to suboptimal feature extraction and reduced performance.
2. **Computational complexity:** Deep learning models, especially those with many layers, can be computationally expensive to train and require substantial computational resources. Training deep models on large datasets can be time-consuming and may necessitate high-performance computing infrastructure.
3. **Lack of interpretability:** Deep learning models often operate as black boxes, making it challenging to interpret the learned features. Understanding why certain features are extracted and how they contribute to the model's decision-making process can be difficult.

c) Examples of Applications:

In computer vision tasks like image recognition, object detection, and facial recognition, it has proven to be highly effective. Convolutional Neural Networks (CNNs) are commonly employed to extract hierarchical features from images, enabling accurate classification and identification. In the field of natural language processing, deep learning techniques such as Recurrent Neural Networks (RNNs) and Transformer models are utilized for feature extraction. These models excel at tasks like sentiment analysis, language translation, and text summarization, where they learn and extract meaningful features from textual data. Additionally, deep learning plays a crucial role in speech recognition and speech-to-text conversion. Models like Deep Neural Networks (DNNs) and recurrent architectures such as Long Short-Term Memory (LSTM) are leveraged to extract relevant features from audio signals, enabling accurate and efficient speech recognition[31].

III. Conclusion

In this survey, we have examined several popular feature extraction methods used in computer vision and pattern recognition. Each method offers unique advantages and limitations, making them suitable for different applications. HOG and LBP are effective in capturing local image patterns and have been successfully applied in face recognition and texture analysis. GLCM provides valuable texture information and finds applications in remote sensing and medical imaging. ORB, SIFT, and SURF are widely used for feature matching and object recognition tasks, with ORB offering a good trade-off between speed and accuracy. Low-complexity coding and decoding methods are suitable for resource-constrained environments. Variogram-based and correlation-based techniques are employed in geostatistics and remote sensing applications. Hough Transform is robust to noise and used in line and shape detection. Wavelet-based approaches provide multi-resolution analysis and are used in image denoising and compression. Deep Learning-based methods, such as Convolutional Neural Networks (CNNs), have achieved remarkable success in various vision tasks due to their ability to learn discriminative features automatically.

It is important to select the appropriate feature extraction method based on the specific requirements of the application, considering factors such as computational complexity, robustness to noise and variations, and the nature of the data. Additionally, combining multiple feature extraction methods or employing hybrid approaches can further enhance the performance and robustness of the system. As technology advances and new techniques emerge, continued research and evaluation of feature extraction methods are essential to address the evolving challenges in computer vision and pattern recognition.

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