Feature Extraction: A Survey of the Types, Techniques, Applications

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***Abstract*—Feature extraction (FE) is an important step in image retrieval, image processing, data mining and computer vision. FE is the process of extracting relevant information from raw data. However, the problem of extracting appropriate features that can reflect the intrinsic content of a piece of data or dataset as complete as possible is still a challenge for most FE techniques. In this paper, we present a survey of the existing FE techniques used in recent times. In this study, it was observed that the most unique features that can be extracted when using GLDS features on images are contrast, homogeneity, entropy, mean and energy. In addition, it was observed that FE techniques are not mainly application specific but can be applied to several applications.**

Keywords—Feature extraction, image processing, application, mining, data

I. INTRODUCTION

Feature extraction (FE) techniques have become an apparent need in many processes which have much to do with computer vision, object detection and location, image processing, image retrieval, speech recognition (SR), data mining, pattern recognition, machine learning and bioinformatics. It is used to extract the most distinct features present in a dataset (image, text, voice) which are used to represent and describe the data. Data is a collection of various prominent features as the common saying for an image "a picture is worth a thousand words" [1]. On the other hand, digital image processing is a processing method which caters for color images, binary images and grayscale images using a computer. The computer is able to retrieve images from a database for a specific domain whether it is a texture or non-texture image known as Image Retrieval (IR). IR is performed to compute images having similar or dissimilar feature space. It is performed by searching, browsing, or retrieving images from a large database which consists of different images. There are three techniques for IR: Text-Based Image Retrieval (TBIR), Content-Based Image Retrieval (CBIR) and Hybrid Image Retrieval (HIR) out of which TBIR is the most commonly used [2]. This technique is mostly used in general purpose applications. IR is also used to extract text from an image. There are two problems associated with TBIR; first is, its associated cost and the other is distorted results which are obtained in semantic IR. To overcome this problem, CBIR technology is used. The efficiency of retrieval of an image using CBIR technology is high, thereby reducing the need for human intervention. CBIR combines various technological elements and finds applications in human perception information sciences, signal and image processing, multimedia, pattern recognition, and human-computer interaction. The algorithms used in CBIR are mainly divided into three parts: Feature Selection (FS), Feature Extraction (FE) and Feature Classification (FC) [3]. Image processing and computer vision are used to select content features from an image. FE is divided into two parts: filters and wrappers. Filters don't use machine learning while wrappers use clustering or classification techniques or recognition techniques. This paper provides a review of different FE techniques. FE plays a crucial role in the different types of processing.

In this paper, we present a survey of the recent developments in FE. FE is a technique used for extracting raw information from an image which is further used for classification. The main concern of FE techniques is to get the information from the original data and depict it in a low dimension in space. Consequently, for large dataset which don't contain much information, the data is transformed into a feature vector. If the features are extracted carefully then, the chosen feature set will extract the relevant information.

II. SURVEY OF THE TYPES OF FEATURE EXTRACTION

Features play a significant role in the area of computer vision or image processing for identification of relevant information. Before image feature extraction, various image pre-processing techniques like normalization, thresholding, binarization, resizing, etc. are performed on the constituent image. Features are broadly classified as general features (GF) and domain-specific features (DSF) as shown in Fig. 1. GF are application autonomous features like color, shape, and texture [4] while DSF are application reliant features which include conceptual and human face features. Both are broadly classified into 3 categories: Pixel-level features (features are evaluated for every pixel), Local features (feature are evaluated from the results of image sub-division) and Global features (features are evaluated for an image). Table I shows the types of image features, their properties and models.

A. Color Features

For the retrieval of information which is in form of a video or image, color features are extensively used for extraction of visual features. Color is one of the key features of images and it is defined based on color spaces or models namely: RGB, HMMD, HSV and LUV [5]. Color features are sturdy to the translation or viewing angle. Color space is used to define the different color features and as the color space is decided for an image, the corresponding color features can easily be obtained from the image. There are large numbers of color features which are provided in literature including color correlogram, color histogram,

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color coherence vector (CCV), and color moments (CM). Among them, CM is the most simplest and effective feature.

There are different types of color spaces used in research, namely: Red-Green-Blue (RGB), Hue-Saturation-Value (HSV), Luminance-chrominance (YCbCr), Hue-Max-Min-Diff (HMMD), and CIE LUV RGB are widely used color space techniques. In HSV, *saturation* (*S*) defines how pure a color is which is represented by Eq. (1). The value of saturation is zero if the *Max* value (maximum value of *R*, *G*, *B)* is zero otherwise it is expressed by Eq. (1).

$$Saturation = \frac{Max - Min}{Max} \tag{1}$$

The *value* (*V*) defines how bright or dark a color is, which is equal to the *Max* value and, Hue (*H*) specifies one color family and angle from 0 º to 360º which is represented by Eq. (2). In Eq. (2), maximum value of is represented by *Max* and minimum value of *R*, *G* and *B* is denoted by *Min*.

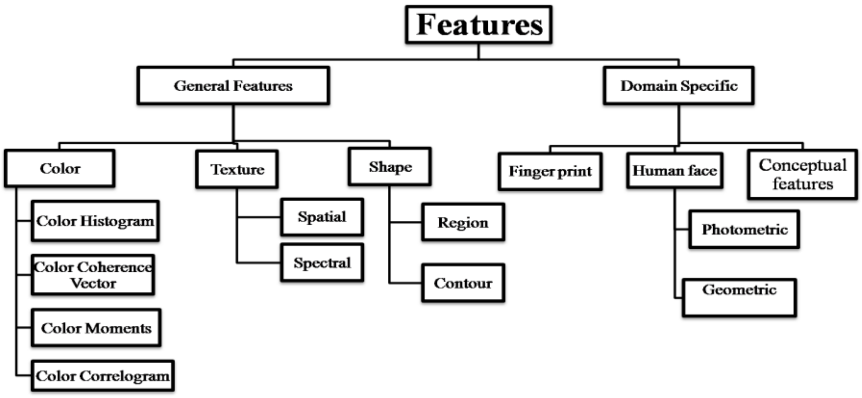

Fig. 1. Classification of feature extraction techniques.

TABLE I. TYPES OF FEATURES, THEIR PROPERTIES AND MODELS.

Feature type	Properties	Models
Color Based Features	Impression, expression and construction, RGB, LUV, HSV and HMMD	a. Contourlet Transform b. Steerable Pyramid c. Gabor wavelet Transform d. K-means based CIS
Texture Features	Homogeneity, entropy, contrast, correlation, sum of square variance, spectral and spatial	a. Gaussian Markov Random Field (GMRF) model b. Homogeneous Texture Descriptor (HTD) c. LoG method d. gLoG method e. HLoG method f. Difference of Gaussian (DoG) method g. Support Vector Machine (SVM)
Intensity features	Mean, Median, Standard Variance, Intensity, Skewness	a. Gaussian mixture model (GMM) b. Stochastic model c. Probabilistic model
Human features	Body shape, size, color, age-group, age, gender, height	a. SVM b. Relevance Vector Machine (RVM) c. Prototype Learner (Prot) d. K means e. Histogram of oriented gradients (HoG)
Finger print features	Arches, Loops, Whorls	a. Fuzzy models b. Markov model c. Fingerprint individuality model d. Stochastic model
Conceptual features	Generic product/object knowledge, flexibility, attributes, mutability	a. Generic process model b. Product/object model c. Feature-based model
Text features	Synonymy, polysemy, circularity, irregularity, area, perimeter, roundness	a. Gaussian Markov RMF b. Fractal model c. Probabilistic model d. Simultaneous autoregressive model e. Vector space model

$$Hue = \begin{cases} 0 & if\ Max == Min \\ 60 * \dfrac{G-B}{Max-Min} & if\ Max == R\ and\ G \geq B \\ 360 + \left(60 * \dfrac{G-B}{Max-Min}\right) & if\ Max == R\ and\ G < B \\ 60 * \left(2.0 + \dfrac{B-R}{Max-Min}\right) & if\ G == Max \\ 60 * \left(4.0 + \dfrac{R-G}{Max-Min}\right) & otherwise \end{cases} \quad (2)$$

YCbCr represents the luminance (Y), blue chrominance (Cb) and red chrominance (Cr) as given by matrix in Eq. (3):

$$\begin{vmatrix} Y \\ Cb \\ Cr \end{vmatrix} = \begin{vmatrix} 0.299 & 0.587 & 0.114 \\ 0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix} \quad (3)$$

The HMMD color space is closer to a perceptually uniform color space. A total of five components are defined: *Hue* is same as given in Eq. (2), *Max* serves as black color present in an image, *Min* defines the white color present in an image, *Diff* give the difference of Max and Min value which determines a the pure/ exact color of an image and *Sum* gives the average of Max and Min values which specifies the brightness of the color. For forming HMMD color space combination of {*H*, *Diff*, *Sum*} or {*H*, *Max*, *Min*} is required.

The CIE (*L**, U*, *V**) color space, also characterize as *CIE LUV*, is adopted by the International Commission on Illumination (*CIE*) in 1976. It is usually used for applications which are concerned with colored lights.

The MPEG standard defines different color descriptors which represent different aspects of the color feature, in addition to color distribution, which represents the spatial structure of color and spatial layout of color. Therefore, a possible way to extract elements could be according to its color. Mainly five tools are defined to describe color namely: Scalable Color Descriptor (SCD), Dominant Color Descriptor (DCD), Group of a frame (GoF) or Group-of-pictures (GoP), Color Structure Descriptor (CSD), Color Layout Descriptor (CLD). The CSD, DCD, and SCD shows the color distribution in an image [6] and GoF, GoP or CLD explains the relation between the group of images or sequences. The CSD gives a dense description of the colors in an image. It permits a description of their statistical properties which includes variance and distribution and supreme color values. DCD on the other hand, provides a compact and effective characterization of colors present in an image. SCD represents the color histogram in the HSV color space which can be concealed using Haar transform. Mainly SCD is used for matching. The GoP is an extended form of SCD in which a group of frames of a video or collection of pictures are used. In this technique, different color properties of the video frames or images are aggregated. CSD aims at classifying confined color distribution using small strutting window. This technique is also based on color histograms. CSD works on only HMMD color space. CLD technique is highly capable in fast browsing and search applications. It is a very compact descriptor which can be applied on images or videos. In CLD, coefficients of Discrete Cosine Transform are used. Out of the various descriptors, CLD and DCD are mostly used because of their advantages. The DCD helps us to effectively describe the dominant colors of an image and the CLD helps in retaining the spatial distribution of the color of an image. These characteristics were decisive when the selection of the descriptors was taken. In DCD the extraction process consists of three stages: a color space conversion, clustering method of color space such as the CIE LUV and percentage calculation of each centroid. In Table II we present the differences in the various color descriptors.

B. Texture Features

Color features just use pixels while texture features use group of pixels. Human visual system use texture for interpretation and recognition of an image. Texture basically explains the visual patterns with homogeneity property. Texture features (TF) are widely divided into spatial TF and spectral TF. The various subdivisions are shown in Fig. 2.

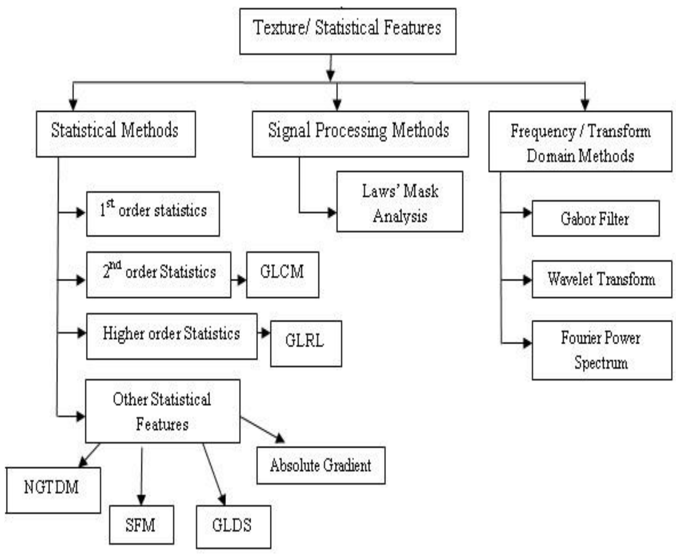

Fig. 2. Different texture feature extraction techniques.

For spatial TF, features are extracted by calculating the pixel in the main image while for spectral TF, images are first transformed into frequency domain (FD) and later the features are extracted for the transformed image.

Gabor filter is widely used for TF extraction as it samples the FD of an image by characterizing the orientation parameters and central frequency. The contrast between these two TF extraction methods is shown in Table III. One common area where spatial TF is used for extraction is in image segmentation [7]. This approach is used to map the disparities in spatial structures of either geometric or stochastic features into their respective gray values.

TABLE II. DIFFERENCES IN THE VARIOUS COLOR DESCRIPTORS.

Color method	Merits	Demerits
DCD	Robust, compact, perceptual meaning	Post-processing needed for spatial information (SI)
CSD	Uses spatial information (SI)	Sensitive to noise, rotation and scale
SCD	Scalable, complex	No SI, less accurate if complex
CM	Robust and compact	sufficient to describe all colors, no SI
CCV	Uses SI	Has high dimension and computational cost
Histogram	Intuitive and simple to compute	Sensitive to noise, high dimension, no SI,
Correlogram	Uses SI	Sensitive to noise, rotation and scaling, high computational cost

TABLE III. DIFFERENCES IN TEXTURE FEATURE EXTRACTION METHODS.

Texture feature method	Merits	Demerits
Spatial	Easy to understand, share similar properties in small neighborhood and when extracted from any shape they don't lose the original information.	Sensitive to distortions and noise
Spectral	Requires less computation and Robust	Need square image regions with sufficient size, can't distinguish between objects made of the same material

This is because segmentation methods are mainly divided into boundary-based, region-based or a combination of both. Other approaches such as the Markov Random Field (MRF) model are robust to noise.

The histogram pixel method of extraction and the fuzzy set theoretical method have also been employed but are highly unsuitable to noisy environments [8]. Some authors have merged texture features with color features to enhance faster image retrieval [9], [10] while authors in [11] have combined global texture (curvelet) and color features for image retrieval. A comparison of the different methods was presented in [12]. Authors in [11], proposed a method that gave an exceptional retrieval interpretation using the global distribution of local features.

Some features that are not easily identifiable can be extracted using FE techniques such as Statistical methods [13], [14], [15]. This includes first order statistics (FOS), Gray Level Run Length Matrix (GLRLM), Gray Level Co-occurrence Matrix (GLCM), Neighborhood Gray Tone Difference Matrix (NGTDM), and Statistical Feature Matrix (SFM). Signal processing FE techniques include law mask features, while transform domain methods consists of Gabor wavelet, Fourier Power Spectrum (FPS) features and discrete wavelet transform as shown in Table IV.

TABLE IV. VARIOUS FEATURES COMPUTED USING TEXTURE AND SHAPE FEATURE EXTRACTION METHODS [13].

Various Texture / Statistical features	Features
First order statistics	Third moment, smoothness, uniformity, mean, standard deviation, entropy
GLCM features	Angular moment, inverse difference moment, contrast, correlation, entropy, difference entropy, variance, difference variance
GLRLM features	Long run emphasis, long run high gray emphasis, Low gray level run emphasis, run length non uniformity, high gray level run emphasis, short run high gray emphasis, short run emphasis, short run low gray emphasis, gray level non uniformity,
GLDS features	Homogeneity, contrast, energy, entropy, mean
NGTDM	Coarsens, contrast, complexity, strength, business
SFM	Coarsens, contrast, periodicity, roughness
FPS	Radial Sum, Angular sum
Gabor filter based	Mean, variance
Shape features	Area, eccentricity, solidicity, perimeter, diameter, Euler number, orientation, convex area, extent, major axis, minor axis

C. *Shape Features*

Shape features (SF) are an important for recognizing and identifying real world objects. They are a dominant visual clue to human being for similarity check/matching. SF are divided into two groups namely: region based (RB) and contour based (CB). RB extracts features from entire object while CB determines SF from the boundary. The Hough Transform (HT) has been outlined as a good technique for feature extraction of geometric features from shapes, also for detecting lines and edges. It finds applications in pattern recognition, image processing and computer vision. In Fig. 3, we give the classification of the various shape representations and their various components.

D. *Motion Features*

Video sequences are the main motion features which provide persuasive clues for its content. MPEG developed some descriptors which are able to capture motion characteristics into effective descriptors.

E. Localization Features

Location descriptors help to locate the regions of features within images or frames as well as to describe spatio-temporal regions in video sequences which concentrate on moving object regions. This is an important aspect of visual tracking especially in video and multimedia processing where FE is important [16].

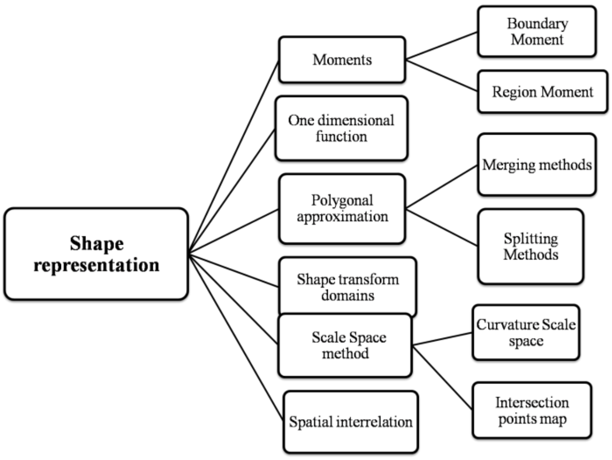

Fig. 3. Classification of the various shape representations.

F. Face Features

Human face perception and recognition is one of the major areas of study in computer vision community. Face recognition consists of four different steps namely: alignment, detection, representation and classification. In face detection, place/ position of the face is recognized, the alignment step ensures the detected face is lined up with a target face; the representation step lets us know the various descriptions related to the face to be detected and finally, the classification step determines whether certain features correspond with a target face or not. There are many applications in which automatic face recognition is desirable and different specific techniques have been proposed. Among these methods, Karhunen-Loeve transform known as Principal Component Analysis (PCA), is one of the prominent techniques that is widely used. Face recognition techniques are categorized into two different approaches: Geometric and Photometric. Geometric approach is based on the size and the position of the characteristics of individual features which includes mouth, eyes, nose, and shape of the head. In the photometric approach, statistical values are extracted and are compared with the closely related methods.

III. APPLICATIONS OF FEATURE EXTRACTION AND THEIR EXTRACTING TECHNIQUES

Feature extraction fundamentally uses features within the object to identify, locate and process regions of interest. In doing this, algorithms are developed using either the supervised learning (classification) approach or the unsupervised learning (clustering) approach [17]. In literature, some studies have shown the various approaches adopted by authors to mark and consider the salient point of FE methods.

This section provides a review of the various methods and applications of FE.

A. Text Mining

Text feature extraction is very useful in text mining and information retrieval. Text mining was first introduced by [18]. It is the process of obtaining useful information from text. Text mining finds applications in data mining and various knowledge discovery methods where data is essential for patient records, health care insurance data, social networks and news outlets. Furthermore, it is used in computer vision and image processing applications such as license plate number identification and recognition [19]. In [20], a survey of the various text mining task and techniques was presented.

B. Speech Recognition

Speech recognition (SR) is the process of extracting, characterizing and recognizing the speech information of a person or of a device for identification purpose (e.g. speaker). SR finds applications in numerous applications namely: for the classification of the various genres of music, for the recognition of individual's emotions (emotion recognition), speech synthesis, speech coding and for speaker recognition. An interesting aspect of the application of SR is in the identification of musical genres. They are categorical labels developed by humans to characterize pieces of music and common characteristics shared by its members. Authors in [21], proposed three feature sets to represent rhythmic content, timbral texture and pitch content for automatic classification of audio signals into their hierarchical music genres. Using their proposed feature extraction technique, a classification of 61% for ten musical genres was achieved. In [22], a frequency based approach was proposed. This approach was used to reduce computational complexity based on an algorithm for onset detection at specific frequencies. Furthermore, authors in [23] presented a new audio-visual fusion technique which uses a coupled hidden Markov model (HMM) for audio-visual SR.

A trending aspect of SR is emotion recognition. This aspect is being used recently in robotic research where affective computing and emotional human-computer interaction is needed [24]. Emotion recognition processing stages are mostly divided into three namely: Feature selection, feature extraction and classification. Comparison of research results in this area largely depends on common databases (DBs) to test newly developed methods. Because of the inadequacy of common databases, research efforts in this area have been hard to evaluate. Performance of emotion recognition majorly depends on how we can extract relevant features invariant to the speaker, language, and contents.

In [25], a comparison of various classifiers HMM, support vector machine (SVM), linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) using two different databases namely, the speaker-independent AIBO database [26]. Superior results were achieved with the SVM classifier with accuracies of 96.3% for stressed/neutral style classification and 70.1% for 4-class speaking style classification. Authors in [27], have developed a SR system that uses a new machine learning classifier called the Extreme Learning Machine (ELM). The authors have highlighted the challenges in computational complexity and the need for memory space of computing device which is common to other methods. An accuracy of approximately 95% was achieved using the N-TIDIGITS18 dataset [28].

Other techniques such as Mel-frequency cepstrum coefficients (MFCC), linear predictive coding (LPC), and local discriminant bases (LDB) have also been used for FE in speech recognition [29], [30]. Although several methods have been proposed in literature, the MFCC still remains the most widely used. Furthermore, authors in [30], have proposed a novel method to calculate MFCC. The authors used speech signal from the Aurora 2 database (Hirsh and Pearce, 2000). The signal obtained has a 10 dB SNR and a spectrum between (0.3-3.4) kHz at a sampling frequency of 8 kHz.

C. Image Processing

Image feature extraction is an important stage in image processing and multimedia processing. Image processing deals with the analysis and manipulation of a digitized images, especially in order to improve its quality. Processing large datasets of images requires some form of feature extraction technique. This approach also finds applications in optical character recognition (OCR) for recognition of handwritten text, typed text, license plate numbers, reading aid for the blind and automatic pattern recognition [31]. Authors in [32], presented a texture feature extracting technique using intuitionistic fuzzy local binary (IFLBP) for images. The technique was proposed as an extension of the original FLBP technique.

Furthermore, [33] presented a comparative study of the various combinations of representations of image features such as the region-based, global and local block-based for image database categorization. In [1], a method to represent images called hierarchical Gaussianization was proposed, which uses GMM for its appearance information and a Gaussian map for its locality information. For image retrieval, a matching of the query of the system is compared with an image database using texture, color, shape or local descriptors for retrieval. Although, it is important to note that text mining also known as text-based mining is a subset of image retrieval techniques. These techniques are classified into three namely: content-based method, text-based method and hybrid method. Content-based image retrieval systems find use in a number of applications such as communication media, scientific research, medical research and in the internet. Also, texture analysis using Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) was employed for image segmentation in [34], [35].

D. Data Mining

Data mining is the process of locating the previously unknown information or extracting information from large databases. Data pre-processing and feature extraction is an important step in data mining to correct erroneous data present in a dataset. Authors in [36], used weber local and bag-of-words descriptors as primitive features for image databases visualization. A survey of data mining classification and feature extraction methods was presented in [37], [38].

IV. RESULTS AND DISCUSSION

In this section, we present some extracted GLDS features from ten images. From the ten images we obtained the parameters presented in Table V. The results show that the contrast of images has a high variation.

TABLE V. FEATURES EXTARCTED USING GLDS FE METHOD.

Image	Homogeneity	Contrast	Energy	Entropy	Mean
1	0.76	296.75	0.54	1.55	4.72
2	0.74	390.13	0.52	1.68	5.79
3	0.83	338.60	0.66	1.22	4.46
4	0.76	201.61	0.53	1.46	3.48
5	0.49	239.12	0.20	2.47	5.83
6	0.66	183.85	0.40	1.84	4.06
7	0.72	241.21	0.49	1.64	4.13
8	0.74	162.17	0.50	1.53	3.29
9	0.68	172.60	0.41	1.74	3.52
10	0.67	136.41	0.39	1.75	3.20

This is caused as a result of the time of the day in which the image is captured. In addition, it is observed that the mean of the images has corresponding high values. This is as a result of the variations in color, its contrast, the picture texture and the time of the day the image is capture.

V. CONCLUSION

Feature extraction is a popular and useful approach in many applications and fields of study. This paper, carried out a survey of the techniques, types and applications of FE. It is observed from this study that the applications of FE determines the types of features to be extracted and in addition, the accuracy and performance of extraction techniques are major factors of concern when performing FE.

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