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Segmentation and Feature Extraction in Medical Imaging: A Systematic Review

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Abstract

Image processing techniques being crucial towards analyzing and resolving issues in medical imaging since last two decades. Medical imaging is a process or technique to find the inner or outer construction of mortal body. The process observes medicinal diagnosis, analyze illnesses and develop data-sets of normal and abnormal imageries. Medical imaging is divided in two folds such as invisible-light medical imaging and visible-light medical imaging. The second type of medical imaging were can be understood by a common person whereas the first type can be interpreted by a radiologist. Analysis of all these require segmentation and feature extraction. In fact a lot of medical imaging techniques are available but authors restrict survey to tumor detection through mammograms or magnetic resonance imaging. In this paper, authors survey on various segmentation and feature extraction methods in medicinal images used for preprocessing.

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Keywords: Medical Imaging; Fuzzy Segmentation; Feature Extraction; Imaging Modality; Segmentation.

1. Introduction

Latest available imaging modalities are based on high resolution imaging that offers multi oriented views for a radiologist. Additionally it backed detailed information for clinical diagnosis and assist radiologist in taking correct possible treatment for a patient. The various medical imaging modalities available are ultrasound, mammograms, x-ray computed tomography, magnetic resonance imaging (MRI), electroencephalography, electrocardiography, endoscopy, elastography, magneto encephalography, tactile imaging, thermograph, and nuclear medicine functional imaging. Additionally, medical image processing includes image appearances, imaging devices, and doctors expert

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awareness. A past information of images situation, biomechanical performance can be vital for scheming an real procedure, particularly once the imageries were prejudiced by noises or incomplete volume belongings. More or less such inconsistencies are due to imaging modalities. A brief description on medical imaging modalities is presented in Table 1.

Table 1. Medical Imaging Modalities

Medical Imaging Modalities	Descriptions
Mammograms	A tool for diagnosis and screening of human breast examination by finding low-energy x-ray images.
Computed Tomography	With help of computer, many different angled x-ray images are produced for cross-section image of a particular area. It allows experts to see inside the human body without cutting it.
Magnetic Resonance Imaging	A medical imaging technique for anatomy or physiological processes of the body for observation of health and disease. Other techniques falls in this category are nuclear magnetic resonance imaging, and magnetic resonance tomography.
Electroencephalography	This tool is used to record electrical activities of the brain by electrophysiological monitoring method.
Electrocardiography	This tool measures the electrical activity in the heart and its recording as a visual trace with use of electrodes placed on the skin of the limbs and chest.
Endoscopy	Endoscope is used to examine the interior of hollow organ or cavity of the body. This instrument is directly inserted in human organ for examination.
Electrograph	Electrograph maps the elastic properties of soft tissues. This will give diagnostic details of a tissue, like cancerous tumors is there in tissues or not.
Magneto encephalography	Magneto encephalography is a neuroimaging technique that maps brain activities by recording magnetic fields produced by electrical currents occurring naturally in the brain.
Tactile Imaging	Translating the sense of touch into a digital image. It is otherwise known as stress imaging, mechanical imaging or computerized palpation.

A computer diagnosis analyzer is used to provide computer generated information to radiologist to assist in taking correct decisions. However, such information like mammogram x-ray images are not easy to interpret, sometimes aimed at a radiologist. Consequently, it is mandatory to improve the poor excellence of imageries by using numerous techniques. This helps a radiology professional doctor in extracting features to interpret better. This phase is an important step towards classification. Accuracy of detection without feature extraction cannot be proper because there may be ambiguity in classification. Another approach in medical imaging is segmentation. Manually segmentation medicinal specialists want to outline the contours slice-by-slice by means of pointing strategies such as a mouse or trackball. This process is prolonged and the consequences may agonize from intra-viewer or inter-viewer inconsistency. In the preceding years, several methods have been projected to accomplish the computer aided segmentation. Each of these phases has lots of research proposed by different researchers. In this survey paper authors will go through all categorization and discuss about the advantages, disadvantages, and compare them for common images. This is highly essential for medical applications and help to study a concrete background. Additionally, authors limit their survey to medical modalities like mammograms and MRIs.

The remaining part of the paper is organized as discussion about medical image processing with various segmentation techniques in medical imaging in Section 2, Section 3 is covering feature extraction techniques in medical imaging and at last followed by conclusion.

2. Segmentation in Medical Imaging

Many researchers proposed different segmentation techniques but still not suggested a common method that can be applicable to all type of applications. Segmentation partitions an image into regions on basis of properties. Each region is homogeneous in nature like brightness, color, texture, and reactivity. In general segmentation identifies the regions of interest in mechanizing or supporting the description of anatomic structures. In this section authors mainly discuss about mammograms and for them image segmentation.

This helps in detecting masses, microcalcifications, and speculated lesions. Also, it helps in approximating breast denseness depending on the segmenting dense tissue regions. A number of image segmentation practices occur in the literature is depicted in the following Figure 1. Keeping view to this review, authors highlight the introductory details about these techniques. However, complete details on these techniques can be obtained from the corresponding references. Commencing the survey it is clearly studied that the segmentation in medical imaging can be broadly classified into three categories such as obsolete techniques, ancient techniques, and recent techniques. Ancient techniques are relatively old techniques as compared to recent techniques, but are still in use. In the following section, authors discuss major concepts associated with these techniques.

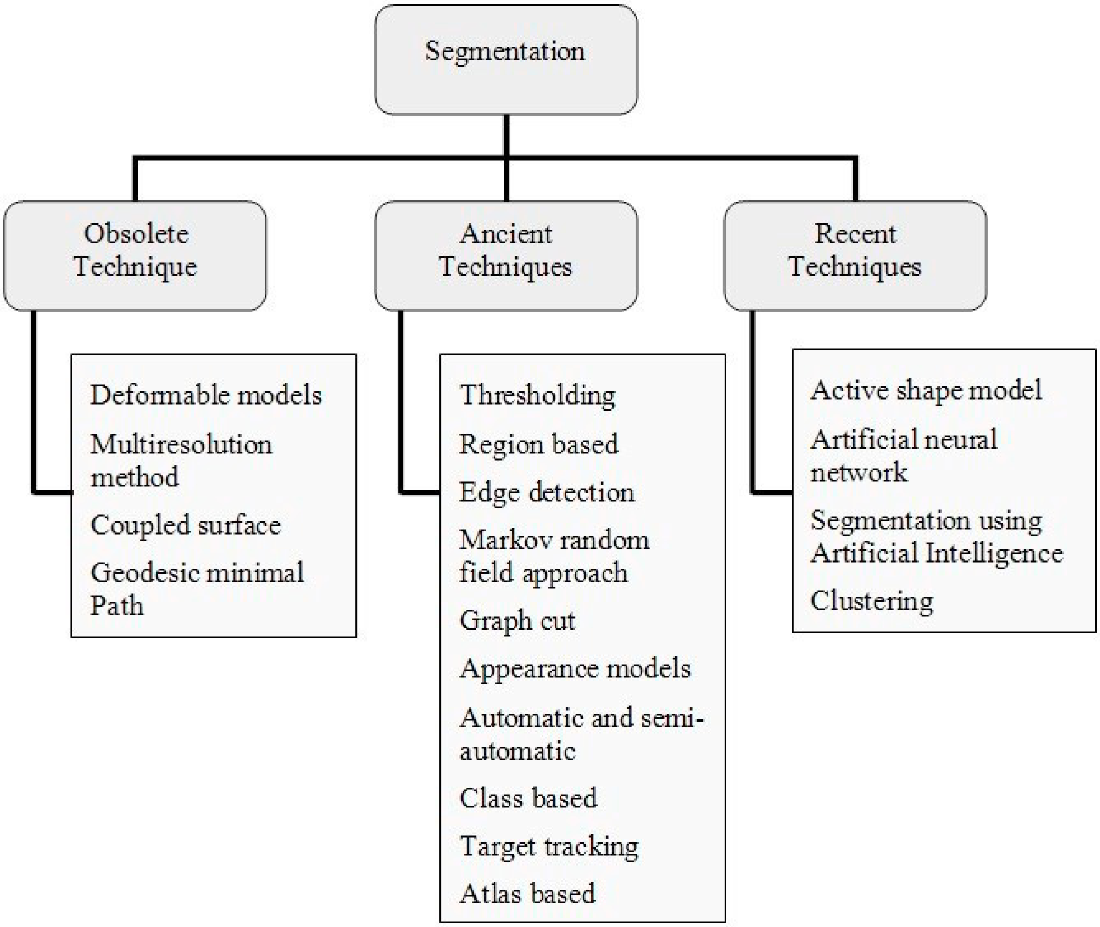

Fig. 1. Various segmentation techniques

2.1. Obsolete segmentation techniques

Obsolete segmentation techniques are developed late 1990s and are mostly not in use. The segmentation techniques which fall under this category are deformable models, multiresolution method, coupled surface, and geodesic minimal math. This section briefly discusses these techniques.

Deformable Models:

Deformable models describe boundaries of objects by means of deformation curvatures or exteriors. It has been extensively being used in segmenting image, especially for segmentation of anatomic structures, in medicinal imageries. It is carried out by including a preceding information of object shape and obliging the resulting borderline to be unremitting and smoothening. The internal forces derived from the curve or surface help in smoothing the curve during deformation. The outside services are calculated grounded on the imageries data to change the curve or surface to the object border.

Multiresolution Method:

A worldwide great excellence resolution appropriate and adjustable to a lot of glitches and data types is multi-resolution method. By way of apiece imageries examination tricky contracts with constructions of a convinced spatial scale, the regular image substances extent must be allowed compliant to the scale of attention. This is attained through a over-all segmentation procedure based on homogeneity meanings in mishmash with local and global optimization.

It also addresses a method for robust estimation of edge orientation using multi-resolution least mean square error estimation. The technique efficiently usages the spatial constancy of minor kernel gradient operators of dissimilar scales to yield more dependable edge position and orientation. The key advantage of this method is that it extracts borderline orientations after data with low signal to noise ratios.

Coupled Surface:

The delinquent of segmenting a volumetric layer of limited wideness is faced in numerous medicinal imaging explores. Bounding facades and the similar environment of the gray level standards in among the facades stay named a layer. Through embryonic two entrenched facades instantaneously, apiece driven by the situation particular image-derived information while sustaining the coupling, a concluding depiction of the bounding facades and involuntary segmentation of the layer are accomplished. A local operator grounded on gray level values is considered to apprehension the info to ambition surface verdict. The usage of such gray level based info in place of the duplicate gradient advances capability to apprehension the homogeneity, and like this it advances the enactment.

Geodesic Minimal Path:

One more technique used for image segmentation is geodesic voting or geodesic density method. This method computes geodesics amid an assumed basis argument and a set of arguments dispersed in the appearance. The geodesic density is well-defined at apiece pixel of the appearance by way of the number of geodesics that neglect this pixel. The target organization agrees to appearance points with a great geodesic density. On the whole, customer offers start and end points on the image and gets the minimal path as output. These minimal paths correspond to minimal geodesics. It finds a set of curves globally minimizing the geodesic active contours energy. Different criteria are also available to obtain automatically a set of end points by giving only one starting point.

2.2. Ancient segmentation techniques

Obsolete techniques are very old and are not in use as of now. Ancient techniques are also old but are still in use in many applications. These techniques include thresholding, region based segmentation, edge detection, Markov random field approach, graph cut, appearance models, automatic and semi-automatic segmentation, class based segmentation, target tracking, and atlas based segmentation.

Thresholding:

The simplest but powerful technique available for image segmentation is thresholding. It is categorized into global and local thresholding. Global thresholding generally separate an image with one threshold whereas local threshold depends on the local characteristic of sub images. Selection of threshold has impotence in segmentation results and its selection is determined by operators' visual assessment. Selection of threshold is generally based on histogram shape, optimization, class separation, spatial information by co-occurrence matrix, and posterior entropy. Details on various thresholding techniques can be found in the research papers.

Markov Random Field Approach:

Markov random field is a pixel labelling probabilistic approach for image segmentation. This pixel labelling segmentation excerpt features from the contribution picture. Apiece pixel in the picture takes a feature vector. Aimed at the complete picture, there is a set of labels. Respectively pixel is dispensed a label. In actual pictures, provinces are frequently homogenous and adjoining pixels typically have comparable belongings such as intensity, color, texture etc. Markov random field (MRF) detentions such appropriate constrictions. Generally, Markov random fields are objective a mixture of basic building blocks as reflection field and concealed labelling field, pixels and their neighbors, cliques and clique potentials, energy function and Gibbs distribution. A subcategory is called a clique if each couple of pixels in this subcategory is neighbors. A graphic depiction is depicted in Figure 2.

Graph Cut:

Graph cut delivers a spotless, supple devising for appearance segmentation. It offers an appropriate language to convert artless confined segmentation cues, and a set of influential computational instruments to excerpt global segmentation from these simple local pixels. The proposed graph cut based segmentation draws a lot of attention because it utilizes both boundary and regional information. Simultaneously, it can achieve global optimal result for the energy function.

Appearance Model:

In collaborating picture segmentation methods an impartial purpose is used which comprises appearance representations as an unidentified adaptable. The impartial purpose is virtuously in terms of unidentified segmentation, using advanced direction elites. This preparation discloses a stimulating prejudice of the perfect to equilibrium segmentation. Likewise, it allows to grow a novel twofold decomposition optimization process that delivers additionally a lower bound. This technique is further hybridized with graph cuts and the hybridization is applied to medicinal picture segmentation.

Automatic and Semi-automatic Segmentation:

In automatic segmentation procedure, the segment boundaries are assigned automatically by a program. The authors also provide a shortcut for better segmentation. Some commonly used semi-automatic methods are intelligent scissors, user steered image segmentation, and fuzzy connectedness. Simultaneously, it is tedious to think for manual segmentation procedures and at the same time fully automatic segmentation never allows any human interference. To overcome this limitation, semi-automatic procedure is preferred for medical image segmentation. It is a 3D approach that integrates both region and boundary based procedures.

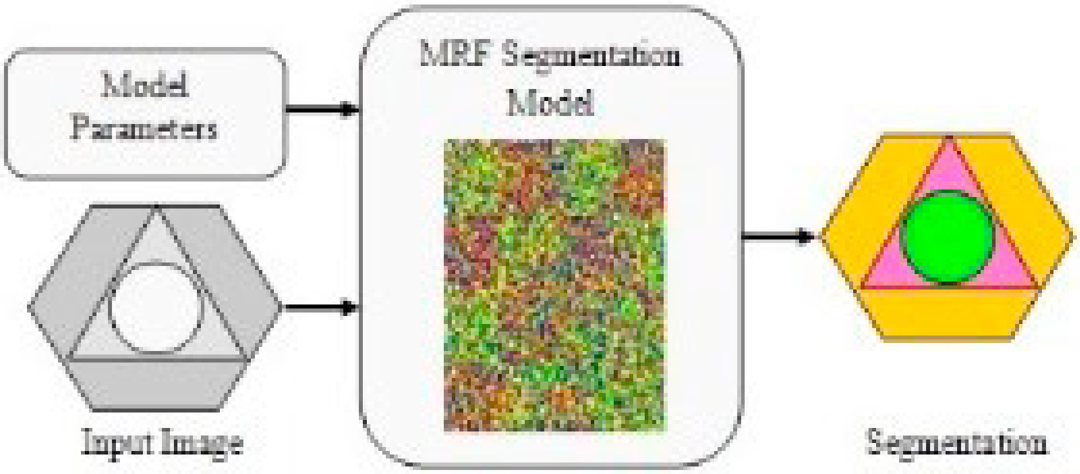

Fig 2. A Pictorial View of MRF Segmentation

Class based Segmentation:

Classifier established segmentation usage pattern recognition methods that effort to divider feature vectors mined since a picture into an assumed set of classes. These classes incline to be administered anywhere features are resultant after reference segmentations such as manual segmentation. The features used in the classification technique are diverse, which can be associated to intensity, texture, or additional belongings of a picture. To demonstrate the power of classification, a simple algorithm is used to randomly search for good segmentation. An unpretentious classifier is the k - nearest neighbors (KNN) classification, where apiece thing is classified grounded on a majority vote of the situation k - closest training samples. In image segmentation, each pixel is labelled with the most common class among the k - nearest neighbors of its consistent feature vector in the feature space. The class based segmentation is successfully practical to medicinal image segmentation, by way of pulmonary nodule discovery in chest, decrease in false assumption for breast cancer detection and brain tissue segmentation in MR data.

Target Tracking:

Object tracking in video pictures, based on image segmentation and pattern matching is also proposed in the literature. Using image segmentation, authors can detect all objects in an image. The images may be of moving or still. Consequently, the target tracking algorithm is applied to multiple moving and still objects. These still or moving objects are captured by using moving camera. It serves as input to a high level tracker whose goal is to correctly associate the sparse detections over time.

Atlas based Segmentation:

The atlas based segmentation has the ability to segment the image with no well-defined relation between regions and pixels intensities. This approach remains usually used when the objects of the similar construction essential to be segmented. It indicates that the objects must be having identical texture, and the information concerning alteration amid these objects is incorporated in spatial relationship amid them, additional objects, or inside their morph metric characteristics.

2.3. Recent segmentation techniques

These segmentation techniques are relatively new in medical imaging. Medical images have some uncertainties. To deal such uncertainties researchers started using intelligent techniques such as neural network, artificial intelligence, fuzzy set, Intuitionistic fuzzy set etc. in medical imaging. In this section authors review segmentation techniques that fall under this category such as active shape model, artificial neural network segmentation, and segmentation using artificial intelligence, and clustering.

Active Shape Model:

Active shape models (ASM) were statistical prototypes of the shape of substances that iteratively distort to appropriate to an object in a new image. The shapes are forced through the point delivery prototypical. It is represented by a set of points that are controlled by the shape model. The active shape model algorithm aims to match the model to a new image.

Segmentation using Artificial Intelligence:

Dissimilar methods were suitable to diverse kinds of `pictures and the excellence of yield of a specific procedure was challenging to amount quantitatively owing to the detail that around might be considerable precise segmentation aimed at a single picture. Image segmentation means a procedure through which a raw input image is partitioned into non-overlapping regions such that each region is homogeneous and the union of any two together districts is heterogeneous. A segmented picture is measured to be the uppermost field self-determining abstraction of an input picture. All-embracing exploration were consuming been completed in producing several diverse tactics and algorithms for picture segmentation, but it is still tough to measure whether one algorithm yields supplementary correct segmentations than another, whether it be for a certain image or set of pictures, or further commonly, for a total class of pictures.

Clustering:

The fuzzy c-means approach integrates concepts of fuzzy set to k-means clustering. This permits an information fact to go to two or more clusters. The belonging of data points to various clusters is carried out with the help of expectation maximization (EM). It intentions on conclusion maximum likelihood estimates of limitations in statistical representations in an iterative way. The EM procedure has been effectively applied to Gaussian mixture modeling, in which a sum of Gaussian workings are combined to fit a multimodal circulation. The resources and covariance of the Gaussian mechanisms can be estimated and updated in the EM iteration, and the resulting multiple Gaussians are combined to procedure a generalized archetypal.

To overcome this limitation, later Intuitionistic fuzzy c-mean technique was introduced. The major contribution in this clustering is the introduction of non-membership and hesitation. The introduced concept was successfully applied to medical images. It was valuable in clustering dissimilar regions of the medicinal images and help to catch irregularities in pictures.

Afterwards a new approach, possibilistic Intuitionistic fuzzy c-means is introduced. The foremost contribution is the introduction of hesitation in possibilistic FCM. Outmoded clustering approaches were powerless to handle the belongings of noisy data and outliers. The proposed technique overcomes the limitation possibilistic fuzzy c-mean and improves the membership assignments and handles noisy data.

3. Feature Extraction

It is nearly impossible to say the best approach aimed at feature extraction for medicinal pictures. This remains no generic feature extraction scheme that the whole thing well for altogether belongings. Altogether these depend happening various applications where authors remained employed with. Approximately basic necessary belongings to be kept in mind aimed at selection of respectable feature extraction are kind of delinquent undertaken, availability of data, dimensionality of data, labeling of data, and supervised or unsupervised method. Arranged the basis of these steps, a researcher may choose a convenient feature extraction approach out of many available feature extraction algorithms. The following Figure 3 depicts an overview of available feature extraction techniques. Authors briefly discuss about these techniques in the following subsections.

3.1. Local binary pattern

Local binary pattern (LBP) is a texture gratified in imagining. The authors were invariant to monotonic fluctuations in gray scale pictures. In addition, the authors are fast to calculate. But, the authors are incapable to distinguish diverse micro outlines, such as boundaries, points, and constant zones. The uncomplicated clue overdue the LBP methodology was to customize the evidence around the texture from a local neighborhood. Initially in LBP, the radius is described for local neighborhood underneath neat deliberation. The LBP operator formerly shapes a binary code that defines the local texture pattern in the neighborhood set of pixels. The binary code is found through smearing the gray value of the neighborhood midpoint as a threshold. Further, the binary code is rehabilitated to a fraction number which signifies the LBP code. So, LBP is a method that uses gray scale invariant texture statistics.

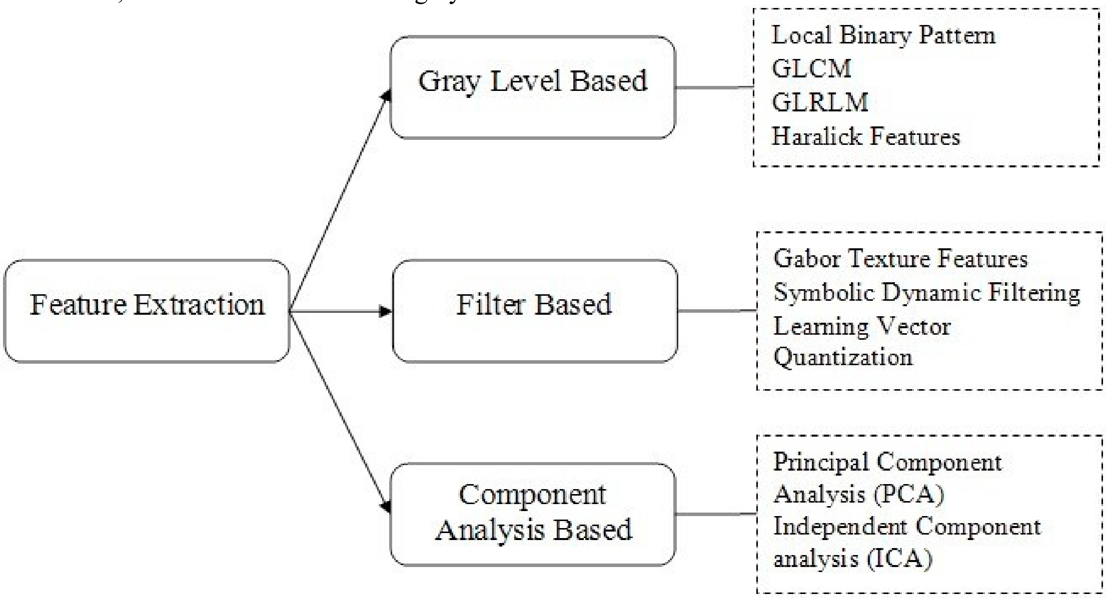

Fig 3. A Broad Classification of Feature Extraction

3.2. Gray level co-occurrence matrix

Gray level co-occurrence matrix (GLCM) is a feature extraction approach basically deals with statistical method. It contemplates the spatial rapport of pixels as the gray level co-occurrence matrix or gray level spatial dependence matrix. The spatial rapport in gray level co-occurrence matrix is defined as the pixel-of-interest. The horizontally adjacent pixels be able to stated additional spatial rapport in the middle of 2-pixels. The element of the subsequent gray level co-occurrence matrix is computed. It is just the sum of the number of times that the pixel value is occurred in the indicated spatial rapport to a pixel with the input image.

3.3. Gray level run length method

Grey level run length method (GLRLM) of encoding is a way to denote strings of symbols in an image matrix. In this case, the grey level run is a set of consecutive, collinear pixels having same grey level. The run length is the number of pixels in the run 0000111100111. In this technique, a run length matrix is used for texture feature extraction. Additionally, run length statistics confine the thickness of a texture in a precise direction. The GLRM is defined by specifying direction and then count the occurrence of runs for each gray levels and length in the same direction.

3.4. Harlick features

Haralick texture features are centered at the co-occurrence matrix designed as of the picures. The co-occurrence matrices are castoff aimed at exposing the gray level spatial dependence laterally like angular relationships, vertical and horizontal advices in the pictures. By conniving co-occurrence matrix numerous altered texture featured can be formed. Haralick projected 13 features consequential from the co-occurrence matrix as angular second moment, Contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation, and maximal correlation coefficient.

3.5. Gabor texture features

Gabor feature extraction is based on Gabor filter. These filters are designed with a view of human visual system and are related to Gabor wavelets. Additionally, the authors have been found to be particularly appropriate for texture analysis. It is linear filter basically intended for edge detection. The Gabor texture features are just a cluster of wavelets. Later, apiece wavelet apprehending vitality at an exact incidence and an exact way. After the collection of energy distributions the texture feature on behalf of the pictures may be haul out.

3.6. Learning vector quantization

Learning vector quantization (LVQ) is a supervised learning method based on vector quantization that can be used when authors have labelled input data. The supervised learning referred vectors are modernized based on the steepest descent method and are used to minimize the cost function. In general, it uses the class information to reposition the vectors so as to improve the classification quality of decision regions. It has two stages self-organizing maps (SOM) followed by LVQ. It is best understood as a pattern classification algorithm. The first step is feature selection in which it identifies reasonably small set of features. These small set of features generally contain the essential information of the input data. In the second step the feature domains are assigned to individual classes.

3.7. Symbolic dynamic filtering

Symbolic dynamic filtering (SDF) extracts low dimensional features after time series data. The symbolic dynamic filtering algorithm encompasses wavelet transformed preprocessing of signals towards facilitate the time frequency localization and de-noising. The presence of wavelet transform involves modification of additional strategy restrictions, such as the wavelet basis and set of scales. Moreover, SDF is a tool for extracting spatial temporal features from stationary time series data. The most important feature of this technique is that of early detection of anomalies in complex dynamical systems.

3.8. Principal component analysis

In case of low dimensions or when there is a requirement of low dimensions, the best method for feature extraction to improve performance is principal component analysis (PCA). Additionally, it directed and functional to mark slanting decision restrictions. It is otherwise known as the Karhunen Loeve transforms (KLT). Principal component analysis are mainly intended for dimensionality reduction while analyzing classification problems. In general while analyzing high dimensional data, it is preferred to identify the features that are superfluous and can be removed from the datasets. Principal component analysis classifier helps in such cases and removes the features that are superfluous. In case when altogether features in feature vector are statistically autonomous, someone might just eradicate the smallest discriminative features from the vector. Sometimes it is observed that, numerous features be contingent happening apiece additional or on an underlying unknown variable. A solitary feature can so embody a combination of multiple types of information by a single value. Removing such a feature would remove more information than required. Trendy principal component analysis, the features are the principal components. The authors are orthogonal to each other and produce orthogonal weights.

3.9. Independent component analysis

Independent component analysis (ICA) is an approach for feature extraction in which information is comprised in accumulation to contribution features. This techniques are ordered as unsupervised learning because it outputs a set of maximal independent component vectors. This unsupervised technique by natural is connected to the contribution dispersal. At the same time, it cannot guarantee good performance in classification problems. The feature pattern can be formed from independent components of the observed data pattern.

4. Conclusion

In this paper authors have discussed various popular image segmentation and feature extraction methods nearly new medical imaging particularly for mammography. Mammography is useful for early detection of breast cancer. If mammograms are directly used without improvement, then the conclusions occupied by a radiologist might lead to unnecessary behavior of the patients. Towards reducing circumstances, various segmentation techniques are used for different perspective. However, due to limitation of other segmentation techniques, clustering based segmentation has been considered as better than others. Even with Fuzzy c-mean based segmentation, there is a limitation. In addition, advantages and limitations of these techniques are stressed upon in this survey. Feature extraction methods obtainable in literature and listed in this article projected altered approaches that may be accessible through diverse classification technique. In excess of the listed feature extraction techniques, principal component analysis and independent component analysis are widely used after the belongings are there of dimensionality reduction, especially due to huge data. But for texture cases, Haralick texture feature is widely used. Similarly for edge detection, Gabor texture features is generally used. The authors believe this survey research will be useful for researchers in medical imaging segmentation and feature extraction. Over all these segmentation methods, the clustering is the best and this is used in various type of applications. Many researchers are still proposing new algorithms and also hybridization of some existing algorithms. Another section is of feature extraction where Harlick texture features and GLMC are mainly applied in various research works.

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