Journal of Visual Communication and Image Representation 55 (2018) 596–626

Contents lists available at ScienceDirect

Journal of Visual Communication and Image Representation

journal homepage: www.elsevier.com/locate/jvci

A survey on image data analysis through clustering techniques for real world applications☆

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ARTICLE INFO

Keywords:
Image clustering
Feature extraction
Real world applications

ABSTRACT

A huge amount of image data is being collected in real world sectors. Image data analytics provides information about important facts and issues of a particular domain. But, it is challenging to handle voluminous, unstructured and unlabeled image collection. Clustering provides groups of homogeneous unlabeled data. Therefore, it is used quite often to access the interesting data easily and quickly. Image clustering is a process of partitioning image data into clusters on the basis of similarities. Whereas, features extracted from images are used for the computation of similarities among them. In this paper, significant feature extraction approaches and clustering methods applied on the image data from nine important applicative areas are reviewed. Medical, 3D imaging, oceanography, industrial automation, remote sensing, mobile phones, security and traffic control are considered applicative areas. Characteristics of images, suitable clustering approaches for each domain, challenges and future research directions for image clustering are discussed.

1. Introduction

These days, a use of Internet is rapidly increasing pave to data explosion, which results into big data. It contains a large amount of image data. For the image data analysis, image processing [1,2]) and data mining [4,3] techniques play an important role. Many software tools [5,8] such as R [9], WEKA [10,11], RapidMiner [12], SciKit [13], KNIME [14], SparkMLlib [6] are available to handle different types of data automatically. But, these tools are not sufficient for detailed analysis of a particular data type as it has limited number of data mining techniques [5]. Hence, it may not be able to handle all the types of data with different characteristics. Mikut and Reischl said that generalized powerful tool for multidimensional data (like image and video) is not available. In 2014, Jovic et al. also studied several tools and concluded that there is no single best tool and each tool has their corresponding strength and limitations [8]. While analysing the image data from large datasets, it is important to partition the given data. It helps to retrieve an important and interesting data easily and efficiently. Clustering is a very useful technique to accomplish this data partitioning task. As image clustering is an unsupervised learning based approach, it is capable to handle unlabelled image data. It also helps in reduction of less significant data from huge dataset. Whereas, it is mainly utilized for image segmentation and Content-Based Image Retrieval (CBIR).

1.1. Overview of clustering

Clustering [15] is an important task of the data mining which aims to partition the given data objects into groups on the basis of similarities among them. Here, data objects are images when image clustering is used for image retrieval and pixels in the case of segmentation. Clustering preserves two properties i.e. maximize intra-cluster homogeneity and inter-cluster heterogeneity. To get similarity between two data objects, distance metric (here, the metric is chosen by the user) is very important. Various distance measures are available according to the type of data. For the numeric data, Euclidean, Manhattan Minkowski or Cosine similarity distances are used. Ranking or Cosine similarity is used for the ordinal data and for the image data, Euclidean, Mahalanobis, Chord distance measures are used to compute the similarity on the basis of extracted features. Clustering is an unsupervised approach as it is capable to handle the unlabeled data. Therefore, it is prevalent in all disciplines involving multivariate data analysis [7]. To get accurate results, similarity computation functions must be strong. Clustering [3] is mainly classified into four basic categories such as partitional [16,17], hierarchical [17,18], density based [19] and grid based [20] methods on the basis of their characteristics (discussed further in this subsection). Nowadays, many hybrid approaches are coming up with different constraints. In Fig. 1, types of the clustering

☆ This paper has been recommended for acceptance by Radu Serban Jasinschi.

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https://doi.org/10.1016/j.jvcir.2018.07.009
Received 20 October 2017; Received in revised form 4 May 2018; Accepted 14 July 2018
Available online 20 July 2018
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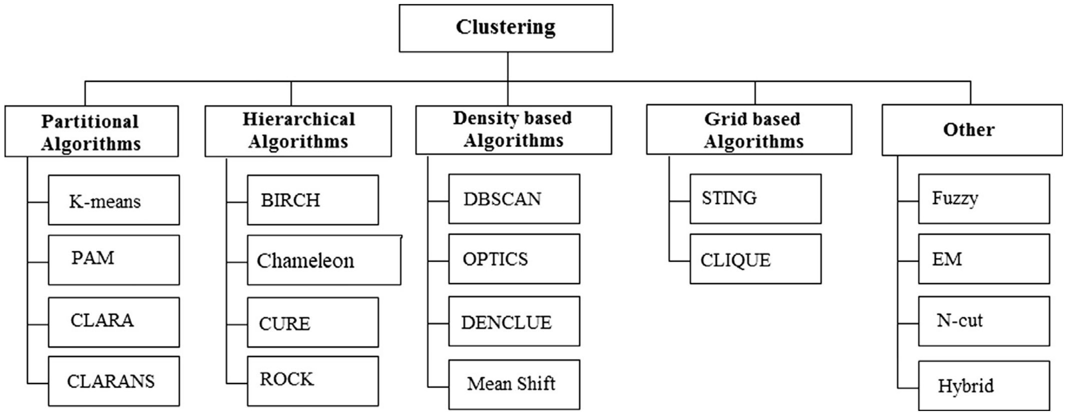

Fig. 1. Classification of Clustering Techniques.

techniques and some of the most popular clustering algorithms of those types are represented.

Partitional clustering outputs disjoint (mutually exclusive) clusters by using an iterative approach. K-means [3] is a most popular clustering algorithm devised in 1955 by Steinhaus which uses mean of the cluster as a centroid of the cluster. ISODATA (Iterative Self Organizing Data Analysis Technique), FORGY, CLUSTER and WISH are the variants of k-means [21]. Other partitional clustering algorithms are PAM (Partitioning Around Medoids), CLARA (Clustering LARge Applications) and CLARANS (Clustering Large Applications based on RANdomized Search) [22]. CLARANS is more efficient and effective approach as compared to PAM and CLARA [23]. Partitional clustering algorithms can be applied only on the datasets with spherical shaped clusters. It doesn't work for the complex datasets.

Hierarchical clustering approach results hierarchy of clusters as an output. Hence, user can get the information at desired level of hierarchy. There are mainly two approaches- agglomerative (bottom up) [24] and divisive (top down) [25]. Agglomerative approach merges data objects at each level on the basis of similarities present between them. Divisive approach splits a single cluster into number of clusters at each level on the basis of dissimilarities found between them. BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) [26], Chameleon [27], CURE (Clustering Using REpresentatives) [21] and ROCK (RObust Clustering using linKs) [28] are the popular hierarchical clustering algorithms. In this type of approach, an error cannot be corrected. If wrong split or merge is done, then previous step cannot be obtained for the correction [29].

Density-based clustering finds the dense regions in given dataset and represents it as a cluster. This approach is able to find the arbitrary shaped clusters. But, it cannot work properly if input dataset has the clusters with various densities. DBSCAN (Density Based Spatial Clustering of Applications with Noise) [30] is a well-known density-based clustering algorithm. This algorithm doesn't perform well, if it is applied on the high dimensional data and Euclidean distance is used as a distance measure [29]. OPTICS (Ordering Points To Identify the Clustering Structure) [31] is an extension of DBSCAN. It provides more flexibility while providing an input. DENCLUE (DENsity-based CLUsTEring) [32] is a combination of partitional and hierarchical clustering methods which performs better than DBSCAN. Mean shift algorithm [33] performs well i.e. it provides better results as compared to existing popular algorithms like k-means, k-nearest neighbor [34,35]. This approach is suitable for tasks of computer vision as compared to parametric approaches [36].

Grid-based clustering techniques partition the data space into number of cells to form a grid structure. Then, it forms clusters with the help of those cells in the grid structure. It requires less processing time which depends on the grid size rather than the data points. STING (Statistical INformation Grid approach) [37] and CLIQUE (CLustering In QUEst) [38] are the grid-based clustering algorithms. STING is a very efficient and highly scalable clustering algorithm [29,37], but this algorithm is not able to consider the distribution of data before construction of grid as well as unable to provide the high accuracy. CLIQUE has characteristics of the grid-based and density-based approach. This algorithm automatically identifies the high dimensional subspaces but quality of the output depends on grid size.

Characteristics of the discussed type of clustering approaches are given as follows:

- Partitional Clustering
  - Outputs mutually exclusive clusters
  - Able to deal with spherical shaped clusters only
  - Uses mean, medoid, etc. as cluster center
  - Distance based partitioning
  - Provides good results for small to medium size data sets
- Hierarchical Clustering
  - Outputs hierarchy of clusters
  - Graph based proximity computation (single, complete or average link)
  - Unable to correct erroneous decision (splits or merges)
  - Needs to use subroutine algorithm
- Density based Clustering
  - Able to deal with arbitrarily shaped clusters
  - Cluster density is an important factor because high density regions are separated by low density regions
  - May filter out outliers
- Grid based Clustering
  - Uses a multi-resolution grid data structure
  - Able to deal with arbitrarily shaped and distance independent clusters
  - Processing time depends on grid size but independent of number of input objects
  - Fast processing time

Fuzzy clustering [39–41], probabilistic model-based clustering [3,42], spectral clustering (N-cut) [43] and expectation–maximization algorithm [47] are the other popular approaches. Fuzzy clustering (e.g. Fuzzy C-Means (FCM)) deals with the vagueness in a cluster membership of the data object. In recent years, methods like GraphEncoder, deep structure with a linear coder and infinite ensemble clustering are developed which performs better for the image clustering. [44–46]. Clustering has a wide application area such as text mining, image analysis (action recognition, medical image analysis, event detection, etc.), web cluster engines, etc. [3,48,49].

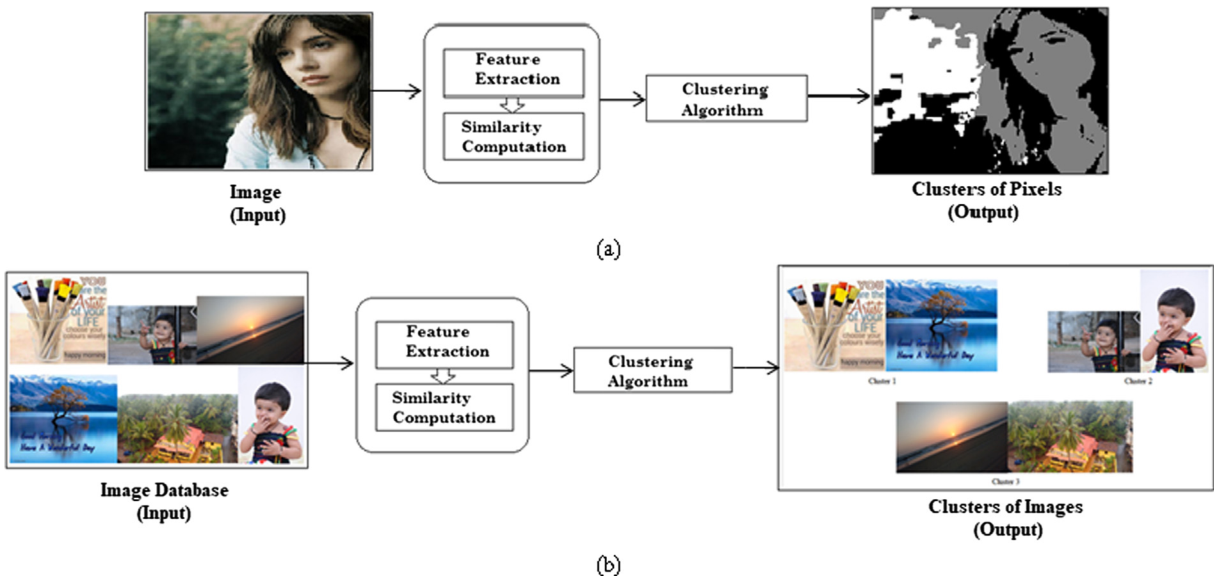

Fig. 2. Framework of the Image Clustering for (a) Image Segmentation (b) Image Retrieval.

1.2. Clustering of the image data and our contribution

The main forms of data include numeric, text and multimedia, which are used as an input for many applications. Numeric and text data are the basic data forms. It requires less storage space and less computational cost as compared to multimedia data. Recently, the use of multimedia data has become rampant. Multimedia data types include image, audio, video and other specialized types which need an excessively high amount of storage space. Image data is an interesting and expressive type of data, but it is complicated to handle. It is a collection of picture elements i.e. pixels. Grayscale, binary, color and indexed color are the types of images. Retrieving a particular image from the large image dataset is a very difficult task. As clustering handles unlabeled data, it is a very useful task to manage the unlabeled image data at various places easily and efficiently. It is also useful to get the interesting region of the image. Image retrieval and image segmentation are the applications of the image clustering.

Image clustering techniques mainly follows two steps as shown in the Fig. 2. First, computation of similarity measure using extracted features. Second, implementation of clustering algorithm. As similarity measure is a basis of clustering, similarities between two images or image segments is computed and then by using this similarity matrix, clustering is done. If given image is used as it is for the similarity computation, this computational task becomes tedious as image data is large in size. Hence, it is very important to extract appropriate features from given image to represent that image. It drastically reduces the computation cost of similarity computation. For image data many popular feature extraction techniques are available which are discussed in the forthcoming section and then discussion on image clustering techniques is provided further. Input given to the system is an image data and output is clusters of the image data. Here, image data is individual image (for image retrieval) or image pixels (for image segmentation).

This survey provides a broad view of research in image clustering used for various applications. It includes old areas such as medical imaging and remote sensing images, as well as newly emerged areas like mobile phones, traffic surveillance, etc. Emerging issues and future scope for each area is provided. In this paper, image clustering for single as well as multiple images is taken into consideration to analyze the clustering approaches properly. Here, region of an image is a cluster for single image and a set of images is a cluster for multiple images as shown in the Fig. 2. We have tried to analyze almost all important papers from the each mentioned area. Pros, cons, future directions and other related information of discussed techniques is summarized in the form of tables.

1.3. Organization

Remaining paper is organized as follows: In Section 2, basic concepts of the feature extraction and its techniques are briefly discussed. In Section 3, broad overview of the clustering techniques for image data from various domains is given and, advantages and limitations of each method are identified. In Section 4, this survey is summarized as well as challenges and future works are discussed. Our study is concluded in Section 5.

2. Feature extraction

Similarity measure is an important part of the clustering process. In image clustering, significant features of the image are used as a representative of the given image. Hence prior to the similarity measure, features of the selected image are extracted. Image features can be low level features such as color, texture and shape or can be high level semantic. With the help of extracted features, similarity between images is computed. Some of the popular image feature extraction methods are discussed below:

Color is a basic but most expressive visual feature of the image [50] as human eye has capability to differentiate thousands of color shades and intensities which helps to receive visual information. It also simplifies the identification and extraction of the object from given image [51]. Color feature is very stable and robust as compared to texture and shape. Generally, invariance properties depend on the considered kind of color feature (e.g. color histogram, color pixels, etc.). Color histogram is invariant under rotation, translation and scale change [52] whereas color pixels are not. Properties of the color feature depend on the approach used to extract the color information. Color histogram is a most common color feature extraction approach. It generates different histograms for similar image having different viewpoints with different lightening conditions [53]. Whereas, color representation through histogram is invariant under rotation and translation [54]. Selection of appropriate color space is the first stage of color feature extraction. Color space [51] is a mathematical model which represents colors. In year 1931, CIE (Comission Internationale de l'Eclairage (International Commission on Illumination)) introduced XYZ (Tristimulus values) color space [55]. RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), CMYK (Cyan, Magenta, Yellow, Key (Black)), YUV (Y- luminance, U and V- Chrominance are the most popular color spaces. CIE L^*u^*v (L^*-luminosity, u^*v^*-chromaticity coordinates) and CIE $L^*a^*b^*$ (L^*-luminosity, a^*- red/green axis, b^*-yellow/blue axis) are also introduced by CIE. RGB is an additive approach so all possible colors can be created using red, green or blue. RGB is not a perceptually uniform color space but HSV, CIE $L^*u^*v^*$ and CIE $L^*a^*b^*$ are the perceptually uniform color spaces [56] which are proportional to the human perception. These color spaces are developed according to the suitability for hardware or applications related to color manipulation. As red, green and blue channels are strongly correlated, changing color space is important in order to decorrelate channels which helps in extraction of features independently on each channel. RGB and CMYK are the hardware oriented color spaces for color monitor/ video camera, printing purpose, respectively. Whereas, HSI (Hue, Saturation, Intensity) is the color space having capability to decouple the information related to colors as well as gray-scale. Hence, HSI color space allows to use many gray-scale techniques [51]. If color space of given image is not suitable to accomplish a specific task, then it can be changed and suitable approach can be applied to accomplish the required task.

Histogram Intersection (HI), Dominant Color (DC) and Color Correlogram (CC) are the most common color-based image descriptors which are discussed as follows: [57]

- HI: Global color features are considered with the help of color histograms. It has characteristics like low computational cost, robust against geometrical modifications such as rotation, resolution and scaling [58].
- DC: It represents the image by using a small number of dominant colors [59].
- CC: Global as well as local distribution of each color in the image are considered [60].

Fierro-Radilla et al. [57] devised new color descriptor which is a combination of dominant color descriptor and color correlogram descriptor. Global distribution of colors in the image is considered by the DC and local color distribution is taken into account by the CC. This method considers both, global as well as local color distribution. Proposed descriptor is faster than CC descriptor. Color similarity is measured with the help of color moments. Mean, median, variance, standard deviation, skewness and kurtosis are the popular color moments. Color feature extraction techniques used for the image retrieval are given in Table 1 [54,64]. In the HSV color space, binary Haar color descriptor outputs better results. PCMD and CHMD provide good results in the CIE $L^*u^*v^*$ and the CIE $L^*a^*b^*$ respectively. QuadHistogram-based color features extraction method is developed with the help of quad-tree to specify the homogenous blocks of different sizes. QuadHistogram is an efficient technique as compared to Color histogram and histogram powered by the complexity of an image [65]. New sets of Fourier–Mellin descriptors such as parallel-orthogonal Fourier–Mellin Descriptors (poFMD), Color Fourier–Mellin Descriptors (CFMD) and Color Fourier–Mellin Descriptors insensitive to bivector choice (CFMDi) are defined by Mennesson et al. [66] with the help of Clifford Fourier Transform (CFT) for object recognition in color images. CFT [67] is a linear combination of the number of classical Fourier transforms and bivector is a distinguished color plane used to parameterize the CFT. These descriptors are an extension of traditional Fourier–Mellin descriptors (which was only suitable for grayscale images) useful for color images. Computational complexity of the color CFT is *O(nlogn)* [68]. Fourier–Mellin descriptors are invariant under direct similarity transformations such as translations, rotations and scale [220,69]. Experimental study is carried out using the modified version of COIL-100 and color FERET image dataset. poFMD performed consistently well in for different datasets as well as on scale change. In 2017, Local Binary Pattern (LBP) - based color descriptor i.e. Ternary-Color LBP (TCLBP) is proposed by Lu et al. [70] for the purpose of recognition of face. Experiment is carried out using four face image datasets i.e. Color FERET, Georgia Tech, FRGC and LFW. TCLBP provided visibly better face recognition results as compared to other existing LBP-based color features.

Texture feature is also widely used by the researchers for digital image processing. Pratt [71] said that "Texture is often qualitatively described by its coarseness". The spatial repetition period of the local structure helps to get the information about the slope of texture. Small period indicates fine texture and large period indicates coarse texture. As texture is a spatial property, one-dimensional histogram is unable to characterize the texture. Hence, two dimensional matrix i.e. gray level co-occurrence matrix is commonly used for the texture analysis [72]. Apart from this, other techniques like wavelet transform, Gabor filter, etc. are also important. Texture feature extraction techniques are discussed further and relevant important information is provided in Table 2. Those techniques are divided into following categories [64]:

1. Statistical approach
2. Structural approach
3. Spectral approach

Table 1
Color feature extraction techniques.

Authors	Color extraction techniques	Basic component	Distance measures
Banu and Nallaperumal [54]	Pixel based Color Moments Descriptor (PCMD)	Pixel value	Euclidean distance
Han et al. [61], Banu and Nallaperumal [54]	Color Histogram Moments Descriptor (CHMD)	Color histogram	Mean of Normalized Histogram Intersection, Histogram Euclidean Distance, Histogram $\chi 2$ Metric Distance, Histogram Mahalanobis Distance, Histogram Quadratic Distance
Han et al. [61], Banu and Nallaperumal [54]	Single Channel Histogram Moments Descriptor (SCHMD)	Color histogram	Mean of Normalized Histogram Intersection, Histogram Euclidean Distance, Histogram $\chi 2$ Metric Distance, Histogram Mahalanobis Distance, Histogram Quadratic Distance
Shi [62], Banu et al. (2010)	Maximum Frequency Symmetrical Color Spatial Feature (MFSCSF)	Maximum color frequency of each region	Mean of distance using maximum color frequency
Han et al. [61], Shi [62], Banu and Nallaperumal [54]	Symmetrical Color Spatial Histogram (SCSH)	Histogram values of each region	Mean of distance using histogram values of each region
Graps [63], Banu and Nallaperumal [54]	Binary Haar Color Descriptor (BHCD)	Haar wavelet function	Hamming distance
Fierro-Radilla et al. [57]	Hybrid Color Descriptor	Dominant colors and color correlogram	–
Mennesson et al. [66]	Fourier–Mellin Descriptors	Clifford Fourier Transform	–
Lu et al. [70]	Ternary-Color LBP (TCLBP)	Local Binary Pattern	Mahalanobis distance

Table 2
Texture feature extraction techniques.

Authors	Texture extraction techniques	Approach type	Characteristics
Kong [73], Malegori et al. [96]	GLCM	Statistical	Simple, Able to provide powerful statistics providing texture related information, Do not understand spatial arrangements of primitive texture elements i.e. macro-texture, Computational complexity increases with level/order of statistics
Kong [73], ElAlami [75]	CCM	Statistical	Able to describe colored textures, Disproportional rise in dimensions of feature space provides higher accuracy in RGB space than color histogram and intensity pattern analysis
Abu Sayeed Md Sohail et al. [80]	GLRLM	Statistical	Extremely sensitive to noise, Do not measure second order probabilities, traditional GLRLM performed poor as compared to local relative GLRLM.
Fogel and Sagi [81], Batool and Chellappa [82]	Gabor filter	Statistical	Provides response similar to the human visual cortex, Reduces joint 2-D uncertainty among space and frequency, Low computational complexity, Provides better discrimination in image if difference between micro-patterns is high
Sonka et al. [55], Bama and Raju [86]	Fourier Spectral Transform	Spectral	Not invariant
Chang et al. 1993, Addison [98]	Wavelet Transform	Spectral	Able to reconstruct exact original signal using frequency localization base, Powerful approach compared to Gabor filter
Liu et al. [89], Liu et al. [49]	LBP	Spectral	Computationally efficient, Median robust extended LBP provides high performance than other variants of LBP
Hu et al. (2016)	3D Haralick co-occurrence matrix	Statistical	Intensity feature, reflects spatial variation

Statistical approach characterizes the stochastic properties of the spatial distribution of grey levels in the image. It is a quantitative measure of arrangement of the intensities. Gray Level Co-Occurrence Matrix (GLCM) and Color Co-Occurrence Matrix (CCM) are the statistical approaches which are commonly used to extract the texture feature and find the spatial dependencies [73–75]. In GLCM, texture is represented as matrix by using grey levels from the image as well as it implies the roughness and repetition of the texture in image. It can distil the character quantity of a texture such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence, maximum probability, etc. [76,77]. Statistical approach is simple, easily adaptable, robust and also easy to implement [78] as compared to others. But, it is very difficult to handle huge amount of data involved in higher order statistics [79]. By using the Gray Level Run Length Matrix (GLRLM), local relative texture feature are extracted in terms of global image properties. This approach is used for the extraction of higher order statistical texture features. GLRLM is a two-dimensional matrix generated by using grey levels and longest run. Each element of the matrix gives total number of occurrences of the runs with a particular length of grey level in the given direction. Local relative GLRLM is compared with traditional GLRLM where it is found that Local relative GLRLM performs better. It is useful to adapt for embedding the local information from extracted features in any global feature extraction method [80]. Gabor filters [81,82] map an image into the feature space from original space by using Gabor filter bank. Frequencies, orientations and smooth parameters of the Gaussian envelope are used to define those filter banks. Compact Gabor filter bank is prepared by the selection of filters which minimizes the computational complexity of texture feature extraction. Gabor filter bank produces low-dimensional feature representation and improved sample-feature ratio which improves the performance. In 2016, Hu et al. provided another statistical approach i.e. Haralick co-occurrence matrix for 3D space. It provides spatial variations from given image. This approach is also referred as an intensity feature.

Structural approach [77] is useful for the analysis of artificial textures. Because, it works on the basis of set of primitive texture elements (micro-texture) which are having particular relationship between them. It also represents the hierarchical structure of the textures i.e. hierarchy of spatial arrangements of primitive texture elements (macro-texture) and provides a good symbolic description of the image.

In spectral approach, filter banks [83] or image pyramids [84] are used to convert the image from its spatial domain into the frequency domain and vice-versa. Using affine invariant features [85], texture segmentation is done where directional information of the texture is used. To get the directional information from a local spectrum Fourier transform, cos2 window is used. Extraction is done with three steps:

1. Apply Fourier transform on the texture block
2. Using Fourier slice analysis, get the contour signature
3. From contour signature extract the affine invariant features

This feature extraction technique is robust against noise but complexity is limitation for it. But with the help of random field, results can be improved. Fourier spectral transform can be used to extract the rotation invariant signatures of the orientation spectrum distribution. Bama and Raju [86] extracted Fourier-based texture features using peak distribution vector. Here, rotation invariant spectral signatures are obtained using spectral texture image representation under Fourier transform and utilized to get vector of peak distribution. This vector has texture properties invariant to the image and surface rotation. Peak Distribution Vector is used to measure the similarity using the sum of square distance between query and the images. Experimentation is carried over randomly chosen 1000 images from photometric texture dataset. As compared to other rotation invariant approach, this approach outperforms with 87.7% retrieval efficiency as well as it is computationally simple and robust. But, it takes more time for computations as compared to considered rotation invariant approach for comparison. Results are semantically unambiguous. As future work, scale invariance property also can be taken into consideration. Wavelet transform [87] is a mathematical function which can be used to represent the image mathematically by transforming signals from region to region the frequency or time scale. Haar, Daubechies, Symlet, Coiflet, Meyer, Mexican Hat, Moriet Wavelet are some of the types of wavelet transform. Wavelet transform is a powerful texture feature analysis. While doing reconstruction, information loss is less if this approach is used.

A LBP is a simple method of spectral approach. LBP is widely adopted as local texture descriptor [88] as it is computationally efficient and provides high performance [89]. Variants of LBP such as sorted consecutive LBP [90], discriminative robust LBP [91] utilized to solve various problems like texture classification, object recognition, respectively. Median robust extended LBP is also utilized for texture classification by Liu et al. [89]. Here, instead of raw image pixel intensities regional image medians are compared. This approach provides best overall performance on the basis of robustness (against noise), distinctiveness and computational cost [88] as compared to other variants of LBP. Fourier-Mellin moments are also utilized for extraction of texture features [92]

Table 3
Shape feature extraction techniques.

Authors	Shape extraction techniques	Invariant to	Robust against noise
Pedrosa (2013)	Salient point-based	Rotation, Translation	–
Laganière [100], Liu et al. (2008)	Edge detection-based	–	Yes
Zang et al. (2008), Ai et al. [103]	Fourier transform-based	Translation, Scaling, Rotation	–
Hong et al. [102]	Integral kernel-based	Translation, Rotation, Uniform Scaling, and Reflection	Yes

"–": Not available.

Only single color/texture feature may not be helpful to get the accurate results for many applications. Combining texture features with the color features will improve the competence. The color moment and local features can be combined to improve the performance of descriptors. Generalized color moment invariants (by analyzing shadow–shading quasi-invariants [94]) are used to construct the color invariant regions. In 2017, color histogram is merged with LBP-based features for texture image retrieval and classification by Liu et al. [95] Several texture image datasets such as Brodatz, Vistex, etc. are utilized for the experimentation where proposed hybrid feature extraction approach outperformed many existing approaches like average RGB, LBP, SIFT-Sale-Invariant Feature Transform [93], etc.

Shape is also a basic and important feature which can be used to describe the image contents. Here, some of the shape feature extraction techniques are discussed and summarized in Table 3 Shapes can be described with the help of salient points [97], which are also referred as saliences or corners. It represents a shape in compact manner and it is invariant to the rotation and translation. These points are having high curvature as shown in the Fig. 3.

Similarity measurement process is given as follows:

1. Detection of the salient points
2. Representation in the form of feature vector
3. Measure the similarity

As in the earlier technique salient points are used to describe the shapes, Liu et al. [99] have used the edges for extraction of shape feature. Those edges are detected using Smallest Univalue Segment Assimilating Nucleus (SUSAN) operator. SUSAN operator [100] is edge and corner detector which works on the basis of local area brightness. Further, moment invariants of the edge map are calculated which is used as a shape feature vector of the given image. This technique is a simple as well as robust against noise, and moment invariants are of a high stability gives very good description of the shape feature.

Zhang et al. [101] proposed Common Fourier descriptor method

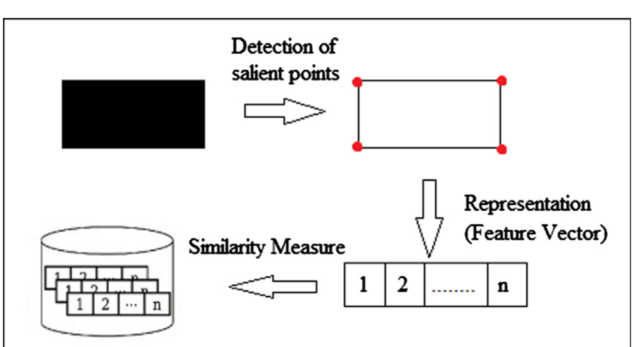

Fig. 3. Shape descriptor using salient points.

where Fourier descriptors with brightness are used for shape feature extraction. By using the Fourier transform for shape signature, Fourier coefficients and standardized pixel brightness are computed. Fourier descriptors are invariant to the geometric transformation i.e. translation, scaling and rotation. Shape feature vector is made up of Fourier descriptors. Change of the start point is used as Fourier descriptor. Centroid distance function is used to compute the shape signature from boundary pixels of the shape. Systems with this technique give better performance. This technique accomplishes a boundary pixels computation using edge detector, shape signature computation and Fourier descriptor computation.

Integral kernels [102] are also used for the shape description. Distinctiveness of the local shape geometry is given by the series of isotropic kernels which provides invariance properties. It is characterized at multiple scales and it forms a signature to provide a compact description of the shape features. This signature is invariant to the similarity group transformation which consist translation, rotation, uniform scaling, and reflection. Range of various kernel sizes is employed. This method is also a robust against noise. Distance between two shapes is calculated based on their shape signatures using Wasserstein distance. Group transformation invariance can be extended by considering a kernel with different characteristics. Affine invariant shape descriptor can be developed by modifying the characteristic kernel as anisotropic.

High level feature extraction methods such as bag of visual words, deep learning, etc. are discussed as follows. Bag of visual words model ([104–107,215] is a popular approach used for the categorization of the images. Extracted key points of the image are quantized into a visual word and image is represented by the histogram of local patches with visual words. Wu et al. [104] proposed a Semantics-Preserving Bag-of-Words (SPBoW) model and Contextual Bag-of-Words (CBoW) is proposed by Li et al. [105]. SPBoW maps semantically related features to a single visual word. CBoW represents the semantic conceptual relations as well as spatial neighboring relations. CBoW performs better as compared to the conventional bag-of-words approach. Usually, visual words are generated by using the clustering approaches. Statistical approaches like Quantization via Empirical Estimation (QEE) or Quantization via Kernel Estimation (QKE) also can be used for the same. Larger visual vocabularies give a high performance, but it makes a bag of visual words approach computationally expensive [107].

Nowadays, deep learning approaches [108,109] have gained a great popularity because it provide the better way of dealing with a huge amount of data. It uses the hierarchical representations for an unlabeled data. Convolutional Neural Network (CNN) (linear or non-linear) [110], deep belief network [111] and convolutional deep belief network [112] are some of the deep learning architectures, used for unsupervised feature learning. Apart from this in 2015, Zhang also proposed an unsupervised feature learning approach which works on the basis of saliency detection. Here, representative patches are collected from the salient regions of the images. Obtained results showed that extracted features are able to characterize complex scenes and provides better classification accuracy [113]. Use of the deep convolutional networks [114];) and effective deep learning [115,116] for image related tasks provides results with higher accuracy than popular approaches like SIFT with fisher vector, sparse coding, LBP, PCA, autoencoder based approach, etc. Zhao et al. [117] proposed balanced local discriminant embedding algorithm and also used CNN to extract deep spectral-spatial features from hyperspectral images. Here, balancing concepts helped to overcome the singularity issue and deals with the data diversity. CNN concepts used for spatial feature extraction overcomes the problem of parameter selection for spatial filtering. Along with it, merging of spectral and spatial discriminant features also helped to gain higher accuracies while classification. Chen et al. [118] also extracted spatial-spectral based deep features from hyperspectral images, where 3D CNN with regularization is utilized. It contains layers like convolutional and pooling. Indian Pines, Kennedy Space Center and University of Pavia are hyperspectral datasets used for the experimentation. For remote sensing image analysis, Romero et al. [119] extracted deep features by using unsupervised learning. Sparse representation based algorithm with greedy layer-wise unsupervised CNN pre-training is utilized for aerial scene, land use and land cover classification using hyperspectral images. This approach outperforms Principal Component Analysis (PCA) and kernel PCA. Liu et al. [120] extracted hidden features from driving behavior data using deep learning for driving behavior visualization. Here, deep sparse auto-encoder is utilized to get 3D hidden features which further mapped to RGB color space for visualization. On the basis of reviewed literature on deep learning, we can say that deep learning provides high accuracy for various learnings tasks, helps in automatic feature extraction, reduce heuristic work and easily adaptable for new domains. But, it needs huge amount of training data and computational power.

3. Clustering algorithms for image data from various domains

Image data can be efficiently analysed with the help of clustering approaches. Image clustering maps images or image segments into the clusters. It helps in the image understanding by using description of the image contents. In this section, clustering approaches applied on the image data from various domains such as medical imaging, 3D images, oceanography, industrial automation, remote sensing, mobile phones, related to security and traffic control are reviewed and future research directions are identified. As ultrasound imaging covers large part of medical imaging, it is also individually discussed and provided as a subsection of medical imaging.

3.1. Medical imaging

As medical imaging plays a significant role in healthcare, it is an important field of research where clustering helps in many ways e.g. disease identification, organ detection, etc. through image segmentation. It is also useful for handling the large medical image datasets. Here, image segmentation is done to get the image part having a particular full or partial organ for clinical diagnosis. Medical images are very complicated in a structure as well as it incorporates number of characteristics. Hence, clustering of the medical image is a challenging task. For medical image clustering, various approaches are used by the researchers. Some of those techniques are discussed below:

Image Clustering Algorithm (ICA) with Object Clustering Algorithm (OCA) is proposed by Haiwei et al. [121] for brain image segmentation. Initially, domain knowledge about the brain image (image shown in Fig. 4. (A)) is determined. This approach contains two parts: (1) Clustering of the Regions Of Interest (ROI) where ROIs or objects are detected by using progressive water immersion method (2) Clustering of the images on the basis of similarity found in the ROI. Here, image similarity is calculated by using the cosine similarity. Time complexity of the OCA is $O(nlogn)$ and ICA algorithm has $O(n^2)$ for the worst case, here n is number of objects. On the basis of precision, recall and e-measure, ICA is compared for different numbers of clusters where it is found that as number of clusters increases precision value decreases. Hence, this approach is useful for dataset having small number of clusters. As future work, complexity of the algorithm need to be reduced and apply modified version of this algorithm on the large and complex data sets.

A clustering technique developed using k-means and improved watershed algorithm is utilized by Ng and Han [122] for the medical image segmentation. K-means is used for the primary segmentation of the original image. Here, Euclidean distance is used for metric learning. It has $O(\tau kn)$ computational complexity which is relatively low and where τ is a number of iterations, k is a number of clusters and n is a number of objects. By using the Sobel operator, edge map is generated. Traditional watershed algorithm [123] is able to produce the complete division of image. But, it has limitations such as over-segmentation and sensitivity to the false edges. To avoid these drawbacks, improved watershed segmentation algorithm is used. It uses automated thresholding on the gradient magnitude map and post-segmentation merging on the initial partitions. This approach is able to avoid the over segmentation problem and provides a more representative results. As future work, hierarchical and fuzzy clustering can be incorporated with proposed method to deal with the hierarchical structure in an object and handle the uncertainty respectively.

Fuzzy clustering method [124] is applied on the image for its segmentation where fuzzy similarity relation is computed in the terms of Euclidean metric. This method is referred as fuzzy similarity relation-based image segmentation algorithm (FSRIS). By using the crisp similarity relation, fuzzy similarity relation is obtained. FSRIS has so many advantages as specified in the Table 4. As a future work, this method will be helpful for other areas like biology, geology, meteorology, chemistry, etc.

To avoid the problem of noise sensitivity of FCM, Possibilistic C-Means (PCM) was proposed by Krishnapuram and Keller [125]. But, results of this approach are highly dependent on initialization. Therefore, Ant Colony Optimization (ACO) based PCM is applied on the noisy medical image by Yu et al. [126] for segmentation. ACOPCM results appropriate number of clusters, automatically. It also achieves higher accuracy as compared to PCM and other hybrid fuzzy methods.

Improved Mountain Clustering (IMC) [127] is applied for the medical image (X-ray image) segmentation. Here, mountain function is used to get the potential value of each data point. To find the dissimilarity among points, Euclidean distance measure is used. It is further used for the diagnosis of diseases like lung cancer and tuberculosis. Quality of obtained clusters is measured using entropy. IMC has less time complexity as compared to k-means and FCM and cluster quality is equally competitive.

Further Improved Mountain Clustering version-2 (IMC-2) is introduced by Verma et al. [128]. To exclude the unwanted data points from the clusters, α (alpha) factor is multiplied with the threshold in order. Here, Global Silhouette Index is used as cluster quality measure. Clusters obtained using IMC-2 are having good quality as compared to other techniques such as IMC, k-means, FCM, EM. It shows noticeable improvement in results of IMC-2 as compared to IMC. It also has less computational complexity as compared to other algorithms.

Liver Magnetic Resonance (MR) images are segmented [129] by using Self-Organizing Map (SOM) [130,131] and hierarchical

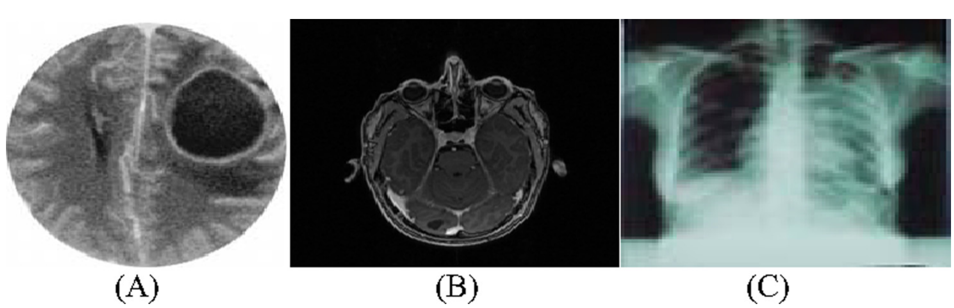

Fig. 4. Samples of medical images (A) Original abnormal brain images [121] (B) MR image of head [122] (C) X-ray image [127].

Table 4
Research summary on clustering algorithms for medical imaging.

Image clustering technique[a]		Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/ future work	Datasets	Analysis of number of clusters
Ng and Han [122]	K-means and improved watershed algorithm	K-means and improved watershed segmentation Algorithm, Sobel filter	K-means with traditional watershed segmentation algorithm	In terms of number of segments	For K-means: simple, low computational Complexity, For improved watershed: over-segmentation is avoided and sensitive to false edges	Crisp clusters, Need to verify results using specific parameters	MR images with different size	Need to provide as input May reduce due to merging
Srinivas et al. [134], Aharon et al. [135]	Dictionary learning based clustering	K-means Clustering algorithm	K-means, FCM	Precision, Recall	Deals with different cluster sizes, High precision and recall	Incorporate visual attributes in dictionary	IRMA test image database (X-ray images)	Need to provide as input
Chi et al. [129]	Hierarchical Agglomerative Clustering with SOM	SOM, Hierarchical agglomerative clustering	–	–	Distinguishes liver from other tissues in a complex liver MR image	Only small number of nodes can result in fast SOM computation, Incorporate features like texture to enhance the results	Liver magnetic resonance (MR) images	Decided by using Q segmentation index
Haiwei et al. [121]	ICA using OCA	Progressive water immersion method, Density-based clustering, Cosine similarity	Same algorithm with different number of clusters	Precision, Recall and E-measure	Deals with arbitrarily structured clusters	As number of clusters increases precision value decreases, High time complexity, Validate on large complex data sets	Real brain CT images	Need to provide as input
Li et al. [133]	Transform graph clustering	DBSCAN, Transform Graph Clustering	On the basis of similarity measure such as color, texture and BGC	Precision, Recall	Find clusters of arbitrary shape, Achieved good accuracy	Enhance the quality of results by combining technique with medical knowledge and need to decrease the computational complexity	CT image	Identified on the basis of density
Verma et al. [127]	IMC	Mountain function (Grid based), Euclidean distance,	K-means, FCM	Cluster entropy, Time complexity	Computational complexity is independent of the Dimension, No need to specify grid resolution	Need to verify results using other parameters	X-Ray image	Decided by the validity function i.e. ratio of compactness to separation
Verma et al. [128]	IMC version-2	Mountain function (Grid based), Euclidean distance	K-means, FCM, EM, IMC	Global Silhouette Index, Visual assessment	High Global Silhouette Index value, Good quality clusters, less computational complexity,	Algorithm can be optimized using multiple similarity matrices	MRI images, dental X-rays, chest X-rays	Decided by algorithm itself
Tabakov [124]	FSRIS	Fuzzy relation	Classical fuzzy C-means clustering	General	Simple, Fast, linear, polynomial complexity, Useful for large datasets and to take better surgery decisions	Need to extend for other areas of application such as biology, geology, meteorology, chemistry, etc. Need to verify results using specific parameters	Computed tomography (CT) image	No need to specify (identified by algorithm itself)

agglomerative clustering [132]. In SOM, map is a group of nodes represented by the prototypes. After the SOM training, prototypes become stable in the 2 dimensional space map. Then, prototypes are clustered using hierarchical agglomerative clustering with single linkage shortest Euclidean distance measure. According to the obtained results, it is found that proposed method is effective and promising as it distinguishes liver from other tissues in a complex liver MR image. But, this technique need to be validated by comparing it with the other popular clustering approaches.

Medical image data is a multidimensional data, therefore initially images are converted into a complete graph and then clustering is carried out by using a graph clustering approach [133]. Nodes and edges of the graph preserve the information related to characteristics and location of the region of interest (ROI). That information is utilized cluster the data by using the Transform Graph Clustering (TGC) algorithm with Euclidean distance. TGC algorithm is developed using density based concepts. Here, 'ε' threshold is used to judge that whether two graphs of the neighborhood belong to the same cluster and if it is found that the nodes in its ε-neighborhood are less than the Minimum Points then stop. Time complexity of this algorithm is $O(n^2)$ in worst case and the general is $O(nlogn)$, here n is number of objects.

Dictionary learning based clustering method [134] is proposed for the content based medical image retrieval. Dictionaries are used for the sparse representation of a cluster having similar images by using Euclidean distance, Mahalanobis distance and Cross correlation measures. K-SVD algorithm [135] is used for the dictionary learning. K-SVD is a generalization of k-means algorithm which is simple and flexible. It works in the conjunction with any pursuit algorithm. Intensity of the pixel is used for similarity computations. Rotation invariance and rich information are taken into consideration. Initial clusters are formed by using the k-means algorithm. Precision and recall values achieved by the proposed method are high as compared to the k-means and the FCM.

3.1.1. Ultrasound/ ultrasonic imaging

Ultrasound/Ultrasonic images are mainly used in the field of medical imaging (also useful in the area of oceanography). It has a speckle noise and intensity inhomogeneity which leads to low signal-to-noise ratio of images. Ultrasound imaging is a challenging task due to the low signal-to-noise ratio of images hence this area is covered separately in this paper.

In 1993, Wong et al. have applied simple k-means algorithm for the ultrasonic image segmentation using geometric distribution of feature vectors. Here, Euclidean distance is used as a distance measure. Boukerroui et al. [137] applied adaptive k-means clustering on the 3D ultrasonic data for the tissue characterization. This algorithm is improved by the energy function. In 1998, ultrasonic images of the ovary have been auto-segmented into the non-ovarian, normal ovarian and abnormal ovarian regions for the detection of ovarian cancer [138]. Here, five-dimensional feature space is formed by five feature energy measurements. Again in 2010, k-means is used for the clustering of fractal dimension in breast ultrasound image by Moldovanu et al. (2010).

FCM clustering with chained distance measure is implemented for the noise reduction, enhancement and reconstruction of the 3D ultrasonic images [140]. These images are contaminated with a noise; hence it is difficult to properly reconstruct the image. Due to this fuzziness (uncertainty) in the measured information, FCM clustering algorithm is helpful to get the good results. Luminal contour detection in the intravascular ultrasound images is carried out by using the fuzzy clustering and mathematical morphology [141]. Fuzzy clustering is applied using the median and the standard deviation of the pixels for the segmentation of image and then morphological filtering is done. FCM clustering is used by Shajahan and Sudha [142] for the segmentation of liver ultrasound image to detect the hepatic tumor. Time complexity of FCM is $O(ndc^2i)$ and the space complexity is $O(nd + nc)$ where n is a number of objects, c is a number of clusters, d is a number of dimensions and i is a number of iterations.

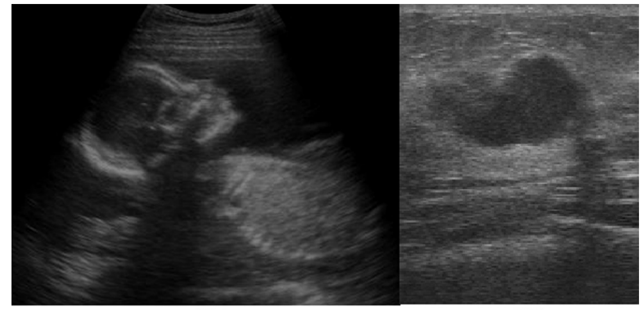
(A) (B)

Fig. 5. Samples of ultrasound/ultrasonic images (A) Original Fetal B-scan image [144] (B) Original breast tumor ultrasound image [147].

To define the liver pathologies, fuzzy competitive clustering based segmentation is carried out by Kissi et al. [143]. Here, ultrasound contrast agents are used to improve the ultrasonic information. Euclidean distance measure is used to compute the distance between points. For the FCM, a number of clusters is required to specify at the initial stage but fuzzy competitive clustering algorithm overcomes this problem. Whereas, Alternative FCM (AFCM) [144] is applied for the segmentation of Fetal B-scan ultrasound image as shown in Fig. 5(A). Here, initially local contrast enhancement and suppression of speckle noise in the ultrasound image is done. Then, AFCM algorithm is applied where new distance measure defined by Wu and Yang [145] is used Results of this method are satisfactory and more robust to outliers as compared to FCM. A two dimensional FCM (2DFCM) algorithm with the spatial constraints [146] is developed with the help of enhanced Speckle Reducing Anisotropic Diffusion (SRAD) filter. Objective function of the 2DFCM is improved using multiplicative model of the differential signal attenuation and log-compressed model of the displayed ultrasound images for the construction of homogenized 2DFCM (2DHFCM). Euclidean distance is used as distance measure. Results of this method are compared with the Gradient Vector Field (GVF) Snake method, where 2DHFCM achieves high accuracy and Pratt's Figure Of Merit (FOM) value due to incorporation of noise reducing methods (oriented to two kinds of artifacts) into the objective function. Spatial FCM clustering [147] is applied on the image intensity component for segmentation of breast tumor ultrasound image as shown in Fig. 5(B). Here, given image is decomposed into sum of two spatial features i.e. image intensity and texture. The sum-of-squared-deviations is taken into consideration for segmentation. This method is compared with different pre-processing based methods on the basis of partition coefficient, partition entropy and area error. Due to use of spatial features, proposed method provides more accurate results than other methods (mentioned in the Table 5).

Azar et al. [148] have used FCM, k-means, k-medoid, Gustafson-Kessel fuzzy [149] and Gath-Geva fuzzy [150] clustering for the speckle detection in cyst and fetus ultrasonic images. All the techniques are compared by feeding different combinations of the statistical features. On the basis of results obtained, it is found that Gustafson-Kessel fuzzy clustering performed well as compared to other methods followed by Gath-Geva fuzzy, Fuzzy c-means, k-means and k-medoid. Here, dice similarity is used as parameter for evaluation. In this study, only same sized rectangular image patches are used. As a future work, investigation should be done to check the sensitivity of the speckle detection scheme for an image patch with different sizes and shapes. Speckle detection performance can be improved by using cone shape patch.

For the detection of 2D motion field in ultrasonic images, algorithm is developed using expectation maximization strategy [151]. It is useful for the detection of organ's motion correlated with respiration. Spatial regions with the similar motions are localized as clusters in the image.

Table 5
Research summary on clustering algorithms for ultrasound/ ultrasonic images.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/future work	Datasets	Analysis of number of clusters
Wong et al. [136], Moldovanuand and Moraru [139]	K-means	–	K-means	–	–	Very simple	Outputs crisp clusters	Ultrasound images	Need to provide as input
Lee et al. [156]	Graph based clustering	Pixel-based	MST, nonlinear coherent diffusion model	FCM	Robustness	Simply structured, Robust to noises, Highly efficient and much flexible	As future work, can be applied for other applicative areas	Ultrasound image of breast	No need to provide as input
Yun and Shu [154]	Spectral clustering algorithm	Pixel-based	Curvelet transform, GLCM, Spectrum graph theory, KNN	–	–	Accurate and effective results	Various features required for automatic label pathological region	Pathological ultrasound images	No need to provide as input
Li et al. [157]	PAORGB	Pixel-based	MST, particle swarm optimization	K-means, Graph-based and FCM	Averaged radial error, volume fraction	Outperforms the conventional methods	Experiment should be carried out on large datasets	Ultrasound breast images	No need to provide as input
Gil et al. [140], Shajahanand et al. (2014)	FCM	Pixel-based	Fuzzy clustering, mathematical morphology	Gold standard Segmented images	–	Fuzziness is considered	Apply for detection of vessel contour	Intravascular ultrasound images	Need to provide as input
Kissi et al. [143]	Fuzzy competitive clustering	Pixel-based	Competitive agglomeration fuzzy clustering	–	–	No need to specify number of clusters in advance	Validate against more datasets, role of the expert is important	Ultrasound images	Need to provide as input
Liu et al. [144]	Alternative FCM	–	FCM	FCM	Robustness	Robust to outliers	Incorporated advanced concepts	Fetal B-scan image	Need to provide as input
Yu et al. [146]	2DHFCM	Pixel-based	FCM	GVF snake	FOM, segmentation accuracy	High accuracy and FOM as compares to other methods	This method can be applied for other applications	Synthetic and fetal aortic arch image	Estimated using 1D histogram of filtered image
Xu [147]	Spatial FCM	–	Spatial features, FCM	Watershed, Active Contour, Median, Wiener, Anisotropic	Partition coefficient, partition entropy, area error	Segments are more clear, Compared with many pre-processing methods	Advanced concepts need to be incorporated	Ultrasound image of breast	Need to provide as input
Chang-ming et al. [155]	Cluster ensemble approach	Pixel-based	K-means, spectral graph theory	Cluster based Similarity Partitioning Algorithm, Meta-Clustering	Accuracy	Better accuracy achieved than other methods, Less computational cost	Experts knowledge can be incorporated	Ultrasound image of cervical lymph node	Need to provide as input
Yang et al. [153]	EM-MPM	Pixel-based	Expectation maximization approach	K-means	Accuracy, Tanimoto Coefficient and Parenchyma Percentage	Finds a better localized segmentation	Need to be apply on clinical data	Ultrasound breast images	Identified by algorithm

"–": Not available.

For the representation of localization of same motion regions, discrete Markov Random Fields (MRF) are used which helps to get the proper clusters and makes it computationally stable. Initial values need to be assigned properly is the limitation for this approach.

To discover the Cirrhosis Grades (this disease can lead to death), k-means and expectation maximization (EM) [152] method is implemented on the ultrasound liver images where textural features are taken into consideration. It revealed the existence of four stages of the cirrhosis. Notwithstanding, more advanced approaches need to be applied for this application.

Expectation Maximization with Maximization of Posterior Marginals (EM-MPM) is implemented in [153] for the identification of tissue distribution in the breast by using 3D ultrasound image to check the risk of breast cancer. Results of EM-MPM are compared with the k-means on the basis of accuracy, tanimoto coefficient and parenchyma where it is found that EM-MPM provides high accuracy results as segmentation results fit very well with the ground truth data. Results are checked for the different tissue densities where accuracy is increased with the density. Hence, it is very much useful for the high tissue density proportions.

Spectral clustering algorithm [154] is applied to segment the pathological region from an ultrasound image. It works on the basis of curvelet and GLCM features where new weight expression is used for metric learning. According to the obtained results, it is found that this method provides accurate and effective segments for the pathological areas.

New ensemble approach with the spectral graph theory is proposed [155] for the segmentation of ultrasound images of cervical lymph node using Cosine similarity measure. Initially, k-means is applied to obtain the base clusters. Using those base clusters, similarity matrix is computed. Then, ensemble method is applied for the segmentation. Basically, ensemble approach has two steps, generation and integration. Generation step outputs multiple clustering solutions and integration step provides a single final cluster by merging the clustering solutions generated by generation step. Improved spectral clustering algorithm is used to combine the different partitions in the integration step.

For the automatic detection of breast tumors, lesions in the ultrasound images are segmented by using graph-based segmentation method [156]. This method works on the basis of minimum spanning trees generated from an image. First, nonlinear coherent diffusion model is applied to reduce the speckle noise. Then, the graph is constructed from the given image and merges the small regions based on the comparison of intra and inter component differences. Experimental results showed that tumors and extracts lesions are detected more accurately by using this approach as compared to FCM.

Parameter Automatically Optimized Robust Graph-Based image segmentation method (PAORGB) [157] is applied to segment the breast tumors from the ultrasonic images. Internal difference, difference between two components and minimum internal difference between two components are used as a distance measure. Here, to avoid the problem of under-segmentation or over-segmentation, particle swarm optimization algorithm is used while assigning the parameter values. It makes this method capable to detect the tumors more accurately and extract the lesions in ultrasound images as compared to FCM.

To detect the thyroid gland region, region of interest based clustering [158] is applied on the ultrasound image of thyroid gland. Here, principal component analysis is used for the preprocessing of a given image. It is useful to diagnose the tumor part. To avoid the background distortion and the region smoothing, morphological process is used. This method decreases the manual analysis error, time consumption, inaccurate results and requirement of intensive trained people to avoid diagnostic errors.

3.2. 3D Imaging

Recently, researchers have turned their focus towards the clustering of three dimensional images. Earlier very few researchers had contributed in this area. Handling of 3D images is required in various areas such as animation, medical and industrial applications. Patel and Greig [159] have done segmentation of 3D acoustic images for the object recognition where thresholding, fuzzy clustering, MRFs and connected components approach are used. Advanced approaches need to be applied on the images from this area.

Yuan et al. [160] have applied fuzzy clustering for the face recognition using 3D facial images. 2D texture data and 3D shape data is extracted for the similarity computations. In FCM, each object is clustered by using the cluster membership value where cluster center is selected such as cost function of a dissimilarity measure should be minimized. Here, fuzzy partitioning is carried out where single object can belongs to multiple clusters. Therefore, one facial pattern belongs to several small-scale networks. Then for the face recognition, parallel neural networks are used. This algorithm is a simple, flexible as well as converges fast. But results of this algorithm are dependent on the initial cluster centers, and number of clusters exists in the given dataset need to be specified [161].

Content-based retrieval of 3D objects is done where again FCM clustering method [162] is applied to cluster the spin image signatures for compact representation of it. Approximate computational complexity of the clustering in this scenario is $O(\Sigma_c\ (ns + np + nn)Tcn_v)$ where c is a number of clusters, nv is a number of mesh vertices, ns, np, nn are the number of spin image sectors and crowns (positive as well as negative) and T is a number of iterations. Due to use of concepts in original spin image approach, efficient retrieval is achieved by using the signature clustering. But, here overall computational cost is too high. As a future work, relationships between spin images, spin image signatures and object parts need to be identified and indexing techniques also can be incorporated.

Self-organizing fuzzy k-means algorithm (Nguyen et al., 2010) is introduced for the identification of 3D line from clouds of point provided by the Stereo camera and 2D images, which automatically determines the optimal number of clusters. It organizes the clusters on the basis of intra-inter cluster distances and results of cluster's performance. After clustering, Eigen-analysis on those clusters is carried out for the estimation of final 3D lines which can be cut into several segments. 3D line extraction using proposed method is compared with 3D line extraction algorithm with RANdom SAmple Consensus (RANSAC) [164] on the basis of time and space complexity where it is found that proposed method is having 10% to 20% less time complexity i.e. $O(N^*k^*j)$ and space complexity is same for the both i.e. $O(d^*N)$ where N is a number of 3D points in point clouds, k is a number of groups, j is a number of iterations and d is a number of dimensions.

Yang and Choe [165] proposed a new clustering approach based on the watershed, interactive segmentation technique and 3D volume extraction. By using graph cuts from the dense nano-scale medical images, 3D volumes are extracted. Those images don't have clear object boundaries. Initially, by using the marker-controlled watershed algorithm, images are segmented where the markers are seed points. Graph is generated using the output of this algorithm where identified regions are represented by the nodes and the edges represent a connection between the adjacent image slices. On the basis of overlapped area, weight of the edge is decided. Optimized global 3D volume can be found by using the graph cuts. Proposed method can extract a single 3D volume but for the extraction of multiple 3D volumes need to be work in future. Watershed algorithm has some limitations such as over-segmentation and sensitivity to the false edges.

For the extraction of Objects Of Interest (OOI) from 3D ultrasound images as shown in Fig. 6, graph-based segmentation method is used [166]. It generates a set of minimum spanning trees; each corresponds to a 3D sub-region. Construction and mergence are two steps of the proposed method where construction is used to generate a graph using image. Then, mergence is to merge the vertices in a graph on the basis of Pair wise Region Comparison Predicate (PRCP) [167]. PRCP decides

Fig. 6. Sample of 3D ultrasound image (Zheng et al. 2012).

whether to delete the boundary connecting two components or not, based on the comparison of intra and inter differences using absolute differences between intensities. This algorithm is robust against noise and has less computational complexity as compared to 3D Snake and FCM clustering algorithms [168].

Affinity aggregation spectral clustering [169] is implemented for the co-segmentation of 3D shapes using Earth-mover's distance measure. Initially, it over-segments the 3D shapes and computes the multiple feature descriptors for each segment. Then, apply affinity aggregation spectral clustering (AASC) on those segments which will results co-segments of the given set of shapes. Spectral clustering splits data into disjoint clusters by using spectral-graph structure of an affinity matrix. AASC is an extended spectral clustering with multiple affinities [170]. AASC tries to find the optimal combination of affinity matrices which will lead to make it more immune to the ineffective affinities and irrelevant features. As size of the dataset becomes large, this method generates better results. Local similarity based affinity aggregation is effective to maintain the consistency of co-segmentation outcomes, but number of clusters need to be specified manually. If descriptor is unable to characterize the shape properly, then the proposed method will not work properly. To overcome this problem, inherent information is required to explore which will be helpful to analyse the shapes. Time complexity of AASC is $O(n^3m)$, where n is number of points and m is number of iterations.

To detect the regions with systematic segmentation quality characteristics, agglomerative hierarchical clustering algorithm is extended with a connectivity criterion [171] which results connected clusters with characteristic quality across several instances. Quality values across the dataset are merged to get the results. This method has provision to analyse and visualize the similarity of segments as per their local quality and also extracts the segments with common quality across the dataset. It is also useful to find the outliers. Initially, consider each mesh point as a cluster from average mesh. Average mesh is formed by points, by using their positions which is computed by averaging all positions of the corresponding points of all the automatically segmented instances. Compute initial distances, neighborhoods and leaves of the cluster hierarchy. Then, iteratively merge two neighboring clusters with a smallest distance between them, according to the segmentation quality until all clusters are merged. Average linkage Euclidean distance is used while clustering.

New approach by Dave et al. [172] is given for the recognition of facial expressions from the 3D sonography baby images where distance based clustering is used to extract the face part. Before applying the clustering algorithm, sampling needs to be done by applying scan-line algorithm to get the sample lines. Here, biggest cluster will represent the face part of the image. This algorithm is very simple but it is important to do the sampling before implementing it.

To assess the left ventricular (LV) function of the heart, automated 3D echocardiographic acquisition and image-processing method is proposed [173]. Here, to segment the given images accurately, global image information and local boundaries are combined. Multi-scale fuzzy-clustering is applied to segment the LV cavity. Then apply 3-D continuous transformation on segmentation results to fit and track the LV endocardial surface which tracks candidate boundaries obtained from the feature asymmetry-based segmentation method followed by the geometric filtering. Use of a good quality dataset helps to provide similar tracking results for the manual and automated segmentation.

Representative clustering (R-clustering) algorithm [174] is introduced for the initial analysis of 3D dynamic brain PET images to study β-amyloid deposition in brains of Alzheimer patients. Here, time-dependent activity for an each voxel is considered as clustered and as independent time series. Basic idea of this approach is conceptually similar to that of independent component analysis. This algorithm is used to determine the blood input function, the tissue-specific time-activity curves and spatial distribution of the tissues with different tracer dynamics from noisy reconstructed sequence of the 3D PET images. Collection of representative time series of each cluster is used to initialize this algorithm. Asymmetric distance measure is used to compute the distance between points. The main difference between this method and methods like k-means is that it do not partition the whole space of given points into the clusters. But, it selects only a small portion of the space. Results obtained from the proposed method are new but un-optimized so this method is required to improve further.

As future work, regularization can be incorporated to R-clustering and subsequent analysis which considers spatial correlations between voxels to enforce the spatial continuity. This method can be efficient for the analysis of dynamic image data in other dynamic modalities of the biomedical imaging which uses contrast agents. Reviewed literature in this field is summarized in Table 6.

3.3. Oceanography

Underwater images are used in the area of oceanography to do the tasks like collection of rock, water, lava samples and try to discover the facts about it. These images are directly affected by the water, atmosphere, pressure and temperature, hence those images are of poor quality. Information in the image is fuzzy in nature because of scattering and absorption of suspended matter in water and the water itself. To handle the various tasks on these images, following clustering techniques are used which are also summarized in Table 7.

Ye et al. [175] have applied k-means approach for the segmentation of underwater images where to update a centroid Winner-Take-All (WTA) method is used. Discrete entropy and relative entropy are the parameters which used to check the quality of the segmented image.

For the detection of edges from underwater images as shown in Fig. 7(A), a variant of k-means method [176] is used. Initially, dark channel prior approach is applied to obtain the clear original image. Gradient of obtained image is computed and the endpoints are detected from the original edge image. Then the variant of the k-means algorithm is applied to classify those endpoints. Here, means of each frame are computed on the basis of frame size and put those values in the mean array. Further, that array is arranged in the ascending order and then it is used for the comparison. Improved k-means algorithm is able to estimate the number of clusters and decreases the number of iterations as compared to traditional k-means algorithm. Therefore, the speed of execution gets increased. This method is able to detect the edge intact and without redundant edges as compared to other edge detection algorithms.

FCM clustering approach [177] is used for the segmentation of underwater images and compared with the other segmentation approaches. Its resulting clusters provide lower value of mutual information, normalized mutual information and redundancy. Hence, it is most suitable for the underwater image segmentation. On the basis of obtained comparative results; it is found that FCM clustering performed well than other image segmentation methods as this method can keep more information of the original image. It has computational complexity of $O(nc^2d)$, here n is a number of objects, c is a number of

Table 6
Research summary on clustering algorithms for 3D images.

Image clustering technique		Image handling approach	Concepts used	Compared with Methodology	Comparative parameters	Pros	Cons/future work	Datasets	Analysis of number of clusters
Yang et al. (2009)	New method using Watershed and Graph cuts	Region-based	Watershed, Interactive segmentation technique, Graph cuts	–	–	Useful in 3D reconstruction	Extract multiple 3D volume structures using two-pass graph cuts	Dense nano-scale medical images	Need to provide as input (using seed points as marker)
Zheng and Huang [166], Chang et al. [168]	3D Graph-based Method	Region based	Graph theory, minimum spanning trees	3D Snake and FCM	Execution time and similarity rate	Robust to noises, Less computational time, improved performance	Use suitable filters for pre-processing and genetic algorithm to overcome under-segmentation and over-segmentation.	3D Ultrasound Images	Automatically identified by algorithm
Wu et al. [169], Huang et al. [170]	Affinity aggregation spectral clustering	–	Spectral clustering	State-of-the-art techniques	Accuracy	Fusion of multiple descriptors, Useful for large datasets	Manual determination of number of clusters	Shape co-segmentation datasets (COSEG)	Need to provide as input
Landesberger et al. [171]	Hierarchical clustering algorithm with a connectivity criterion	–	Agglomerative clustering	–	–	Similarity of segments as per local and global quality can be analysed, Useful to find outliers	Need to extend the scalability and compare with other clustering algorithms	Liver, Cochlea and Facial nerve real dataset	Final clusters are generated through merging
Patel and Greig [159], Yuan et al. [160]	FCM	Pixel-based	Texture and shape features, fuzzy clustering	–	–	One pattern can belongs to several clusters	Output dependents on the initial cluster centres,	3D facial images	Need to provide as input
Assfalg et al. [162]	FCM	Pixel-based	PCA, Spin images signatures, Fuzzy clustering	Based on features such as shape, geometric moments, etc.	Precision, Recall	Superior performance as compared to other methods considered for comparison	High overall computational cost, incorporate the indexing techniques	Core-art database	Need to provide as input
Nguyenand and Sukhan [163]	Self-organizing fuzzy k-means	Pixel-based	SOM, Fuzzy clustering, K-means	3D Line extraction using RANSAC	Time and space complexity	Automatically determines optimal number of cluster	Accuracy and performance optimization and integrate line matching and 3D reconstruction for complete 3D line identification	Stereo camera images	Automatically determines number of cluster
Dave et al. [172]	Distance based clustering	–	Basic distance based clustering approach	–	–	Very simple	Data need to be sampled, compare with other clustering algorithms	3D Sonography Images	Automatically generates clusters
Mitra et al. [174]	R-clustering	–	Time-series clustering technique	–	–	Good initial guess for the subsequent factor analysis.	Validate the approach, apply in other time-series analysis problems	3D PET image	Need to provide as input

"–": Not available.

Table 7
Research summary on clustering algorithms for oceanography.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/ future work	Datasets	Analysis of number of clusters
He et al. [176]	Modified k-means	Pixel-based	K-means, dark channel prior approach	Traditional edge detection algorithms	Redundancy	Detect the edge intact and without redundant edges, Faster than traditional k-means approach	Advanced clustering approaches need to be applied	Underwater images	Estimated using algorithm
Padmavathi et al. [177]	FCM	Pixel-based	FCM	Edge based, watershed, Region growing, Quad-tree segmentation, Adaptive thresholding	Gray level energy, discrete, relative entropy, NMI and redundancy	Simple, Results with low redundancy	Features like spatial information need to be taken into account	Underwater images	Need to provide as input
Shi-long et al. [178]	Modified fast FCM	Pixel-based	FCM, spatial neighbour information, relative information loss	FCM	Execution Time	Improved quality of real-time operation	Need to experiment on colored underwater images	Underwater images having objects	Need to provide as input
Shi-long et al. [179]	Adaptive FCM	Pixel-based	FCM, Spatial information	FCM	Partition coefficient, partition entropy	Able to suppress the noise	Apply for other images having noise like ultrasound images	Marine images	Need to provide as input
Friedman et al. [180]	VDP	–	Bayesian nonparametric model	EM with GMM	Accuracy	No need to specify number of clusters, High accuracy achieved	Complexity increases as size of the dataset increases	Underwater stereo images	Automatically identified by algorithm

"–": Not available.

clusters, d is a number of dimensions.

To deal with noise in the underwater images, features like spatial information need to be incorporated with FCM clustering. Thus new FCM algorithm is developed by Shi-long et al. [178] which works based on the spatial neighbor information. Here, Euclidean distance is used for metric learning. This method outputs high quality segments of the image, but time complexity is also high. But, autonomous underwater vehicle needs such clustering algorithm which produces high quality segments within less amount of time hence this algorithm is modified with relative information loss of re-sampled image to the original image. This algorithm is referred as modified fast FCM algorithm. Time required by the modified algorithm is less as compared to earlier one.

Adaptive FCM segmentation algorithm with spatial information [179] is applied on the underwater color images as shown in Fig. 7(B). This approach works on the basis of characteristic distance and I1I2I3 color space. Characteristic distance is computed with the help of weighted sum of distance between two pixels and spatial neighborhood distance and adaptive weight. On the basis of experimental outcomes, it is found that this algorithm can suppress the noise and find the high quality clusters.

Variational Dirichlet Process (VDP) model for clustering [180] is implemented on underwater stereo images as shown in Fig. 7(C) for pool-based active learning. VDP is Bayesian nonparametric model which is used for uncertainty sampling. This method can determine the number of clusters automatically. VDP achieves higher accuracy as compared to the expectation–maximization approach due to incorporation of active learning and ability to determine the structure of unlabelled data. Accuracy is deterministic for the given dataset and only changes for the random sample method. It has computational complexity of $O((n + d^3)(\log n)^2)$, Here n is a number of objects and d is a number of dimensions. VDP can be incorporate along with other methods as a future work.

3.4. Industrial automation

Industrial automation is necessary to obtain the high accuracy and quality of outcomes. It also helps in proper monitoring and analysis of industrial processes. Clustering is useful for managing the images and segmentation of it which can be further utilized for accomplishing the tasks such as finding defective parts, object detection, etc.

Pun and Ali [181] implemented k-means and expectation maximization clustering methods on images as shown in Fig. 8 to cluster the mineral materials such as electro-fused magnesia oxide for the industry automation. Density based clustering is compared with these algorithms on the basis of mean and standard deviation between clusters. Here, on the basis of obtained results it is found that k-means is more suitable for this task. But, advanced techniques need to be tested for this task.

OPTICS clustering algorithm [182] is applied on the voxelized 3-D CAD data from German car manufacturer and American plane producer to analyze and compare the similarity models. It helps in finding and grouping the similar parts. Here, feature-based object function and extended feature-based object function are used for metric learning. This algorithm is relatively insensitive to input parameters and able to give more information about the cluster structure. It has computational complexity of $O(n\log n)$, here n is number of objects.

Silhouette point fuzzy clustering approach [183] is used to recognize the garment style by analysing the photo which provides valuable information for the guidance of manufacturing and designing task. To extract the pattern silhouette, garment images are scanned line by line for analysis and eight-points connecting method is applied. Then silhouette is classified into certain garment style. The garment silhouette is represented by ring and line-line data structure. By using fuzzy clustering method, garment silhouette is partitioned into the dress pieces.

Image clustering method [184] is applied for the object monitoring

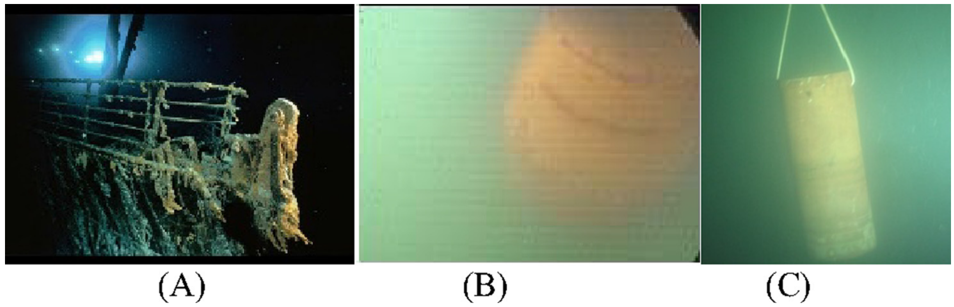

Fig. 7. Samples of underwater image (A) [176] (B) [178] (C) [180].

Fig. 8. Sample images used in mineral industry [181].

using interactive computer systems. Markov transitions model is used for the quasi-stationary objects. Then normalized cross-correlation coefficients are estimated and on the basis of CAD, matrices of the cluster transitions probability, global dispersion and entropy correlative measures are computed for the quasi-stationary objects states. Reviewed literature in this field is summarized in Table 8.

3.5. Remote sensing

Remote sensing image clustering is useful to identify the targets automatically and extract useful information without manual intervention. Remote sensing images have wide applicative area such as geographical information system, agriculture, forestry, oceanography and so on. Here, we are going to discuss the clustering techniques applied on the remote sensing images and also summarize it in Table 9.

Gaussian mixture model clustering [185] is experimented on the multispectral remote sensing images by using MRF. Clustering is carried out based on the spectral as well as the spatial feature information. Pseudo-likelihood information is computed on the basis of MRF which is used to find the clusters automatically. Based on the experiment carried out, it is found that use of spatial information leads to formation of highly compact clusters. This method can also handle the large datasets. Bayesian information criterion and pseudo-likelihood information criterion is used for the comparison. Proposed method provides better outcomes as compared to hierarchical and classical mixture model.

Tang et al. [186] used MRF-based clustering method for the semantic clustering of remote sensing images. This method is referred as Modified Latent Dirichlet allocation (MLDA) with MRF. Clustering is carried out on the basis of two leveled spatial context information in two different ways. MLDA is used to model the collection of images where semantic information and spatial information is combined. By using folded Gibbs Sampler, model parameters are estimated and finally with the help of graph cut energy minimization technique image clusters are obtained in the MRF framework. Proposed method compared with “k-means with MRF” where qualitative as well as quantitative analysis is done. Overall entropy is computed to measure the performance of algorithms, where proposed method has less entropy and able to provide the well separated clusters. MLDA with MRF achieved better accuracy as compared to k-means with MRF.

Ant colony clustering [187] is implemented to cluster the remote sensing image which works on the concept used by the ants in their real-life environment to find the food source. Here, image data is referred as ants with various attributes, cluster centers as food source and number of clusters as number of food sources. Weighted Euclidean distance is used here as a measure of distance. This method is able to find the optimal solution with minimum iterations as well as showed the advantages like self-organization, cooperation and communication.

Dot density function Weighted FCM (WFCM) clustering [188] is applied to segment the remote sensing image where spectral and spatial features are considered. Distance is measured using Euclidean norm. This approach is compared with k-means algorithm based on scaling percentage, mean and standard deviation where WFCM performed well.

For segmentation of remote sensing image as shown in Fig. 9(B), Single point iterative Weighted FCM (SWFCM) clustering method [189] is used. Euclidean distance is used for metric learning. This approach is robust against noise hence it doesn’t affect the quality of results negatively. To improve the convergence speed, appropriate initial centers of the clusters are selected by the proposed method which leads to reduction of computation time. For comparative study, traditional FCM and its variants are considered and it is carried out on the basis of parameters such as kappa coefficient, accuracy, number of iterations and time cost. Experimental results showed that SWFCM provides high accuracy and convergence speed with a little prior knowledge. In the future, better weights of data attributes need to be found and try to set initial cluster centers without prior information.

For the detection and localization of marine spills, system is developed by Fustes et al. [190] with the help of remote sensing, geographic information system and cloud computing. Variants of fuzzy clustering techniques are used to isolate the dark areas in the SAR images by using segmentation process. K-means, FCM, Spatially constrained Kernelized FCM (SKFCM), FCM wavelets, wavelets SOM, local threshold and SKFCM with local threshold are the techniques used for the segmentation. On the basis of true positive and true negative outcomes, these techniques are compared where it is found that SKFCM with local threshold method provides best results. Because, local threshold approach works well for the smaller spots and combination with SKFCM are useful for the larger spots.

Automatic Histogram-based FCM (AHFCM) algorithm [191] is applied for the clustering of remote sensing images. This algorithm has two steps. First, compute the slope of each point of the histogram in two directions and cluster the each band of a multispectral image by using FCM algorithm. Second, initialize and determine the number of clusters by using automatic fusion of labeled images. Here, Euclidean distance is used as a distance measure. This approach is compared with FCM, k-means, Fast Global FCM (FGFCM) and Kernelized Fast Global FCM (KFGFCM) clustering algorithms by computing Davies-Bouldin (DB) index, Xie-Beni (XB) index and partition index. AHFCM algorithm has best values of all the indices for most of the images considered for the experiment. Computational time is required more for AHFCM as size of

Table 8
Research summary on clustering algorithms for industrial automation.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/future work	Datasets	Analysis of number of clusters
Pun and Ali [181]	K-means	–	K-means	Expectation maximization clustering, density-based clustering	Mean, standard deviation	Simple, best for the magnesia Clustering, helpful to convert manual sorting task into automated sorting process	Required to experiment on large sized datasets	Digital images of mineral materials	Need to provide as input
Kriegel et al. [182]	OPTICS	–	Density based clustering	–	–	Helps in reduction of cost for developing and producing new parts	Optimization is needed	3D CAD data	Automatically identified by algorithm
Wang et al. (2008)	Silhouette point fuzzy clustering	Pixel-based	FCM, Silhouette point extraction	–	–	Useful for textile industries	Need to apply advanced techniques	Garment images	Need to provide as input

"–": Not available.

image increases. Optimization of this method is need to be done and it can be applied for the tasks like feature extraction or object detection as future work.

Generalized FCM method with Spatial information (GFCM_S) [192] is implemented for the clustering of hyper-spectral remote sensing images. Only 'k' number of nearest cluster centers are taken into account by this method out of 'K' number of clusters during clustering process. Mean of spectral distance is used for metric learning. This method is compared with FCM, FCM with spatial information, GFCM by using parameters like overall accuracy, partition index and separation index where GFCM_S achieved best results. GFCM_S has lowest value for the partition index and highest value for the separation index.

Parallel ISODATA clustering [193] is implemented for the clustering of remote sensing images based on MapReduce. Here, CIE $L^*a^*b^*$ (CIELAB) color space is used to improve the accuracy of color values. This method has good scalability as well as it reduces the computational time as number of nodes increases. It effectively processes the remote sensing images. Hardware devices with high performance showed superiority of MapReduce. Hadoop does not support the image format therefore images need to be transform into text files. Comparative study for this approach is need to be done.

Context-sensitive hybrid method based on FCM and Gustafson–Kessel Clustering (GKC) [194] is introduced for the change detection in multispectral and multi-temporal remote sensing images. Mahalanobis distance is used for metric learning. Performance of this algorithm is optimized by using Genetic Algorithm (GA) and Simulated Annealing (SA). On the basis of fuzzy cluster validity index (Xie–Beni), performance evaluation is done and compared with existing MRF and neural network based algorithms. It is found that, proposed approach required less amount of processing time and no need to have a prior knowledge about distributions of pixels.

By using watershed algorithm [123] and Gustafson-Kessel fuzzy clustering, new image clustering algorithm is proposed in [195]. For the image segmentation, watershed algorithm is used and Gustafson-Kessel fuzzy clustering is performed to cluster the image segments. Adaptive distance norm is used as a distance measure. For the performance evaluation, following parameters are used:

1. Partition coefficient: High value of a partition coefficient indicates best clustering results.
2. Partition entropy: Low value of a partition entropy represents best clustering results.

Proposed algorithm is experimented on the remote sensing images as shown in Fig. 9(C) which have high noise level. But, it is robust against noise and preserves important information. Therefore, better image edges are appeared in the results and overall output is also good.

Yi et al. [196] have devised object-oriented semantic clustering method for the high-spatial-resolution remote sensing images. It uses neighborhood spatial information for Probabilistic Latent Semantic Analysis (PLSA). Object-oriented semantic clustering method is experimented on the QUICKBIRD image as shown in Fig. 9(A). It compared with k-means clustering and ISODATA on the basis of qualitative and quantitative analysis where parameters such as number of patches, perimeter-area fractal dimension, edge density and overall entropy are taken into account. Comparative study showed that the proposed method provides more compact clusters than other methods and achieves lower value for the overall entropy.

On the basis of mean shift algorithm [33], new re-clustering technique is proposed [197]. Using this technique, arbitrary shaped clusters can be found and there is no need to specify the number of clusters initially. This technique is worked on the basis of local spatial information [198] and spectral similarity [199]. In re-clustering technique, initially divide the original image into homogenous image segments and then cluster image segments. Remote Sensing Images (RSI) are used for the experimentation.

Table 9
Research summary on clustering algorithms for remote sensing.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons /future work	Datasets	Analysis of number of clusters
Li et al. [193]	Parallel ISODATA	Pixel-based	ISODATA, Map-Reduce	–	–	Provide good scalability, reduce computational time	Very complicated, not support image format so transformation required, validation required	RSI	Clusters are refined through splitting or merging
Yi et al. [196]	Object-oriented semantic clustering	Pixel-based	Aspect model and spatial correlation among neighbour pixels	K-means and ISODATA	No. of patches, area fractal dimension, edge density overall entropy	Compact clusters, overall entropy is lower	–	Panchromatic QUICKBIRD image	Obtained through minimum description length criterion
Rongjie et al. [200]	Agglomerative clustering	Object-Oriented	Agglomerative clustering	K-means and artificial extraction	Number of broken spots	Reduces number of broken spots	Need to increase execution efficiency	High-resolution RSI	Generated through merging
Kurtz et al. [201]	Divisive method	Pixel-based	Binary partition trees, Divisive clustering	Based on datasets with different resolution images.	Precision, recall, F-measure, kappa index, weighted harmonic mean of F-measure	Able to restrict areas of homogeneous classes of radiometric intensity	Knowledge of geographer expert can be incorporated for better results,	Spatial resolution optical images	Provided by using mapping with regions
Gómez-Chova et al. [202]	Kernel entropy component analysis based spectral clustering	Pixel-based	Kernel entropy component analysis, spectral clustering	K-means, KPCA plus k-means, and kernel k-means	Kappa index	Able to preserve entropy of input data with less number of features	Need to apply for other application on RSI such as agriculture, homeland security, and urban monitoring, high computational cost	MERIS images	Need to provide as input
Wang et al. [204]	Spectral active clustering method	Pixel-based	Spectral clustering	Spectral clustering and semi-supervised spectral clustering	Accuracy	Accuracy is high, outperforms other methods	Prior knowledge is important to get good results	High-resolution remote sensing image	Need to provide as input
Tasdemir et al. [205]	Approximate spectral clustering ensemble	Pixel-based	Spectral clustering	Based on different datasets	Accuracy, ARI, and NMI	Deals with various characteristics clusters, used for large datasets	Ensemble is limited on only one kind of representative selection	Statlog, Boston, Bengisu, KARD and VARN Dataset	Need to provide as input
Tang et al. [186]	MLDA-MRF	Pixel-based	MRF, Modified Latent Dirichlet Allocation model, graph theory	K-means with MRF	Overall entropy	Better accuracy, well separated clusters	Spatial information need to be incorporated, priori knowledge about distributions of changed and unchanged pixels required	Panchromatic QUICKBIRD image	Obtained through minimum description length criterion
Masi et al. [208]	Correlation clustering	Super-pixel-based	Graph cutting approach, ILP	Greedy, with and without markers based	Energy and time	Improved quality of segmentation, preserves more details	unfeasible as number of nodes increases	Large IKONOS multispectral image	–
Liu et al. [185]	Gaussian mixture model clustering	Pixel-based	GMM, MRF, spectral and spatial features	Hierarchical and classical mixture model	Bayesian information criterion and pseudo-likelihood information criterion	Classified areas provides continued boundaries	Need to experiment on images other than multispectral images	Multispectral image	Automatically identified by using pseudo-likelihood information criterion
Zhang Yu et al. [187]	Ant colony clustering	–	Ant colony optimization algorithm	–	–	Optimal solution with minimum iterations, no need to set the initial cluster centre	Too many parameters, Determination of appropriate initialization parameters	RSI of area in changbai mountains	Identified using ants through intelligent searching

(continued on next page)

Table 9 (*continued*)

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons /future work	Datasets	Analysis of number of clusters
Liu et al. [188]	WFCM	Pixel-based	FCM, spectral and spatial features	K-means	Scaling percentage, mean and standard deviation	Standard deviation is less, accuracy is improved	Need to consider other comparative parameters	LANDSAT TM data of Canon city, USA	Need to provide as input
Fan et al. [189]	SWFCM	Pixel-based	FCM	FCM and its variants	Kappa coefficient, accuracy, no. of iterations and time complexity	High accuracy and high convergence speed	Prior knowledge to set initial cluster centres, optimization of weights for data attributes is needed	UCI datasets, public Berkeley segmentation dataset	Better clusters are achieved through iterative updates
Ghosh et al. [194]	Context sensitive hybrid approach	Pixel-based	Fuzzy c-means, Gustafson–Kessel clustering, genetic algorithm, simulated annealing	Existing Markov random field (MRF) and neural network based algorithms	Fuzzy cluster validity index, overall error	Less time consuming, No need to have prior knowledge of pixel distribution	Proper selection of values of fuzzifiers is required	Multispectral and Multi-temporal remote sensing images	–
Hamed et al. [195]	Combination of watershed and G-K fuzzy clustering	Pixel-based	Watershed algorithm and G-K fuzzy clustering	Gustafson-Kessel fuzzy clustering	Partition coefficient, Partition entropy	Robust against noise, better image edges are appeared	Many parameters are involved	Remote sensing images	Decide based on experiments (cross validation method)
Ghaffarian and Ghaffarian [191]	AHFCM	Pixel-based	Histogram, FCM	FCM, K-means, FGFCM and KFGFCM	Davies-bouldin (DB) index, Xie-beni (XB) index and partition index	Best values of all the indices are achieved	Computational time increases as size of image increases, optimization is required, apply on large datasets	Two aerial, two satellite images and hyper-spectral image.	Determined by automatic fusion of labelled images
Aydav et al. [192]	GFCM_S	Pixel-based	FCM, special information	FCM, FCM with spatial information, GFCM	Overall accuracy, partition index and separation index	Low value for partition index and high value for separation index	Prior knowledge about number of clusters is required	Hyper-spectral RSI	Need to provide as input
Li et al. [206]	Multi-objective fuzzy clustering	Pixel-based	FCM	FCM, FCM_S1, MRFFCM	Percentage of correct classification and kappa	Provides effective and stable results	Computational optimization need to be done, Color components can be incorporated	Real SAR images	Need to provide as input
Nascimento et al. [207]	Seed expanding clustering	Pixel-based	Approximate clustering, Otsu's thresholding	Supervised version	Precision, recall and F-measure	Automatically considers similarity threshold	Investigate explosion-controlled strategy of cluster growing	Sea surface temperature images	Algorithm finds clusters

"–": Not available.

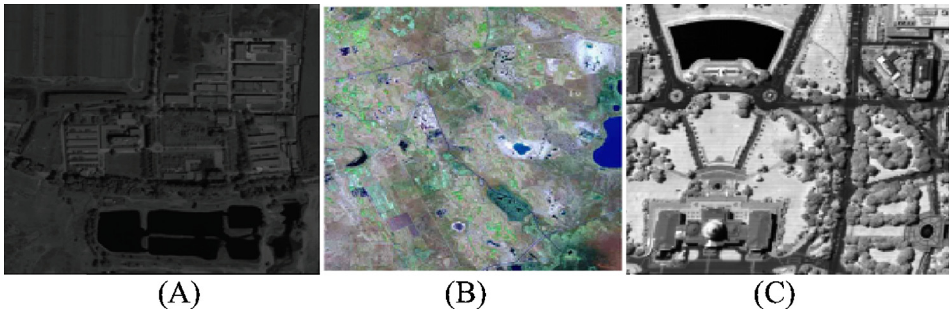

Fig. 9. Samples of remote sensing images (A) QUICKBIRD image [186] (B) Zhalong wetland original remote sensing image [189] (C) Hyper-spectral remote sensing image [195].

Agglomerative hierarchical clustering [200] is applied for the segmentation of high-resolution remote sensing image. Difference between combination of spectral and shape characteristics is taken into consideration while similarity computations. This algorithm extracts boundaries of complicated regions and settles interference of internal details from those regions. It also decreases the broken spots from segmentation outcomes. This approach has computational complexity of $O(n^3)$, here n is number of objects. Results of this method are compared with k-means algorithm and artificial extraction. Agglomerative hierarchical clustering performed well as compared to k-means and able to get results approximately similar to the artificial extraction. As future work, optimization of this method should be done in order to increase the execution efficiency.

Hierarchical top-down (divisive) method is adopted by Kurtz et al. [201] to extract the urban patterns (complex or structured objects) from Very High Spatial Resolution (VHSR) optical images. This method is based on the tree-cuts in the binary partition trees. Here, Euclidean distance is used as a distance measure. It can handle VHSR images without facing problems related to the large size and level of details of the data. It is also able to restrict the areas of homogeneous classes of radiometric intensity. This approach can be improved by correcting the borders in extracted regions which is affected by the resolution gaps and due to use of the bottom up approach. Per-class accuracy is measured with the help of precision index, recall index, F-measure. Global accuracy is computed by using kappa index and weighted harmonic mean of F-measure.

Kernel entropy component analysis based spectral clustering [202] is applied on the remote sensing image data. Clustering is carried out on the basis of nonlinear features which maximally retain the entropy of input data with less number of features. The data structure in terms of maximum divergence between clusters are determined by using angular clustering of the mapped data. Results of the proposed approach are compared with the outcomes of k-means, KPCA plus k-means, and kernel k-means by computing kappa index. It showed that comparatively the proposed method performed well. It has computational complexity of $O(n^3)$, here n is number of objects. Future work can be carried out by adding labeled and noise information in the kernel entropy component analysis and experiment it for other applications of the remote sensing images.

Approximate spectral clustering [203] is applied on the remote-sensing images for segmentation. It works based on the hybrid criterion merging density and the distance information. It provides highly accurate clusters.

Spectral active clustering method [204] is proposed for the segmentation of a high-resolution remote sensing image. Here, similarities matrix is generated by using histogram intersection kernel. This technique actively queries the oracle to get weak pairwise constraints to improve the performance of image clustering. Weak prior knowledge from actively selected pairwise constraints is very helpful in getting the good results. Accuracy is computed to compare the spectral active clustering with spectral clustering and semi-supervised spectral clustering. Comparative study showed that spectral active clustering outperforms other methods.

Approximate Spectral Clustering Ensemble 2 (ASCE2) [205] is introduced for the clustering of high spatial resolution remote-sensing images which is applied for agricultural monitoring. It combines the partitions obtained by different similarity representations using Euclidean distance measure. It is based on the data representative level ensemble approach which leads to limit the ensemble on one type of representative selection. Evaluation of the technique is done with the help of accuracy, adjusted rand index, and normalized mutual information which shows that clustering quality is improved.

For the change detection in Synthetic Aperture Radar (SAR) images, Multi-Objective FCM clustering (MOFCM) [206,226] is applied. Here, two objective functions are used one for preserving the details and another for removing the noise. This method provides a set of results with various trade-off relationships between two objectives hence users can select one or more solutions as per their requirements. As a measure of distance, Euclidean distance is used. MOFCM is compared with FCM, FCM with Spatial information (FCM_S) and MRF- FCM with help of kappa value and percentage of correct classification. It is found that MOFCM achieves more effective and stable results with distinct features and it is more suitable as multi-objective optimization method.

Seed expanding clustering algorithm [207] is adopted for the automatic recognition of coastal upwelling by using the Sea Surface Temperature (SST) images. It labels boundary oriented pixels which leads to iterative expansion of the boundary as cluster grows. This algorithm is further extended as self-tuning version of it. Precision, recall and F-measure are computed and results are compared with the results of supervised version of the method. Seed expanding clustering with Otsu's thresholding performed well as compared to the self-tuning version of seed expanding clustering. Explosion controlled approach of a cluster growing need to be analysed for self-tuning version of the algorithm for the determination of optimal threshold values.

Correlation clustering [208] is applied for the image segmentation where super-pixel representation of the image is done with the help of watershed transform. This algorithm is a variant of graph cutting approach. With the help of real-world high-resolution remote sensing image, its efficiency is proved. Its complexity increases rapidly with the size of an image. But, correlation clustering improves the quality of segmentation as well as it preserves all the relevant details. Here, optimal cut is obtained by solving the Integer Linear Programming (ILP) problem. This approach is compared with greedy and with and without markers on the basis of energy and time. ILP becomes quickly unfeasible as number of nodes increases. Visual quality and complexity is a major issue for the high-resolution images which need to be solved as future work.

3.6. Mobile phones

Due to the large amount of image data acquisition in the mobile phones, effective handling of the image data from a mobile phone is

Fig. 10. Samples of image data from mobile phones (A) Nature image (B) Good morning wish image (C) Baby image.

becoming an important issue nowadays. Mobile phones contain a wide variety of data such as personnel image data generated by camera, downloaded images, Bluetooth image data and many more as shown in Fig. 10. As a result of extreme use of messaging applications like WhatsApp, Hike as well as social network applications such as Facebook, Twitter, etc., a large amount of image data accumulates rapidly in the mobile phone. As this research area is new and less work is done on this topic, researchers need to turn their focus on it.

To organize the personal image collection from a mobile phone automatically, probabilistic model-based clustering with statistical estimation [209] is used where temporal and spatial information is taken into account. Mahalanobis distance is used as a distance measure. This method is optimized with the help of expectation maximization approach. This approach is over-complex but has good properties like ability to assign data to a cluster flexibly.

Geo-Visual clustering [210] is carried out for the information retrieval from smartphone with Android OS where k-means is incorporated with geo-location and visual features. Hubeny's distance is used here for metric learning. This approach is compared with the method based on only geo-location information by using grades which are measured based on the poor, fair, good, very good and excellent. Here, due to incorporation of visual information Geo-Visual clustering achieved highest average score.

Simple Linear Iterative Clustering (SLIC) method [211] is used in the object segmentation method for the generation of super-pixels. It corrects initial segmentation errors and it is useful for the touch screen devices. Here, super-pixels with the combination of color space and spatial space are considered for metric learning. Reviewed literature in this field is summarized in Table 10.

3.7. Security

In this section, two aspects are taken into consideration for the survey of image clustering methods which are given as follows:

- Clustering methods applied on the image data (such as X-ray baggage images) for a general security purpose
- Clustering methods applied on the images having security issues (e.g. tampered images)

Online k-means method [212] is applied over the X-ray baggage images for the codebook generation which is further helpful for the threat object detection in the security screening settings. Here, Euclidean distance is used as a distance measure. Online k-means is compared with traditional k-means clustering on the basis of memory requirement, size of the dataset. Here, it is found that this algorithm reduces the memory requirement and it is suitable for the clustering of large datasets. But optimization of the method is need to be done for the real time application.

Watermarking authentication technique is devised by Hamouda et al. [213] for tampered images as shown in Fig. 11 which works based on Chaos and FCM clustering. FCM clustering makes relationship between image blocks for improving the tamper localization, detection accuracy and watermarking system security. Method is validated under different attacks such as text addition, content removal, copy and paste and collage attack. This method is compared with Chen and Wang's approach [214], Li and Yuan's approach [106,215] and Bakrawy et al.'s approach [216] on the basis of image quality with the help of Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSR).

Kernel-based FCM (KFCM) clustering technique [217] is applied to determine the density of pest in a plant for food security. Features are extracted with the help of neural network approach. By using clusters obtained from the KFCM, density of insects is determined which is further used to identify the pest density. This method needs to be validated by comparing with other methods.

Mobile phone spam image filtering system is proposed where graph partitioning algorithm of the spectral clustering [218] as well as the k-means is applied on the large dataset of e-mail spam images. Performance of this method is compared based on the multiple image descriptors such as RGB histogram feature and Pyramid Histogram Of visual Words (PHOW) descriptor with gray, RGB, and opponent color mode. Sensitivity, specificity, accuracy and F-measure are the parameters used for the performance evaluation where PHOW with RGB based method performed well. Reviewed literature in this field is summarized in Table 11.

Due to increase in the number of vehicle users, management of traffic related issues is being challenging task. Traffic surveillance system is useful to deal with this problem up to some extent where image clustering is useful in various ways. Hence, clustering methods applied for the traffic control are discussed as follows and summarized in Table 12.

Fast mean shift algorithm with Gaussian kernel [219] is applied for filtering of traffic image as shown in Fig. 12. This method is compared with standard mean shift algorithm which showed that fast mean shift algorithm required less number of iteration as well as less computational time. As a future work, this method can be improved by combining with other optimization approaches.

Multi-frames clustering [220] is adopted for the vehicle detection. It works on the relationship between consecutive multi-frames. Then, the traffic surveillance system is developed by Salvi [221] to detect and track the moving vehicles in different night time environments. Here, spatial clustering is applied to process the bright objects to classify moving vehicles in a traffic scene.

Real time obstacle detection is done by using stereovision on mobile devices with low-computational hardware which needs to use sparse stereo reconstruction. Then the super-pixel segmentation is carried out where SLIC [222] is applied to extract the super-pixels. All pixels-based new distance measure is defined here. Accurate results are obtained in low-speed traffic scenarios and at short-medium distances for the real-time processing. This work can be extended for long distance and medium–high speed traffic scenarios. Image segmentation is done with the help of SLIC by Li et al. [223] to detect the road. Complexity of this algorithm is $O(n)$ (here n is number of objects) hence time consumption for the SLIC is less than the k-means.

Table 10
Research summary on clustering algorithms for mobile phone images.

	Image clustering technique	Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/ future work	Datasets	Analysis of number of clusters
Ito et al. [210]	Geo-Visual clustering	–	K-means	Approach based on the only geo-location	Grade based	Achieved good grades as compared to other method	Need to optimize the method	Image shared on the web	Need to provide as input
Gallo et al. [211]	SLIC	Pixel-based	SLIC	–	Overall accuracy	Useful for touch screen devices, able to reduce initial errors	Need to apply advanced techniques for such applications	Oxford Flower 17, Weizmann Horses and Drezzy	Need to provide as input
Pigeau and Gelgon [209]	Probabilistic based clustering with statistical estimation	–	Probabilistic model	–	–	Provides realistic direction	Over-complex, need to validate method by comparison	Personal collection of 500 images	Need to provide as input

"–": Not available.

For vehicle identification and traffic accident detection, vehicle image segmentation is carried out by using the Spatial Constrained FCM (SCFCM) [224] algorithm. To check the robustness, SCFCM is compared with k-means, Ostu's algorithm, traditional FCM and other improved FCM (FLICM) on the basis of various parameters such as noise robustness, optimal cluster numbers and time consumption. It results FLICM and SCFCM have achieved satisfactory results for the noise robustness as compared to other methods and the SCFCM outperformed other methods for remaining parameters.

Dynamic Time Warping (DTW) based clustering algorithm [225] is adopted for the segmentation of long-term flow and dominant flow extraction from traffic videos which characterizes the movements of vehicles. Here, flow segment is temporal sequence of the image segments.

For pedestrian detection, Affinity propagation clustering based clustered poselet models [206,226] are used which automatically selects representative pedestrian parts. Combination of Procrustes and visibility distance is used for metric learning. In complex traffic environments, number of false alarms is reduced. But, performance of the algorithm needs to be improved by using parallel computing concepts.

3.8. Other domains

Apart from above fields, there are few more applicative domains like face related applications, social image analysis [231], etc. where image clustering contributes well. Face recognition [232], face detection [233], face tagging [234], etc. are the face related tasks accomplished using image clustering. Event photo mining [235], image tag refinement [236], etc. are some of the tasks in social networks which uses image clustering.

4. Discussion and future work

4.1. Feature extraction techniques

In this paper, feature extraction techniques are studied for the computation of similarity between images or image patches. To get the more accurate results, it is better to use the high level features like semantic features as using color, texture or shape features individually is not sufficient to get the good results for many applications. As alternative merging one feature with another (e.g. use color and texture together) will help to improve the efficiency of the technique.

Color feature is invariant to the direct similarity transformations such as translations, rotations and scale, but it may differ for a particular color feature extraction method used. Color histogram is widely used for the color feature extraction. Texture features is mainly divided into three categories i.e. statistical, structural and spectral. Statistical approach is simple and easily adaptable as compared to structural and spectral approach for the extraction of texture features. GLCM is the commonly used method for the texture feature extraction. But, GLCM (statistical method) is not able to understand the hierarchical structure of the texture and GLRLM is extremely sensitive to the noise. Local relative GLRLM performs better than the traditional GLRLM. It is useful to embed the local information along with global features. Use of the Gabor filter bank provides a good quality texture features which produces the low-dimensional feature representation and the improved sample-feature ratio. Wavelet transform is also one of the powerful texture feature analysis technique because while doing the reconstruction using this approach, information loss is less. LBP is computationally efficient and provides high performance, hence it is adopted widely for texture feature extraction. In the shape feature extraction, SUSAN operator is a simple, robust against noise and moment invariants with a high stability. This approach gives very good shape feature description. Another approach using integral kernels forms translation, rotation, scaling, and reflection invariant signature for providing compact description of the shape features with multiple

Fig. 11. Sample image of content removal attack (A) Original watermarked image (B) Tampered image [213].

scales. Use of integral kernels make it robust against the noise. By considering kernel with different characteristics for the group transformation invariance, it can be extended further and affine invariant shape descriptor can be developed by using an anisotropic kernel. Rather than using these individual low level features, combination of it performs better. Advanced feature extraction approaches like bag of visual words, deep learning-based approaches (e.g. linear or non-linear convolutional neural network, deep belief network, effective deep learning, etc.) are very useful to get the high accuracy. Use of multiple similarity matrices will also help in improving the overall accuracy.

Analysis of metric learning is provided in each domain where it is found that most of the researches have used Euclidean distance as a distance measure. Researchers need to do experiment using recent metric learning approaches such as deep multimodal distance [227], high-order distance-based multi-view stochastic learning [228,230], weakly supervised metric learning [229], etc. Adopting manifold learning [228,230] approaches while feature extraction improves the performance of system.

4.2. Image clustering techniques

All the basic clustering approaches as well as many advanced clustering approaches are applied in the field of medical imaging. Although lots of literature found in this domain, still further research needs to be done because this field is related to health issues which is one of the primary needs for the living beings. It is necessary to optimize the discussed methods using advanced concepts like deep learning in this domain for getting the maximum possible accuracy of the results. Inclusion of expert's knowledge will be very helpful for this field. Most of the researchers have used only pixel based approaches for the extraction of knowledge from image. Hence, experiments using block based, object based and aspect based approaches will provide the new insight of this domain. Existing algorithms in this field mainly used for the disease identification which can be further applied for the problems in biology or medicine. Ultrasound/ ultrasonic images are used mainly in the medical field. As these images contain more noise, many researchers have used variants of fuzzy clustering to deal with the fuzziness in the image. Here, rough clustering will be useful technique as alternative to the fuzzy clustering. Density based clustering technique like DBSCAN will be useful while dealing with the ultrasound/ ultrasonic images as it is robust against noise and provides arbitrary shaped clusters. These images are also found in the domain of oceanography but less research work is found in this field as compared to medical imaging. Researchers have scope to contribute in the oceanography field using ultrasound/ ultrasonic image clustering.

On the basis of reviewed literature, it is found that recently researchers turn their focus on the 3D image clustering, hence less work is done up till now in this field. Many of them have used graph-based clustering which is able to deal with 3D images easily. Here, fuzziness is also taken into consideration. In this area, except density based clustering methods other basic type of clustering are experimented. However, many advanced hybrid clustering approaches are need to be applied. Experimentation using block-based or object based image handling approach also need to be done. Less number of methods from this domain are validated by comparing with standard approaches using variety of evaluation parameters. As 3D images are advantageous for other field like industrial automation and medical, deep research work is needed for applications in these fields.

Image clustering for the oceanography is a new area of research as well as only few researchers have contributed in this field. Most of the researchers working in this area preferred fuzzy clustering to deal with underwater images having fuzzy nature. Only few other basic clustering techniques are experimented in this field. As underwater images are noisy in nature, techniques which are robust against noise such as DBSCAN, adaptive FCM, etc. are useful for this field or incorporation of noise reduction approaches will be helpful.

Industrial automation is one of the very important fields where researchers have to contribute to minimize the errors and improve the outcomes with fewer efforts in less time. In this area, only few clustering techniques (only basic and popular) are experimented. Advanced clustering approaches need to be implemented and evaluated under various conditions for physical automation as well as prediction and management tasks. As sentimental analysis using social media contributes a lot in marketing predictions, image clustering will be helpful to accomplish this task and also useful further to expand the business.

Research in the field of remote sensing is going on from long ago, variety of image clustering algorithms have experimented on the remote sensing imagery for many tasks. Mainly, fuzzy and graph-based clustering approaches are used because remote sensing images are fuzzy in nature due to high level noise and graph-based approaches helps to deal with locations in images. In future, advanced zooming techniques can be incorporated for extracting the detailed information of an image to improve the results. Here, the use of approaches having ability to deal with large sized datasets is advantageous hence incorporation of parallel computing concepts will help a lot.

Use of the mobile phones becomes very common in recent years which give rise to this field of research. Reviewed literature shows that only few popular clustering algorithms are applied on the images from mobile phones. Too much work needs to be done in this area to overcome the problems in future such as important data retrieval from a huge dataset, removal of the unwanted data, etc. Software should be developed for the retrieval of interesting images where loss of important images should be avoided and it should be compatible for the various types of mobile phones.

Image clustering for a security purpose plays an important role in optimizing security systems. Nowadays terrorism becomes a big threat for the people, hence images such as X-ray baggage images, public area surveillance images or social media images need to be handled quickly by automated systems for threat detection. Public area surveillance images captured by the cameras in shopping malls or other crowded areas need to be observed and try to track the suspicious activities. Clustering of these images with face recognition details as well as deep social data analytics (Tang et al., 2015) will help to get the informative results quickly to deal with security related problems. Apart from this,

Table 11
Research summary on clustering algorithms for images related to security.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Advantages	Limitations/ future work	Datasets	Analysis of number of clusters
Turcsany et al. [212]	Online k-means	Pixel-based	K-means, visual codebook	Traditional k-means	Memory requirement, size of the dataset	Reduces memory requirements, useful for large datasets	Optimization need to be done for real time application	X-ray baggage images	Need to provide as input
Hamouda et al. [213]	FCM	Block-based	FCM	Chen and Wang's approach (1 7 3), Li and Yuan's approach (1 7 4) and Bakrawy et al.'s approach (1 7 5)	PSNR, MSR	Improves tamper localization, accuracy of detection	Need to apply for color images	Grayscale watermarked images	Need to provide as input
Vinushree et al. (2014	Kernel-based FCM	Pixel- based	FCM	–	–	Solution for important security issue	Required to deal with noisy images, method need to be validated, apply on large datasets	Image of leaf with insect	Need to provide as input

"-": Not available

Table 12
Research summary on clustering algorithms for traffic control.

Image clustering technique		Image handling approach	Concepts used	Compared with methodology	Comparative parameters	Pros	Cons/ future work	Datasets	Analysis of number of clusters
Yu et al. (2009)	Fast mean shift algorithm	Pixel- based	Mean shift algorithm	Standard mean shift algorithm	Number of iteration, computational time	High speed achieved, less number of iteration required	Need to improve by combining with other optimization approaches	Traffic images	Automatically identified by the algorithm
Petrovai et al. [222]	SLIC	Super-pixel-based	SLIC	K-means	Time complexity, Accuracy	High accuracy, over-segmented super-pixels are merged to avoid mixing of road and non-road parts, applicable to parallel structures	Advanced features need to be incorporated	Road image	Need to provide as input
Zhou et al. [224]	SCFCM	Pixel- based	FCM, Spatial information	K-means, Ostu's algorithm, FCM, FLICM	Noise robustness, optimal cluster numbers, time consumption	Robust against noise, achieves optimal number of clusters, less number of iterations are required	Parallel computing can be used for optimizing performance	Vehicle image	Obtained through new searching algorithm
Li et al. [206]	Affinity propagation clustering for clustered poselet models	Region-based	Affinity propagation clustering	–	–	Highly reliable robust in complex environments number of false alarms reduced	Performance need to improve, more discriminative features can be combined to improve accuracy, incorporate parallel computing	TUD-Pedestrian dataset	Identified through self-organizing

"–": Not Available.

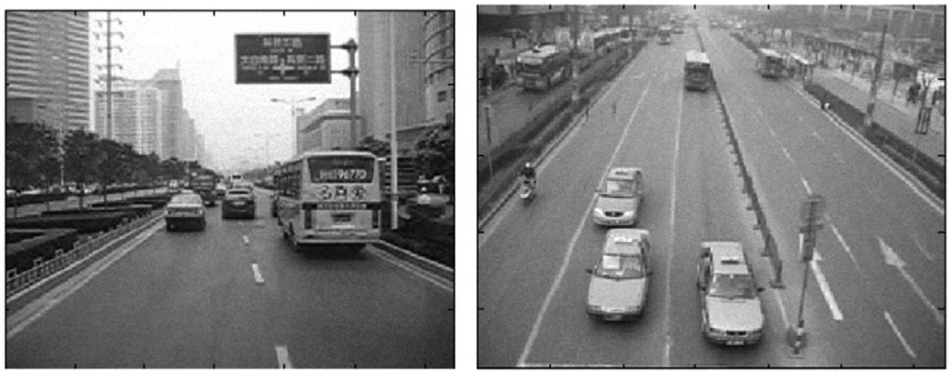

Fig. 12. Sample images of road traffic [219].

image clustering is also helpful to detect distorted image which is a part of image security. Reviewed literature says that only few basic clustering approaches are applied in this area. Real time analytics of images captured by the CCTV camera will play an important role in detection of suspicious activities which helps to avoid disaster at public places. Hence researchers need to focus on a real time analytics of these images.

Flow of a heavy traffic is increasing rapidly which makes the task of surveillance and managing traffic related issues difficult to handle. Image clustering is helpful to do this task efficiently. Few researchers have turned their focus on this topic. But, many advanced clustering methods need to be experimented for this purpose to get optimized outcomes. Implementation of a clustering technique with an advanced zooming technique will provide the more accurate results for this problem. Real time analytics is important for this field also.

Transformed k-means [237], enhanced fast density-peak-based clustering [238], cluster sampling arithmetic algorithm [239], integral channel density peaks clustering [240], Modified Dynamic Fuzzy C-Means (MDFCM) [241], multi-graph clustering [242], etc. are some of the recently developed advanced clustering techniques. Transformed k-means provides high accuracy as compared to k-means and its variants hence can be used as an alternative for it. It also avoids the problems like generation of empty clusters as well as specifies the number of clusters itself. Enhanced fast density-peak-based clustering outperforms conventional and ranking-based clustering methods and provides high accuracy using multiple real world datasets. It also determines the number of clusters automatically. Cluster sampling arithmetic algorithm guarantees the data integrity and requires the less data processing time. Integral channel density peaks clustering is capable to identify number of clusters clearly and centroids of the clusters automatically. This approach provides an effective performance for image segmentation. MDFCM clustering using artificial neural network is able to provide results in very short span of time. Hence, it is very useful for the real-time applications. Exploration of these techniques in above discussed fields will be advantageous. As use of the digital technology is increasing in many fields, existing approaches need to be validated for the large image datasets. Cluster sampling arithmetic algorithm, transformed k-means, k-means, CLARANS and BIRCH are some of the existing clustering techniques which are able to handle the large datasets.

Overall summary of all the domains is given in Table 13 and comparison of all the domains based on the existing research work is done in Fig. 13. To evaluate clustering techniques, suitable evaluation measures are provided in Table 14.

4.3. Challenges in image clustering

- **Complex input data i.e. image:** Complex nature of an image in the terms of its size, type, details, relations between pixels and many other parameters makes it difficult to cluster the image data. To simplify this complex data, represent the image with principal components of the given image. Data reduction techniques, appropriate feature selection and use of high computational machines are some of the ways to handle this problem up to some extent.
- **Feature selection:** Feature selection is highly dependent on a specific area of the application. Hence, initially particular problem need to be analyzed and accordingly select the significant features in order to get the high quality results.
- **Need to handle the noisy data:** An images from the fields such as medical imaging and oceanology have high level of noise as compared to other discussed areas therefore approaches which are robust against noise need to be applied. To remove noise from a given image data, preprocessing should be carried out.
- **Scalable image clustering:** As a speed of image data accumulation is too high nowadays, scalability becomes an important issue. Scalable image clustering approaches should be developed where researchers can embed the concepts of parallel computing.
- **Handling of uncertain data in the cluster:** There are many images in the given dataset which can be a part of two or more clusters because those images are having properties of both the clusters. To deal with such images, only few techniques like FCM or some extended versions of the FCM are applied. As implementation of the fuzzy methods is complex, work of image clustering in this direction needs attention of the researchers.
- **Quick outcomes for the real time application:** Pattern recognition through clustering for the real time applications requires quick outcomes otherwise usefulness of the results degrades. Degree of this reduction completely depends on a particular application. To get the results in less amount of time, researchers can incorporate a data parallelism or a task parallelism.
- **High storage requirement:** As image is a complex data type, it requires a large amount of space to store this data and perform various operations on it. Parametric approach uses representative parameters computed from an original data to perform a task, development of such methods will be helpful to handle this problem because there is no need to store the complete original data.

5. Conclusion

In this paper, survey of image feature extraction and clustering techniques used in various domains for an image analysis is carried out and future scope for each domain is provided. Each clustering algorithm has its own capabilities and limitations which are mentioned in the provided tables. Exploration of important images from the large image datasets can be done easily and efficiently by using the advanced image clustering algorithms under various constraints to fulfill the user's requirements. Images from different domains have different characteristics which are provided along with the suitable clustering approach.

Table 13
Summary on various application domains.

Image data collected from	Characteristics of the images	Challenges	Data sources	Characteristics of the preferred clustering techniques	Suitable clustering techniques
Medical imaging	Contrast sensitive, blur and noisy, CT and MRI images have high resolution than PET images	Need to obtain highly accurate results, Need to handle noisy images, Need to identify ambiguous data	http://www.jsrt.or.jp/jsrt-db/eng.php http://brainweb.bic.mni.mcgill.ca/brainweb/ http://www.via.cornell.edu/databases/lungdb.html http://www.isi.uu.nl/Research/Databases/SCR/	High accuracy, robust against noise	Robust Overlapping Co-clustering, IMC version-2, Transform graph clustering, Shared nearest neighbor clustering
Ultrasound/ ultrasonic imaging	High noise and deformations, less expensive, more widely available	Need to handle noisy images, (if used for medical field) high accuracy is important	http://splab.cz/en/download/databaze/ultrasound http://www.vicomtech.org/demos/us_tracked_dataset/UsTrackedDataset.htm	Robust against noise	Shared nearest neighbor clustering, Graph-based clustering, DBSCAN
3D images	Provide a more detailed information, to express the geometry uses three dimensions	Need to obtain results with minimum computational cost	http://www.dsi.unive.it/~rodola/data.html http://kinectdata.com/	Proper use of the information for better results, minimum computational cost	3D graph-based method
Oceanography	Low color and contrast, reduced visibility, noisy	Need to handle noisy images	http://www.aqualifeimages.com/ http://www.whoi.edu/page.do?pid = 11038&c = 2&cid = 25587&tid = 282	Use of image enhancement techniques, robust against noise	Adaptive FCM, VDP, DBSCAN, Rough set clustering
Industrial automation	Clear, provide detailed information of a product/machine parts	Need to obtain quick and accurate results with minimum computational cost and voluminous data	http://archive.ics.uci.edu/ml/datasets/Steel + Plates + Faults http://archive.ics.uci.edu/ml/datasets/StoneFlakes	Fast processing, scalable (for data), low computational cost, fault detection	K-means, K-medoid, STING, CLARANS, BIRCH, Transformed K-means
Remote sensing	Provide broad view of an area, noisy, panchromatic images have high spatial resolution than multispectral images and volume of digital data is larger for multispectral images	Need to deal with high volume noisy data	http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html http://sedac.ciesin.columbia.edu/data/set/ulandsat-cities-from-space http://isp.uv.es/data_rs.html http://peipa.essex.ac.uk/benchmark/databases/#remote-sensing	Robust against noise, low space utilization	Correlation clustering, combination of watershed and GK fuzzy clustering
Mobile phones	Dynamic, varying lighting conditions heterogeneous, low cost, quality of images depends on mobile phone or source of image (e.g. social network, messenger, etc.)	Need to handle large data with less memory and processing capacity, Need to deal with heterogeneous data	https://purl.stanford.edu/rb470rw0983 https://purl.stanford.edu/vn158kj2087 http://riemenschneider.hayko.at/vision/dataset/task.php?did = 292 http://riemenschneider.hayko.at/vision/dataset/task.php?did = 84	Able to deal with heterogeneity (size, type, quality, etc.), scalable	Piecemeal principal direction divisive partitioning technique, Shared nearest neighbor clustering
Security purpose	Use different colors to represent objects (in X-ray security images), contain very important information, quality depends on device used to capture the image	Need to obtain accurate results quickly, Need to deal with uncertainty	http://www.northeastern.edu/alert/transitioning-technology/alert-datasets/	Fast processing, high accuracy, suspicious activity detection	Rough set clustering, STING, Affinity propagation clustering, Genetic algorithm, MDFCM
Traffic control	Provide valuable evidences for police and other security related people, noisy	Need to obtain accurate results with noisy images	http://benchmark.ini.rub.de/?section = gtsdb&subsection = dataset http://www.cvl.isy.liu.se/research/datasets/traffic-signs-dataset/ http://www.gavrila.net/Datasets/Daimler_Pedestrian_Benchmark_D/Daimler_Pedestrian_Segmentatio/daimler_pedestrian_segmentatio.html	High accuracy, image enhancement	Rough set clustering, Correlation clustering, Affinity propagation clustering

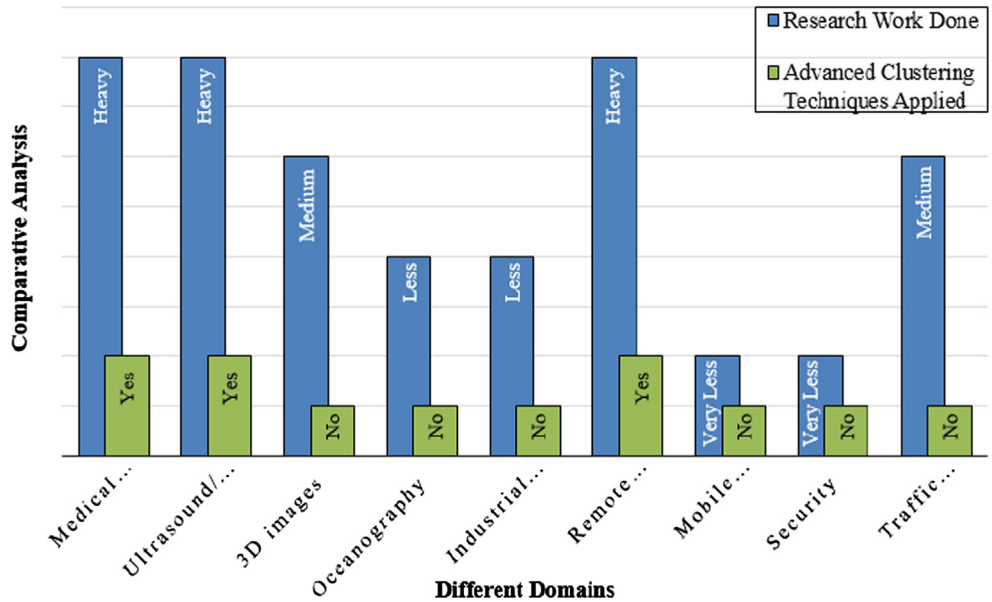

Fig. 13. Illustration of comparative analysis of different domains based on the existing work.

Table 14
Cluster evaluation metrics.

Evaluation metric		Equation	Better clusters if value is	Value range	Limitation
Silhouette Coefficient		$S = \frac{b-a}{max(a,b)}$	High (indicates dense and well separated clusters)	−1 to 1	Value is higher for convex cluster
Adjusted Rand Index		$RI = \frac{a1+b1}{C_2^N}$ $ARI = \frac{RI - E[RI]}{Max(RI) - E[RI]}$	High	−1 to 1	Need to know the information about ground truth classes
Mutual Information based Scores	Normalized Mutual Information	$NMI\,(C_i,\,C_j) = \frac{MI\,(C_i, C_j)}{\sqrt{H(C_i)H(C_j)}}$	High	0 to 1	Need to know the information about ground truth classes
	Adjusted Mutual Information	$AMI = \frac{MI - E[MI]}{\max(H(C_i), H(C_j)) - E[MI]}$			
Homogeneity		$h = 1 - \frac{H(C\mid K)}{H(C)}$	High	0 to 1	If the number of clusters is large, random labeling unable to yield zero scores,
Completeness		$c = 1 - \frac{H(K\mid C)}{H(K)}$			
V-measure		$v = 2\frac{h.c}{h+c}$			
Fowlkes-Mallows Scores		$FMI = \frac{TP}{\sqrt{(TP+FP)(TP+FN)}}$	High	0 to 1	Need to know the information about ground truth classes
Calinski-Harabaz Index		$S(K) = \frac{Tr(B_K)}{Tr(W_K)} \times \frac{N-K}{K-1}$	High	Random	Value is higher for convex cluster
Sum-of-Squared-Error Criterion		$E(C) = \sum_{i=1}^{k} \sum_{o \in C_i} d(o,\, cen_i)^2$	Low	0 to ∞	Need to accept a degree of error practically
Davies-Bouldin Index		$DB = \frac{1}{N} \sum_{i=1, j \neq 1}^{N} max\left(\frac{\sigma_i + \sigma_j}{d(cen_i, cen_j)}\right)$	Low	-∞ to ∞	Not suitable for overlapping clusters
Dunn Index		$D = \frac{d_{min}}{d_{max}}$	High	0 to ∞	Computationally expensive, Not suitable for noisy data
C-index		$C = \frac{S - S_{min}}{S_{max} - S_{min}}$	Low	0 to 1	Difficult to find optimal index for different number of clusters
F-measure		$F = 2\frac{P.R}{P+R}$ $P = \frac{TP}{TP+FP}$ $R = \frac{TP}{TP+FN}$	High	0 to 1	Degree of andness is fixed to 0.77.

Notations: *a*: Mean distance between a sample and all remaining points from same class, *b*: Mean distance between a sample and all other points from next nearest cluster, *a1*: No. of pairs of elements that are in the same class and in the same cluster, *b1*: No. of pairs of elements that are in different classes and in different clusters, B_K: Between group dispersion matrix, *C*: Ground truth class, *cen*: Centroid, d_{min}: Minimum distance between two points from different clusters, d_{max}: Maximum distance of two objects from the same cluster, *FP*: False Positive, *FN*: False Negative, *H(C)*: Entropy of class, *MI*: Mutual Information, *o*: Object, *N*: No. of samples, *K*: Cluster, *P*: Precision, *R*: Recall, *S*: Sum of distances between all pairs of objects in same cluster, S_{min}: Sum of minimum distances from all pairs, S_{max}: Sum of maximum distances from all pairs, *TP*: True Positive, W_K: Within group dispersion matrix, *σ*: Mean distance between a sample and all other points from a cluster.

To improve the accuracy of outcomes, incorporation of advanced techniques (like deep learning), multiple similarity matrices is suggested. On the basis of reviewed literature, it is found that most of the discussed areas have used the fuzzy clustering approaches. It would be better to use rough set clustering as an alternative to the fuzzy clustering as it is less computationally complex and simpler than the fuzzy approach. Important bio-inspired approach like genetic algorithm is also used by only few researchers. Graph-based clustering is mainly adopted for the 3D image clustering and the remote sensing imaging. It can be also used for the mobile data image clustering. Implementation of 3D image clustering is very helpful in the areas such as medical imaging and industrial automation. For image clustering of underwater images, advanced clustering techniques need to be applied to help in the underwater research. Image clustering approaches for the industrial automation should be optimized by incorporating the advanced concepts to get the accurate and quick results. In mobile phones, a huge amount of data accumulates every day hence scalable image clustering techniques should be developed. Nowadays security is an important issue therefore image clustering needs to be applied on the image data from areas like social media, dataset generated by surveillance cameras placed at public places to identify suspicious activities. Advanced zooming techniques can be incorporated to improve the results of image clustering for remote sensing and traffic control. Much research has been carried out on medical image clustering, however optimization is necessary to obtain highly accurate results. As advanced ultrasound image clustering approaches are robust against noise, those will be useful to deal with noisy images from the field of oceanography. As less research work is done in the field of clustering for 3D images, oceanography, industrial automation, mobile phone images and images related to security, these fields have wide scope for further research. It is important to develop more advanced applications and tools for the image mining.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

We have no conflict of interest.

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