Optimized Unsupervised Image Classification Based on Neutrosophic Set Theory

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In this presentation, a new technique is used to an unsupervised learning image classification based on integration between neutrosophic sets and optimization linear programming.

Abstract.

Neutrosophic sets are used to segment the image into three main components namely objects (*O*), edges (*E*), and Background (*B*).

The neutrosophic image components (*O*,*E*,*B*) are corresponding to the neutrosophic sets components (*T*, *I* ,*F*).

The components of neutrosophic image valued in $[^-0,1^+]$ are representing the association intensities degree of pixel for each image components.

Netrosophic image components are contributed to solving one of the important problems in image classification known as "overlapping" within cluster.

While, the problem of overlapping between clusters is solved by using optimization linear programming.

Introduction.

Since several decades, the world is witnessing a remarkable development in the science of computer vision.

The principle of computer vision is based on deal with the images and methods of treatment.

Hence the interest of researchers in the computer vision with image processing, which is concerned, in essence, on the methods and many different algorithms.

Among these algorithms are image classification algorithms.

Classification is the field devoted to the study of methods designed to categorize data into distinct classes.

Introduction - cont.

This categorization can be divided to distinct labeling of the data (supervised learning [1]), division of the data into classes (unsupervised learning [2]), selection of the most significant features of the data (feature selection [3]), or a combination of more than one of these tasks [4].

[1] Lu, Dengsheng, and Qihao Weng. "A survey of image classification methods and techniques for improving classification performance.", International journal of Remote sensing 28.5 (2007): 823-870.
[2] Lee, Te-Won, and Michael S. Lewicki. "Unsupervised image classification, segmentation, and enhancement using ICA mixture models." Image Processing, IEEE Transactions on 11, no. 3 (2002): 270-279.
[3] Guyon, Isabelle, and André Elisseeff. "An introduction to variable and feature selection." The Journal of Machine Learning Research 3 (2003): 1157-1182.
[4] Saeys, Yvan, Iñaki Inza, and Pedro Larrañaga. "A review of feature selection techniques in bioinformatics." bioinformatics 23.19 (2007): 2507-2517.

Introduction - cont.

Unsupervised image classification (UIC) starts by partitioning the image data into groups (or clusters).

The classes in UIC are unknown, according to similarity measure, groups of image data can be compared with reference to data by an analyst [5].

UIC can be categorized into two main groups namely Hierarchical [6] and Partitional [7] algorithms.

[5] Omran, Mahamed GH, Andries Petrus Engelbrecht, and Ayed Salman."Differential evolution methods for unsupervised image classification." Evolutionary Computation, 2005. The 2005 IEEE Congress on. Vol. 2. IEEE, 2005.
[6] Deng, Jia, Alexander C. Berg, Kai Li, and Li Fei-Fei. "What does classifying more than 10,000 image categories tell us?" In Computer Vision–ECCV 2010, pp. 71-84. Springer Berlin Heidelberg, 2010.
[7] Yang, Shulin, Liefeng Bo, Jue Wang, and Linda G. Shapiro. "Unsupervised Template Learning for Fine-Grained Object Recognition." In NIPS, pp. 3131-3139. 2012.

Introduction - cont.

In hierarchical clustering algorithms (HCA) a sequence of clustering with each clustering being a partition of the data set are showing as a tree [8].

[8] Murtagh, Fionn, and Pedro Contreras. "Algorithms for hierarchical clustering: an overview." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 2.1 (2012): 86-97.

HCA is characterized by two advantages, first the number of classes does not need be specified *a priori* and the others they are independent of th initial condition.

However, HCA is suffers from be a static algorithm and its inability to solve the overlapping clusters problem [9].

[9] Elavarasi, S. Anitha, J. Akilandeswari, and B. Sathiyabhama. "A survey on partition clustering algorithms." learning 1.1 (2011).

Introduction - cont.

HCA are divided according to the clusters construction methods or according to the similarity measure. For methods construct the clusters by recursively partitioning the instances in either a top-down or bottom-up fashion.

These methods can be subdivided as agglomerative [10] and divisive [11] methods.

[10] Meila, Marina, and David Heckerman. "An experimental comparison of several clustering and initialization methods." arXiv preprint arXiv:1301.7401 (2013).
[11] Gaidon, Adrien, Zaid Harchaoui, and Cordelia Schmid. "Recognizing activities with cluster-trees of tracklets." BMVC. 2012.

Whereas, the merging or division of clusters is performed according to some similarity measure, chosen so as to optimize some criterion (such as a sum of squares).

The hierarchical clustering methods could be further divided according to the manner that the similarity measure is calculated [12].

[12] Jain, A.K. Murty, M.N. and Flynn, P.J. Data Clustering: A Survey. ACM Computing Surveys, Vol. 31, No. 3, September 1999.

Introduction - cont.

On the other hand, partitional clustering algorithms (PCA) are based on image data set segmentation into a specified number of clusters.

PCA can be treated as an optimization problem as a result of reliance on the square error function to minimize certain criteria.

Both HCA and PCA algorithms are participate in advantages and drawbacks.

There are two categories from PCA namely Iterative [13] and non-iterative [14] algorithms.

[13] Dong, Weisheng, et al. "Sparsity-based image denoising via dictionary learning and structural clustering." Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011.

[14] Hanauer, Matthias, and Andreas Koehn. "Perturbative treatment of triple excitations in internally contracted multireference coupled cluster theory." The Journal of chemical physics 136.20 (2012): 204107.

Introduction - cont.

K-means algorithm [15] is the most widely used in iterative partitional algorithms.

[15] Zhao, Z. L., Bo Liu, and Wei Li. "Image clustering based on extreme K-means algorithm." IEIT Journal of Adaptive & Dynamic Computing 2012.1 (2012): 12-16.

The basic idea for k-means algorithm is to find a clustering structure that minimizes a certain error criterion which easures the distance of each instance to its representative value.

The most well-known criterion is the Sum of Squared Error (SSE) [16], may be globally optimized by exhaustively enumerating all partitions, which is very time-consuming, or by giving an approximate solution using heuristics.

[16] Celebi, M. Emre, Hassan A. Kingravi, and Patricio A. Vela. "A comparative study of efficient initialization methods for the k-means clustering algorithm." Expert Systems with Applications 40.1 (2013): 200-210.

Introduction - cont.

Another partitioning algorithm, which attempts to minimize the SSE is the K-medoids [17] or partition around medoids (PAM) [18].

[18] Kaufman, L. and Rousseeuw, P.J., 1987, Clustering by Means of Medoids, InY. Dodge, editor, Statistical Data Analysis, based on the L1 Norm, pp. 405-416, Elsevier/North Holland, Amsterdam.

Lillesand and Kiefer [19] presented a non-iterative approach to unsupervised clustering with a strong dependence on the image texture.

[19] Mirik, Mustafa, and R. James Ansley. "Comparison of groundmeasured and image-classified mesquite (Prosopis glandulosa) canopy cover." Rangeland Ecology & Manag. 65.1 (2012): 85-95.

Researches [20-21] have shown that the iterative algorithms are more efficient than its counterpart non-iterative, where it does not rely too much on data points order.

[20] Bringmann, Björn, Siegfried Nijssen, and Albrecht Zimmermann. "Pattern-based classification: a unifying perspective." arXiv preprint arXiv:1111.6191 (2011).
[21] Voisin, Aurélie, et al. "Classification of very high resolution SAR images of urban areas." (2011).

Introduction - cont.

There are other unsupervised classifications methods are used recently represented in Density-based Methods [22] which assume that the points that belong to each cluster are drawn from a specific probability distribution.

[22] Kriegel, Hans-Peter, et al. "Density- based clustering." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 1.3 (2011): 231-240.

Model-based Clustering Methods [23], these methods attempt to optimize the fit between the given data and some mathematical models.

[23] Bouveyron, Charles, and Camille Brunet. "Simultaneous model-based clustering and visualization in the Fisher discriminative subspace." Statistics and Computing 22.1 (2012): 301-324.

Unlike conventional clustering, which identifies groups of objects; model-based clustering methods also find characteristic descriptions for each group, where each group represents a concept or class.

Introduction - cont.

The most frequently used induction methods are decision trees [24] and neural networks [25].

[24] Barros, Rodrigo Coelho, et al. "A survey of evolutionary algorithms for decision-tree induction." Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on 42.3 (2012): 291-312.
[25] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks." NIPS. Vol. 1. No. 2. 2012.

Grid-based Methods [26], these methods partition the space into a finite number of cells that form a grid structure on which all of the operations for clustering are performed.

[26] Willems, Thomas F., et al. "Algorithms and tools for high-through put geometry-based analysis of crystalline porous materials.“ Microporous and Mesoporous Materials 149.1 (2012): 134-141.

The main advantage of the approach is its fast processing time [27].

[27] Han, J. and Kamber, M. Data Mining: Concepts and Techniques. Morgan Kaufmann Publishers, 2001.

Introduction - cont.

Soft-computing Methods, In addition to neural networks, there are some methods that belong to soft computing methods such as Fuzzy Clustering [28], Evolutionary Approaches for Clustering [29] and Simulated Annealing for Clustering [30].

[28] Izakian, Hesam, and Ajith Abraham. "Fuzzy C-means and fuzzy swarm for fuzzy clustering problem." Expert Systems with Applications 38.3 (2011): 1835-1838.
[29] Zhou, Aimin, et al. "Multiobjective evolutionary algorithms: A survey of the state of the art." Swarm and Evolutionary Computation 1.1 (2011): 32-49.
[30] Dowsland, Kathryn A., and Jonathan M. Thompson. "Simulated annealing." Handbook of Natural Computing. Springer Berlin Heidelberg, 2012. 1623-1655.

In this paper, a new an unsupervised image classification technique is used based on neutrosophic sets [31] and optimization linear programming [32].

[31] Maji, Pabitra Kumar. "Neutrosophic soft set." Annals of Fuzzy Mathematics and Informatics 5.1 (2013): 2287-623.
[32] Hromkovic, Juraj. Algorithmics for hard problems: introduction to combinatorial optimization, randomization, approximation, and heuristics. Springer-Verlag, 2010.

Introduction - cont.

Neutrosophic set is considered a part from neutrosophy theory which is interested in the studies of origin, nature and scope of neutralities, as well as their interactions with different ideational spectra.

The idea of neutrosophy theory depends on event or entity, where between an idea <A> and its opposite <Anti-A>, there is a continuum power spectrum of neutralities <Neut-A>.

Truth value (T), indeterminacy value (I) and falsehood value (F) are representing neutrosophic components referring to neutrosophy, neutrosophic logic, neutrosophic set, neutrosophic probability, neutrosophic statistics [33].

[33] Smarandache, Florentin. Introduction to Neutrosophic Measure, Neutrosophic Integral, and Neutrosophic Probability. 2013.

In neutrosophic set, the indeterminacy is quantified explicitly and the truth-membership, indeterminacy-membership and falsity-membership are independent.

The neutrosophic set is a generalization of an intuitionistic set, classical set, fuzzy set, paraconsistent set, dialetheist set, paradoxist set, and tautological set.

Introduction - cont.

Linear programming is constrained optimization, where the constraints and the objective function are all linear.

It is called "programming" because the goal of the calculations help you choose a "program" of action [41].

[41] Kumar, Amit, Jagdeep Kaur, and Pushpinder Singh. "A new method for solving fully fuzzy linear programming problems." Applied Mathematical Modelling 35.2 (2011): 817-823.

The linear programming model, for neutrosophic image classification problem, involves on two main parts called constraints and objective function.

Constraints are describing the query images as lower and upper weights for neutrosophic query image components.

On neutrosophic image clustering classification to be maximized a linear objective function means that categorization of similar images in clusters with out overlapping within or between clusters.

General Framework.

This paper presents a novel system to image clustering namely Optimization neutrosophic image classification system (ONsICS).

As shown in *Figure 1* next slide, ONsICS consists of two techniques are neutrosophic image processing and optimization image clustering.

Neutrosophic image processing is used to convert gray image to enhanced binary image (EBI) based on object, edge and background of image components.

Each image can be represented as neutrosophic components (T, I, F) and stored the extracted image components feature as a vector in database.

All similar image features are gathered together in a one category by using neutrosophic image clustering (NsIC) technique.

Image clusters are optimized by using linear programming to solve image overlapping problem as shown in *Figure 1* next slide.

General Framework - cont.

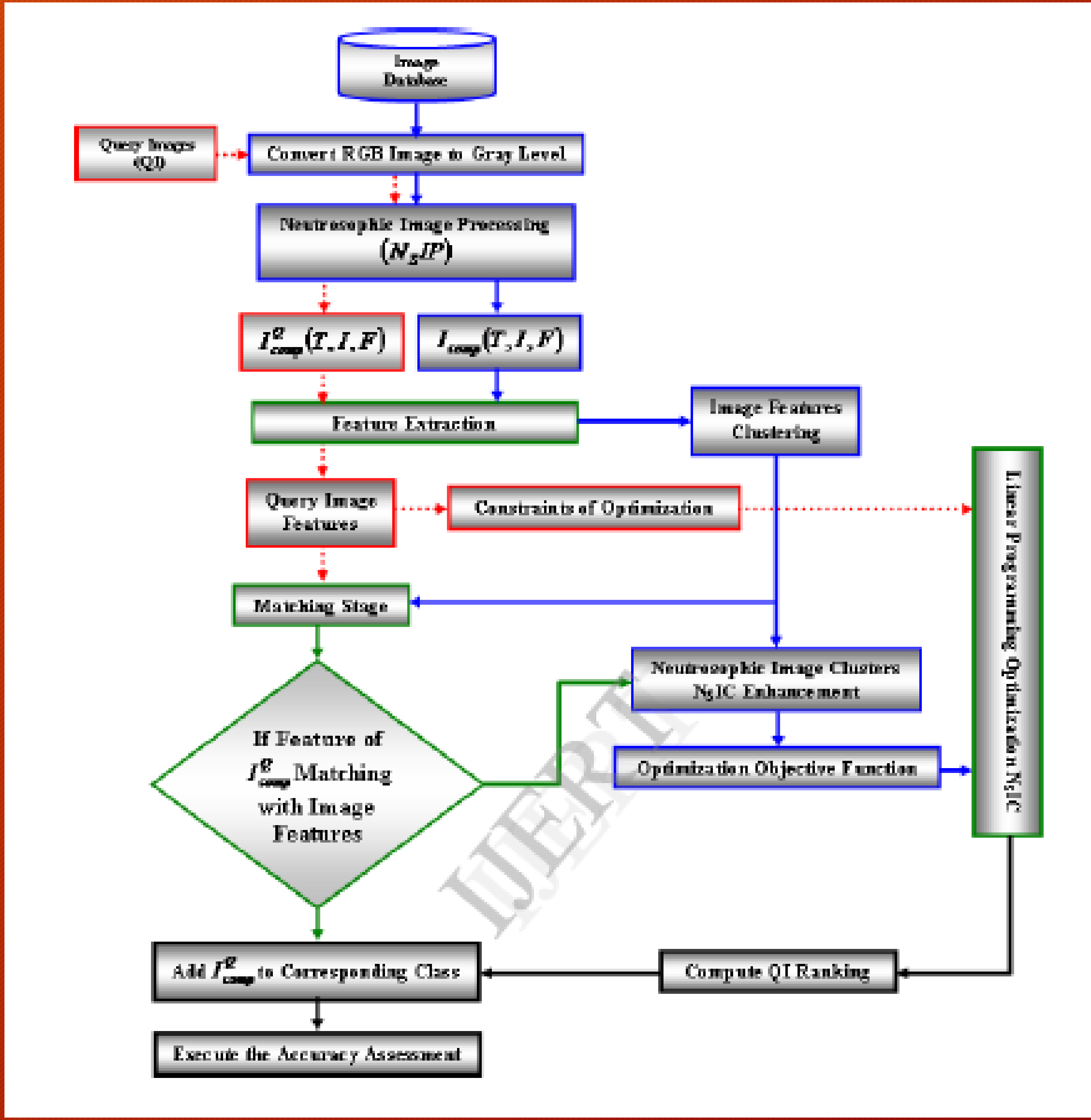

Figure 1: Optimization image clustering flowchart.

Neutrosophic Image Processing.

Let I_{img} be a Universe of discourse represents image and I_{comp} is a set of I_{img} represents image components (as object, edge, background) which is composed by bright pixels. Aim of the neutrosophic image domain $(N_S D)$ is transferring image I_{img} to neutrosophic domain by describing the pixel by three membership sets $T, I \text{ and } F$ as $P_{Ns}(T, I, F)$ [43]. The pixel can represents as:

$$P_{Ns}(i,j) = \{T(i,j), I(i,j), F(i,j)\} \quad where,$$

$T(i,j)$ is the probability belonging to white pixels set. It is defined as:

$$T(i,j) = \frac{\bar{g}(i,j) - \bar{g}_{\min}}{\bar{g}_{\max} - \bar{g}_{\min}}$$

$$\bar{g}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} g(m,n)$$

Where, $\bar{g}(i,j)$ is the local mean value of pixels of the window.

Neutrosophic Image Processing - cont.

$I(i,j)$ is indeterminate set. It is defined as:

$$I(i,j)=\frac{\delta(i,j)-\delta_{min}}{\delta_{max}-\delta_{min}}$$

$$\delta(i,j)=abs(g(i,j)-\bar{g}(i,j))$$

Where, $\delta(i,j)$ is the absolute value of difference between intensity $g(i,j)$ and its local mean value $\bar{g}(i,j)$.

$F(i,j)$ is non white pixels set. It is defined as:

$$F(i,j)=1-T(i,j)$$

A. Neutrosophic Image Entropy:

Neutrosophic image entropy [44] is defined as the summation of the entropies of three sets $T, I, and\ F$, which is employed to evaluate the distribution of the elements in the neutrosophic domain:

Neutrosophic Image Processing - cont.

$$En_I = -\sum_{i=\min\{I\}}^{\max\{I\}} p_I(i) \ln p_I(i)$$

$$En_F = -\sum_{i=\min\{F\}}^{\max\{F\}} p_F(i) \ln p_F(i)$$

where $En_T, En_I, and\ En_F$ are the entropies of the sets T , I and F , respectively. $p_T(i), p_I(i), and\ p_F(i)$ are the probabilities of elements in T , I and F, respectively, whose values equal to i .

$$En_{Ns} = En_T + En_I + En_F$$

$$En_T = -\sum_{i=\min\{T\}}^{\max\{T\}} p_T(i) \ln p_T(i)$$

Neutrosophic Image Feature Extraction.

Image feature extraction is the first step to image retrieval system.

Neutrosophic image (N_SIm) is divided into three matrices are represented as images called object, edge and background.

Each image is consisting of matrix representing the probability white pixel values for object component and probability of non white pixel values for background component while the intermediate matrix expresses the probability of the boundary between the white and non-white pixels.

The combinations of pixel brightness value in (N_SIm) components are calculated by using a widely method namely Gray Level Co-occurrence Matrix (GLCM) [].

The spatially related in various directions with reference to distance and angular relationships for co-occurring pairs of pixels is one of the most important advantages for GLCM calculations.

Neutrosophic Image Feature Extraction - cont.

The feature extraction for (N_SIm) components by GLCM is based on pixel and its next neighbor pixel.

The Contrast, Energy, Homogeneity and Correlation are the parameters of GLCM which calculated by:

$$Contrast = \sum_{i=1}^{m}\sum_{j=1}^{n}(i-j)^2 I_{comp}(i,j), \quad where$$

$$0 \le i \le m \;,\; 0 \le j \le n$$

$$(m,n)\ is\ image\ dimentions$$

$$Energy = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(I_{comp}(i,j)\right)^2$$

$$Homogeneity = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{I_{comp}(i,j)}{1+|i-j|}$$

$$Correlation = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{\{i \times j\} \times I_{comp}(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y}, \quad where$$

μ_x, μ_y are mean of probability matrix.

σ_x, σ_y are standard deviations of probability matrix.

Neutrosophic Image Clustering.

Image clustering can classify similar images into the same group. Let image data set be $\mathrm{Im} = \{I'_{comp}, i = 1,2,\ldots,n\}$, and I'_{comp} be an image in a d-dimensional space. Image clustering problem is to find image category $Cl_{im} = \{Cl_{im_1}, Cl_{im_2}, \ldots, Cl_{im_n}\}$, which satisfies:

$$\mathrm{Im} = \bigcup_{i=1}^{m} Cl_{im_i}$$

$$Cl_{im_i} \neq \Phi \quad for\ i = 1,2,\ldots,m$$

$$Cl_{im_i} \cap Cl_{im_j} = \Phi \quad for\ i,j = 1,2,\ldots,m,\ i \neq j$$

Neutrosophic Image Clustering - cont.

Among clustering methods, the fuzzy c-means algorithm is widely used. An objective function for a clustering method is important to define. The objective function of fuzzy c-means is defined as:

$$J_m(U,E) = \sum_{k=1}^{n}\sum_{k=1}^{c}(\mu_{ik})^m \left\|x_k - e_i\right\|^2$$

Where m is constant, and $m > 1$. Cluster i is expressed as $e_i\left(i = 1,2,\dots,c\right)$. The membership between sample k and cluster is expressed as;

$$\mu_{ik}\begin{pmatrix} i = 1,2,\dots,c, \\ k = 1,2,\dots,n \end{pmatrix}, \text{ where,}$$

$$\mu_{ik} \in \{0,1\},\ \forall i,k;\ \sum_{i=1}^{c}\mu_{ik} = 1, \forall k$$

Neutrosophic Image Clustering - cont.

can be computed by:

$$\mu_{ik} = \frac{c}{c + \sum_{j=1}^{c} \left(\frac{\|x_k - e_i\|}{\|x_k - e_j\|} \right)^{\frac{1}{m-1}}}$$

where e_i is the cluster center and can be computed by:

$$e_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m}, \quad 1 \le i \le c$$

The mean and the variance of μ_{ik} for the cluster are computed as:

$$\overline{\mu_i} = \frac{\sum_{k=1}^{n_i} \mu_{ik}}{n_i}, \quad \sigma_i^2 = \frac{\sum_{k=1}^{n_i} \left| \mu_{ik} - \overline{\mu_i} \right|^2}{n_i}$$

Where, the fuzzy partition matrix is $\mu_i = \{\mu_{i1}, \mu_{i2}, \ldots, \mu_{in_i}\}$.

Neutrosophic Image Clustering - cont.

A. Neutrosophic image clusters enhancement.

The indeterminacy of image pixel $I_{comp}(i,j)$ is determined by its intensity value $I(i,j)$. Strength of the correlation between neutosophic image components T and F with I are influenced by the distribution of the pixels and the entorpy of I.

The set $I_{\text{Im}} \subseteq [0,1]$ may represent not only indeterminacy but also vagueness, uncertainty, imprecision, error, etc. So, the overlapping problem will appear within and between neutrosophic image cluster as shown in figure 3.

Threshold processing will solve the overlapping problem within and between neutrosophic image clusters by determine the mysterious region between background and objects. In gray level domain, $(\lambda - mean)$ operation for image Im_{GL} is defined as:

$$\text{Im}_{GL}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} \text{Im}_{GL}^{\text{mod}}(m,n)$$

Where w is the size of the window, $(m,n)$is the location of the pixel centered the window. A $\lambda - mean$ operation for $P_{Ns}, \overline{P}_{Ns}^{\lambda}$ is defined as:

Neutrosophic Image Clustering - cont.

A. Neutrosophic image clusters enhancement.

$$\overline{P}_{Ns}^{\lambda} = P(\overline{T}(\lambda), \overline{I}(\lambda), \overline{F}(\lambda))$$

$$\overline{T}(\lambda) = \begin{cases} T & I < \lambda \\ \overline{T} & I \geq \lambda \end{cases}$$

$$\overline{T}^{\lambda}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} T(m,n)$$

$$\overline{F}(\lambda) = \begin{cases} F & I < \lambda \\ \overline{F} & I \geq \lambda \end{cases}$$

$$\overline{F}^{\lambda}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} F(m,n)$$

$$\overline{I}^{\lambda}(i,j) = 1 - \frac{\overline{H}(i,j) - \overline{H}_{\min}}{\overline{H}_{\max} - \overline{H}_{\min}}$$

Where $\overline{H}(i,j)$ is the homogeneity value of $\overline{T}^{\lambda}$ at (i, j) .
w is the local window size.
After $\lambda - mean$ operation subset T became more homogeneous after removing the noise. By using a simple threshold method can be segnent the subset T accurately.

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

Optimization $(N_S \operatorname{Im})$ Classification (ONsIC) method presents a new method to determine the best category to include the query images, where the characteristics of clusters are represented by neutrosophic sets. Suppose that a set of clusters $Cl = \{Cl_1, Cl_2, \ldots, Cl_m\}$ which consists of m neutronsophic image clusters (NsIC) from which the most preferred cluster is to be selected to including the query image. Each NsIC is assessed on n different components as $\{im_1^{comp}, im_2^{comp}, \ldots, im_n^{comp}\}$. The evaluation of the cluster Cl_i with respect to the component of im_j^{comp} is a neutrosophic set. The neutrosophic index I_{ij} is such that the larger I_{ij} the higher a hesitation margin of NsIC Cl_i with respect to the components of im_j^{comp} whose intensity is given by T_{ij}. The NsIC matrix is given in the following form:

Neutrosophic Image Clustering - cont.
B. Optimization neutrosophic image clustering.

$$
N_S IC = \begin{array}{c|cccc}
 & I^1_{comp} & I^2_{comp} & \cdots & I^n_{comp} \\
\hline
Cl_1 & (T_{11}, I_{11}, F_{11}) & (T_{12}, I_{12}, F_{12}) & \cdots & (T_{1n}, I_{1n}, F_{1n}) \\
Cl_2 & (T_{21}, I_{21}, F_{21}) & (T_{22}, I_{22}, F_{22}) & \cdots & (T_{2n}, I_{2n}, F_{2n}) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
Cl_m & (T_{m1}, I_{m1}, F_{m1}) & (T_{m2}, I_{m2}, F_{m2}) & \cdots & (T_{mn}, I_{mn}, F_{mn})
\end{array}
$$

Where the characteristics of NsIC (Cl_i) are given by:

$$Cl_i = \left\{ \frac{I^1_{comp}}{T_{i1}, I_{i1}, F_{i1}}, \frac{I^2_{comp}}{T_{i2}, I_{i2}, F_{i2}}, \dots, \frac{I^n_{comp}}{T_{in}, I_{in}, F_{in}} \right\}, \quad where, 1 \le i \le m$$

$N_S IC(Cl_i)$ can present by another form as:

$$Cl_i = \left\{ \langle Cl_1, [K^l_{i1}, K^u_{i1}] \rangle, \langle Cl_2, [K^l_{i2}, K^u_{i2}] \rangle, \dots, \langle Cl_n, [K^l_{in}, K^u_{in}] \rangle \right\} \quad where$$

$[K^l_{ij}, K^u_{ij}]$ is closed NsIC interval computed by:

$$[K^l_{ij}, K^u_{ij}] = \left[\min\left(\frac{T_{ij} + I_{ij}}{2}, \frac{1 - F_{ij} + I_{ij}}{2} \right), \max\left(\frac{T_{ij} + I_{ij}}{2}, \frac{1 - F_{ij} + I_{ij}}{2} \right) \right]$$

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

Obviously, $0 \leq K_{ij}^{l} + K_{ij}^{u} \leq 2$ for all $Cl_i \in Cl$ and $im_j^{comp} \in im$. The degrees to the alternative NsIC Cl_i satisfies and does not satisfy the can be measured by the evaluation function (E). The evaluation function $E(Cl_i)$ of alternative NsIC Cl_i can be expressed as:

$$
\begin{aligned}
E(Cl_i) &= \left[K_{ij}^{l}, K_{ij}^{u}\right] \wedge \left[K_{ik}^{l}, K_{ik}^{u}\right] \wedge \ldots \wedge \left[K_{ip}^{l}, K_{ip}^{u}\right] \vee \left[K_{iQ}^{l}, K_{iQ}^{u}\right] \\
&= \left[\min\{K_{ij}^{l}, K_{ik}^{l}, \ldots, K_{ip}^{l}\}, \min\{K_{ij}^{u}, K_{ik}^{u}, \ldots, K_{ip}^{u}\}\right] \vee \left[K_{iQ}^{l}, K_{iQ}^{u}\right] \\
&= \left[\max\{\min\{K_{ij}^{l}, K_{ik}^{l}, \ldots, K_{ip}^{l}\}, K_{iQ}^{l}\}, \max\{\min\{K_{ij}^{u}, K_{ik}^{u}, \ldots, K_{ip}^{u}\}, K_{iQ}^{u}\}\right] \\
&= \left[K_{Cl_i}^{l}, K_{Cl_i}^{u}\right]
\end{aligned}
$$

$where, 1 \leq i \leq m$, and $(\wedge\ and\ \vee)$ denote the minimum and maximum operator of neutrosophic set respectively.

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

Obviously, $0 \le K_{ij}^{l} + K_{ij}^{u} \le 2$ for all $Cl_i \in Cl$ and $im_j^{comp} \in im$. The degrees to the alternative NsIC Cl_i satisfies and does not satisfy the can be measured by the evaluation function (E). The evaluation function $E(Cl_i)$ of alternative NsIC Cl_i can be expressed as:

$$
\begin{aligned}
E(Cl_i) &= [K_{ij}^{l}, K_{ij}^{u}] \wedge [K_{ik}^{l}, K_{ik}^{u}] \wedge \ldots \wedge [K_{ip}^{l}, K_{ip}^{u}] \vee [K_{iQ}^{l}, K_{iQ}^{u}] \\
&= [\min\{K_{ij}^{l}, K_{ik}^{l}, \ldots, K_{ip}^{l}\}, \min\{K_{ij}^{u}, K_{ik}^{u}, \ldots, K_{ip}^{u}\}] \vee [K_{iQ}^{l}, K_{iQ}^{u}] \\
&= [\max\{\min\{K_{ij}^{l}, K_{ik}^{l}, \ldots, K_{ip}^{l}\}, K_{iQ}^{l}\}, \max\{\min\{K_{ij}^{u}, K_{ik}^{u}, \ldots, K_{ip}^{u}\}, K_{iQ}^{u}\}] \\
&= [K_{Cl_i}^{l}, K_{Cl_i}^{u}]
\end{aligned}
$$

$where, 1 \le i \le m$, and $(\wedge \; and \; \vee)$ denote the minimum and maximum operator of neutrosophic set respectively.

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

The score of alternative NsIC $S_c(Cl_i)$ can be evaluated by:

$$S_c(Cl_i) = 2(T^u_{Cl_i} - T^l_{Cl_i})$$
$$= 2\left(\max\left(\left(\frac{T_{Cl_i} + I_{Cl_i}}{2}\right), \left(\frac{1 - F_{Cl_i} + I_{Cl_i}}{2}\right)\right) - \min\left(\left(\frac{T_{Cl_i} + I_{Cl_i}}{2}\right), \left(\frac{1 - F_{Cl_i} + I_{Cl_i}}{2}\right)\right)\right)$$

An accuracy function A_c is used to evaluate the degree of accuracy of neutrosophic elements as follows:

$$A_c(Cl_i) = \frac{1}{2}(T^l_{Cl_i} + T^u_{Cl_i})$$
$$= \frac{1}{2}\left(\min\left(\left(\frac{T_{Cl_i} + I_{Cl_i}}{2}\right), \left(\frac{1 - F_{Cl_i} + I_{Cl_i}}{2}\right)\right) + \max\left(\left(\frac{T_{Cl_i} + I_{Cl_i}}{2}\right), \left(\frac{1 - F_{Cl_i} + I_{Cl_i}}{2}\right)\right)\right)$$

The larger value of $A_c(Cl_i)$ represents the more degree of accuracy of an element Cl_i in the neutrosophic set. Based on the score function S_c and the accuracy function A_c the degree of suitability that the corresponding cluster Cl_i satisfies the query images component can be measured by:

$$W(E(Cl_i)) = (S_c(E(Cl_i)))^2 - \left(\frac{1 - A_c(E(Cl_i))}{2}\right)$$

Neutrosophic Image Clustering - cont.
B. Optimization neutrosophic image clustering.

The coefficients in $W(E(Cl_i))$ have been chosen so that $W(E(Cl_i)) \in [0,1]$. The larger value of $W(E(Cl_i))$, the more suitability to which the alternative NsIC (Cl_i) satisfies to query image components, where $1 \le i \le m$.

Assume that there is a query images wants to choose an alternative NsIC which satisfies the components of QI_j, *where*, $1 \le j \le n$, each QI_j have a different degree of components $(\hat{T}, \hat{I}, \hat{F})$. Where,

$$0 \le \hat{T} \le 1,$$

$$0 \le \hat{I} \le 1,$$

$$0 \le \hat{F} \le 1,$$

$$and \;\; 0 \le \hat{T} + \hat{I} + \hat{F} \le 3$$

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

$\left(\hat{T}, \hat{I}, and\ \hat{F}\right)$ are the degrees of membership (object), indeterminacy (edge) and non-membership (background) of the images $im_j^{comp} \in im^{comp}$ to the vague concept importance of criterion respectively.

The weight of query image components lies in closed interval $\left[w_j^l, w_j^u\right]$ where,

$$[w_j^l, w_j^u] = \left[\min\left(\frac{\hat{T}_j + \hat{I}_j}{2}, \frac{1-\hat{F}_j + \hat{I}_j}{2}\right), \max\left(\frac{\hat{T}_j + \hat{I}_j}{2}, \frac{1-\hat{F}_j + \hat{I}_j}{2}\right)\right]$$

Where, for each query images are $0 \le w_j^l \le w_j^u \le 1$.

Neutrosophic Image Clustering - cont.

B. Optimization neutrosophic image clustering.

Then the suitability degree of alternative NsIC (Cl_i) satisfies the query images components can be measured by:

$$R(Cl_i) = \max\left\{ (W(Cl_i))^2 - \left(\frac{1-T(Cl_i)}{2}\right) \left(S_c\left(\left[\hat{r}_{ij}^{l}, \hat{r}_{ij}^{u}\right]\right)\right)^2 - \frac{1-A_c\left(\left[\hat{r}_{ij}^{l}, \hat{r}_{ij}^{u}\right]\right)}{2} \right\}$$

The optimal weights value can be computed via the following programming:

$$R(Cl_i) = \sum_{j=1}^{n} \left(\left(2\left(K_{ij}^{u} - K_{ij}^{l}\right)\right)^2 - \frac{1 - \frac{\left(K_{ij}^{l} + K_{ij}^{u}\right)}{2}}{2} \right) w_{*}^{j}$$

Subject to the conditions:

$$w_j^{l} \le w_{*}^{j} \le w_j^{u}$$

$$where,\ j = 1, 2, \ldots, n$$

Conclusion.

This paper presents a new technique to unsupervised classification for images based on neutrosophis sets and optimization linear programming.

Neutrosophic theory was used to transform the gray image to neutrosophic image components (O, E, B). Indeterminacy set (E) was worked on determine the objects boundaries with high precision.

Determining the boundaries of objects accurately blunted the effect of the overlapping problem within the cluster.

Neutrosophic image clustering method based on fuzzy c-means is used. Neutrosophic image clustering has been enhanced by using the λ-mean operation which helped on solve the overlapping problem between clusters.

Optimization neutrosophic image clustering is achieved by using the weight coefficient between image clusters and images category as an object function in linear programming problem.

Conclusion - cont.

Whereas, the constraints of linear programming problem are the weight limits for query images.

Practical results conducted on neutrosophic image clustering technique has proved its efficiency where it was to obtain the high performance rate in the accuracy of the resulting clusters as well as high values of recall and precision measures.

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