Fuzzy Logic Based Gray Image Extraction and Segmentation

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Abstract: Image segmentation and subsequent extraction from a noise-affected background, has all along remained a challenging task in the field of image processing. There are various methods reported in the literature to this effect. These methods include various Artificial Neural Network (ANN) models (primarily supervised in nature), Genetic Algorithm (GA) based techniques, intensity histogram based methods etc. Providing an extraction solution working in unsupervised mode happens to be even more interesting a problem. Fuzzy systems concern fundamental methodology to represent and process uncertainty and imprecision in the linguistic information. The fuzzy systems that use fuzzy rules to represent the domain knowledge of the problem are known as Fuzzy Rule Base Systems (FRBS). Literature suggests that effort in this respect appears to be quite rudimentary. In the present article, we propose a fuzzy rule guided novel technique that is functional devoid of any external intervention during execution. Experimental results suggest that this approach is an efficient one in comparison to different other techniques extensively addressed in literature. In order to justify the supremacy of performance of our proposed technique in respect of its competitors, we take recourse to effective metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE) and Peak Signal to Noise Ratio (PSNR).

Index Terms - Fuzzy Rule Base, Image Extraction, Fuzzy Inference System (FIS), Membership Functions, Threshold methods, Soft Computing, Fuzzy Image Processing, Feature based modeling

1 Introduction

In traditional computing methodology, the prime considerations are precision, certainty, and rigor. By contrast, the principal guidelines of soft computing [1] revolve around the following: tolerance for imprecision, uncertainty, partial truth and approximation. It will help to achieve tractability, robustness and low solution cost. This leads to the remarkable human ability of understanding distorted speech, deciphering sloppy handwriting, comprehending the nuances of natural language, summarizing text, recognizing and classifying images, driving a vehicle in dense traffic and, more generally, making rational decisions in an environment of uncertainty and imprecision. Soft computing is a consortium of methodologies that works synergetically and provides in one form or another flexible information processing capability for handling real life ambiguous situations. The guiding principle is to devise methods of computation that lead to an acceptable solution at low cost by seeking for an approximate solution to an imprecisely/precisely formulated problem. The theory of fuzzy logic [2] provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning.

The conventional approaches to knowledge representation lack the means for representing the meaning of fuzzy concepts. As a consequence, the approaches based on first order logic and classical probability theory do not provide an appropriate conceptual framework for dealing with the representation of commonsense knowledge, since such knowledge is by its nature both lexically imprecise and non-categorical. Fuzzy Logic is usually regarded as a formal way to describe how human beings perceive everyday concepts. In Fuzzy Image processing, fuzzy set theory [3] is applied to the task of image processing. Fuzzy Image Processing is depends upon membership values [4], rule-base and inference engine. Unlike classical logic systems, Fuzzy Logic (FL) aims at modeling the imprecise modes of reasoning, which is the human ability to make a rational decision when information is uncertain and imprecise. FL starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. Membership criteria are not precisely defined for most classes of objects normally encountered in the real world. A fuzzy set is characterized by a membership function, that takes values in the interval [0, 1], such that the nearer the value to unity, the higher the membership grade. The uncertainty in image extraction and subsequent segmentation from noise affected scene effectively handled by Fuzzy Logic. According to [5], fuzzy approaches for image segmentation can be categorized into four classes: segmentation via thresholding, segmentation via clustering, supervised segmentation and rule based segmentation. Among these categories,

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rule based segmentation are able to take advantage of application dependent heuristic knowledge and model them in the form of fuzzy rule base. In our case, the heuristic knowledge gathers by the process of already exist threshold segmentation methods that helped us to build the rule base. Thresholding is a simple shape extraction technique. If it can be assumed that the shape to be extracted is defined by its brightness, then thresholding an image at that brightness level should find the shape. Thresholding is clearly sensitive to change in illumination: if the image illumination changes then so will the perceived brightness of the target shape. Unless the threshold level can be arranged to adapt to the change in brightness level, any thresholding technique will fail. Its attraction is simplicity: thresholding does not require much computational effort. If the illumination level changes in a linear fashion, then using histogram equalisation will result in an image that does not vary. Unfortunately, the result of histogram equalisation is sensitive to noise: noise can affect the resulting image quite dramatically and this will help us to determine the minute changes in the original images clearly. Image Segmentation and subsequent extraction from noise-affected scene happen to be crucial phase of image processing. The complex process of human vision is yet not comprehensively explored, in spite of several decades of dedicated study on the problem, may it be from the perspective of basic science or from the viewpoint of research on intelligence. In computer vision, the complex process of recognizing shapes, colors, textures and subsequently grouping them automatically into separate regions or objects within a scene continues to be an open research avenue, intrinsically because of the uncertainty associated with it. Out of the twin objectives of segmentation and extraction, championed earlier, image segmentation appears to be a low-level image-processing task that aims at partitioning an image into regions in order that each region/ group consists of homogeneous pixels sharing similar attributes (intensity, colors etc.). The problem becomes even more challenging with the presence of noise in the image scene where the uncalled noise components need to be eliminated while preserving the image content as much as possible. Naturally, the extraction of objects prevalent in an image content from a noise affected background. The visual features such as shape, color and texture are extracted to characterize images in the phase of image extraction. Each of the features is represented using one or more feature descriptors. During the process, features and descriptors of the query are compared to those of the images in order to calculate rank of each indexed image according to its distance to the query. The extraction task transforms rich content of images into various content features. Feature extraction is the process of generating features to be used in the selection and classification tasks. Feature selection reduces the number of features provided to the classification task. Those features that are likely to assist in discrimination are selected and used in the classification task. Features that are not selected are discarded [6]. After the features are extracted, a suitable classifier must be chosen. A number of classifiers are used and each classifier is found suitable to classify a particular kind of feature vectors depending upon their characteristics. The classifier used commonly is Nearest Neighbor classifier. The nearest neighbor classifier is used to compare the feature vector of the prototype with image feature vectors stored in the database. High-level feature extraction concerns finding shapes in computer images. To be able to recognise faces automatically, for example, one approach is to extract the component features. This requires extraction of, say, the eyes, the ears and the nose, which are the major face features. To find them, we can use their shape: the white part of the eyes is ellipsoidal; the mouth can appear as two lines, as do the eyebrows. Shape extraction implies finding their position, their orientation and their size. This feature extraction process can be viewed as similar to the way we perceive the world: many books for babies describe basic geometric shapes such as triangles, circles and squares. More complex pictures can be decomposed into a structure of simple shapes. Modular approaches partitions the classification task into some sub-classification tasks, solve each sub-classification task, and eventually integrates the results to obtain the final classification result. In other words, partitioning of the classification task is carried out such that each sub-problem can be solved in a module by exploiting the local uncertainties and exploiting the global uncertainties can combine the results of all the modules. The performance of each module can be improved by giving importance to the features based on their class discrimination capability for the output classes present in the module. In many applications, analysis can be guided by the way the shapes are arranged. The task of pattern classifier is to search the structure. This search becomes complicated because of the presence of uncertainties associated with the structure. Thus, the whole pattern classification process involves manipulation of the information supplied by the instances. The instances contain the information about the process generating them, and the extracted features reflect this information. The structures present inside the features represent the information in an organized manner so that the relationship among the variables in the classification process can be identified. Finally, in the last step, a search process recognizes the information from the structure. Now, if a new pattern is encountered, the machine detects the structure in which the input pattern belongs, and based on the structure the pattern is classified. Therefore, once the structure is found, the machine is capable of dealing with new situations to some extent. The issue of choosing the features to be extracted should be guided by the following concerns:

1. The features should carry enough information about the image and should not require any domain-specific knowledge for their extraction.
2. They should be easy to compute in order for the approach to be feasible for a large image collection.

3. They should relate well with the human perceptual characteristics since users will finally determine the suitability of the retrieved images.

In the other hand, two steps have to be considered in order to address any segmentation problem:

Step 1: Formalize the segmentation problem, a mathematical notion of homogeneity or similarity among image- regions need to be considered.

Step 2: An efficient algorithm for partitioning or clustering has to be derived particularly to carry the earlier step out in a computationally efficient manner.

The problems of image segmentation become more uncertain and severe when it comes to dealing with noisy images. The vagueness of image information arising out of admixture of the different components has been dealt with soft computing paradigm. Numerous articles and several surveys on gray /monochrome image segmentation techniques have to be reported in this regard [7] [8][11].

A formal definition of segmentation of an image can be defined as in [9]. Segmentation of image I is a partition P of I into a set of M regions {Rm, m=1, 2…M} such that:

$$\textbf{1.}\quad \cup_{m=1}^{M} R_m = I \ \textbf{with} R_m \cap R_n = \Phi,$$

$$m \neq n, 1 \leq m, n \leq M$$

$$\textbf{2.}\quad H(R_m) = \textbf{true} \ \forall\, m, 1 \leq m, n \leq M$$

$$\textbf{3.}\quad H(R_m \cap R_n) = \textbf{false} \ \forall\, R_m \ \textbf{and} \ R_n$$

$$\textbf{adjacent}, 1 \leq m, n \leq M$$

Figure 1: Segmentation definition

Here H is the predicate of homogeneity. A region is homogeneous if all its pixels satisfy the homogeneity predicate defined over one or more pixel attributes such as intensity, texture or color. On the other hand, a region is connected if a connected path exists between any two pixels within the region.

Because of the large diversity of segmentation methods, it is indeed difficult to exhaustively review each individual segmentation techniques up to now. However, segmentation methods can be broadly classified as [9][10][11][12][13]:

1. Region or boundary-based;
2. Graph-based;
3. Histogram-based;
4. Pixel based;
5. Area based;
6. Physics based;

This chapter is presented in the following manner. In the section 2, we would like to discuss survey of recent methodologies in this area; section 3 proposes our present work; section 4 clarifies the results and analysis followed by conclusion.

2 SURVEY

Gray scale image segmentation approaches are based on either discontinuity and/or homogeneity of gray level values in a region. The approach based on discontinuity, tends to partition an image by detecting isolated points, lines and edges according to abrupt changes in gray levels in two adjacent regions in the scene. The approaches based on homogeneity include thresholding, clustering, region growing and region splitting & merging. Several surveys are reported in the literature to this effect. Fu et al. discussed segmentation from the viewpoint of cytology image processing [7]. The paper categorized various existing segmentation techniques into three classes:

1. Characteristic feature thresholding or clustering
2. Edge detection and
3. Region extraction.

The segmentation techniques were summarized and comments were provided on the pros and cons of each approach. The threshold selection schemes based on gray level histogram and local properties as well as based on structural, textural and syntactic techniques were described [7][8][9]. Clustering techniques were regarded as "the multidimensional extension of the concept of thresholding". Some clustering schemes utilizing different kinds of features (multi-spectral information, mean/ variation of gray level, texture, color) were discussed. Various edge detection techniques were presented, which were categorized into two classes - parallel and sequential techniques. The parallel edge detection technique [10][11] implies that the decision of whether a set of points is on an edge or not, depends on the gray level of the set and some set of its neighbors, which includes high emphasis on spatial frequency filtering, gradient operators, adaptive local operator, functional approximations, heuristic search and dynamic programming, relaxation and line & curve fitting, while the sequential techniques make decision based on the results of the previously examined points. A brief description of the major component of a sequential edge detection procedure was provided in [7][9]. In those papers region merging, region splitting and combination of region merging and splitting approaches briefly introduced. Haralick et al. classified image segmentation techniques into six major groups [8]:

1. Measurement space guided spatial clustering
2. Single linkage region growing schemes
3. Hybrid linkage region growing schemes

4. Centroid linkage region growing schemes
5. Spatial clustering schemes and
6. Split & merge schemes.

These techniques are compared on the problem of region merge error, blocky region boundary and memory usage. The hybrid linkage region growing schemes appear to be the best compromise between having smooth boundaries and few unwanted region merges. One of the drawbacks of feature space clustering is that the cluster analysis does not utilize any spatial information. The article also presented some spatial clustering approaches, which combine clustering in feature space with region growing or spatial linkage techniques. It provides a good summary of kinds of linkage region growing schemes. The problem of high correlation and spatial redundancy of multi-band image histograms and the difficulty of clustering using multi-dimensional histograms are also discussed. Sahoo et al. surveyed segmentation algorithms based on thresholding and attempted to evaluate the performance of some thresholding techniques using uniformity and shape measures [9]. It categorized global thresholding techniques into two classes:

i. point-dependent techniques (gray level histogram based)
ii. region-dependent techniques (modified histogram or co-occurrence based).

Histogram thresholding is one of the widely used techniques for monochrome image segmentation. It assumes that images are composed of regions distributed with different gray level ranges. As for color images, the situation is different from monochrome images because of presence of multiple features. Multiple histogram-based thresholding is able to decompose color space by thresholding histogram component-wise. Guo et al. adopted entropy based thresholding method [18]. Mode seeking is decided by the multi-modal probability density function (pdf) estimation and the mode can be found by thresholding the pdf. In the above approaches, thresholding is performed with only one color component at a time. Thus the regions extracted are not based on the information available from all three components simultaneously because the correlation among the three components is neglected. This problem can be solved if we can get hold of such an approach that the points in the 3D space are projected onto it and the projected points can be well separated. Generally, two or more characteristic features form a feature space and each class of regions is assumed to form a separate cluster in the space. The reason to use multiple characteristic features to perform image segmentation is that, sometimes, problems might crop up which are not solvable with one feature but is also solvable with multiple features. The characteristic features may be any features that could be used for the segmentation problem, such as the gray level value of multi-spectral images, gray level histogram, mean, deviation, texture, etc. Discussion on probabilistic relaxation and several methods of multi-thresholding techniques was also available in [8][11]. Spirkovska et al. regarded image segmentation in a machine vision system as the bridge between a low-level vision subsystem including image processing operations (such as noise elimination, edge extraction etc.) to enhance the image quality on one hand and a high-level vision subsystem including object recognition and scene interpretation on the other [10].

Most gray level image segmentation techniques can be extended to color images, such as histogram thresholding, clustering, region growing, edge detection, fuzzy approaches and neural networks. Gray level segmentation methods can be directly applied to each component of a color space. The results can be combined in some way to obtain a final segmentation result. Segmentation may also be viewed as image classification problem based on color and spatial features [11]. Therefore, segmentation methods can be categorized as supervised or unsupervised learning /classification procedures. Power et. al. compared different color spaces (RGB, normalized RGB, HSI- hybrid color space) and supervised learning algorithms for segmenting fruit images [14]. Supervised algorithms include Maximum Likelihood, Decision Tree, K-Nearest Neighbor, Neural Networks, etc. Hance et al. explored six unsupervised image segmentation approaches [15]:

1. Adaptive thresholding
2. Fuzzy C-means (FCM)
3. SCT/center split
4. PCT (Principal Components Transform) median cut
5. Split and merge
6. Multi-resolution segmentation.

Some algorithms resort to combination of unsupervised and supervised methods to segment color images. Hu et al. used unsupervised learning and classification based on the FCM algorithm and nearest prototype rule [16]. The classified pixels are used to generate a set of prototypes, which are optimized using a multilayer neural network. The supervised learning is utilized because the optimized prototypes are subsequently used to classify other image pixels. Eom et al. employed a neural network for supervised segmentation and a fuzzy clustering algorithm for unsupervised segmentation [17]. Histogram thresholding is one of the widely used techniques for monochrome image segmentation. It assumes that images are composed of regions distributed with different gray level ranges. The histogram of an image can be separated into a number of peaks (modes) each corresponding to one region and there exists a threshold value corresponding to valley between the two adjacent peaks. However, there is limitation since all the existing thresholding techniques having notional resemblance to gray scale images.

In order to obtain the maximum information between two sources, mode (regions with high densities) and valley (regions with low densities), Guo et al. adopted entropy based thresholding method [18]. Mode seeking is decided by the multi-modal probability density function (pdf) estimation and the mode can be found by thresholding the pdf. A network for classifying an image into distinct regions can be subjected to either supervised or unsupervised learning. The learning would be supervised if external criteria and/or intervention are used and matched by the network output otherwise the learning is unsupervised [19].

Genetic algorithm is another search strategy based on the mechanism of natural selection and group inheritance in the process of biological evolution [20][21]. It simulates the cases of reproduction, mating and mutation in sexual reproduction. GA looks each potential solution as an individual in a group (all possible solutions) and encodes each individual into an encoded domain where the genetic operators [21] can be effectively applied.

Fuzzy systems and Artificial Neural Network (ANN) are soft computing approaches to modeling expert behavior. The goal is to mimic the actions of an expert who solves complex problems. In other words, instead of investigating the problem in detail, one observes how an expert successfully tackles the problem and obtains knowledge by instruction and/or learning. Let us consider the significance of querying and rule generation, by referring to the example of decision making system generally followed up in medical diagnostics. The models are generally capable of dealing with non-availability of data, and can enquire the user for additional data when necessary. In the medical domain, for instance, data may be missing for various reasons; for example, some examinations can be risky for the patient or contraindications can exist, an urgent diagnostic decision may need to be made and some very informative but prolonged test results may have to be excluded from the feature set, or appropriate technical equipment may not be available. In such cases, the network can query the user for additional information only when it is particularly necessary to infer a decision. Again, one realizes that the final responsibility for any diagnostic decision always has to be accepted by the medical practitioner. So the physician may want to verify the justification behind the decision reached, based on personal expertise. This requires the system to be able to explain its mode of reasoning for any inferred decision or recommendation, preferably in rule form, to convince the user that the reasoning is correct. Human operators have an advantage over control and protection systems in terms of their experience and ability to assimilate a wide spectrum of information and new data. In contrast, computers have the advantage of being able to process such information much faster than their human counterparts. Fuzzy logic has that capability of taking advantage of the operators' experience and the fast data processing capability of computers. A learning process can be part of knowledge acquisition. In the absence of an expert or sufficient time or data, one can resort to reinforcement learning instead of supervised learning. In general, if one has knowledge expressed as linguistic rules, one can build a fuzzy system. On the other hand, if one has data or can learn from a simulation or the real task, ANN's are more appropriate [22]. Compared to neural network model, fuzzy model integrate the knowledge representation and reasoning mechanism with the priori expert experience and knowledge, consistent with people's habits of mind, its structure and membership function parameters have obvious semantic meaning, it can be easily understood its internal operation mechanism by studying the rules of fuzzy system, in conclusion, the explanation is the most prominent feature of a fuzzy model. How to automatically construct the fuzzy systems with accuracy and proper explanation from data analysis, is the key point of this research area. The explanatory of Fuzzy classification system, so far has no clear definition, but is generally believed that the explanatory of fuzzy classification system is closely related with the number of the characteristics variables, the number of fuzzy rules, and the characteristics of membership functions, and the fuzzy classification system with fewer number of feature variables, fewer number of fuzzy rules has better explanation ability. In feature extraction [23], we generally seek invariance properties so that the extraction process does not vary according to chosen (or specified) conditions. That is, techniques should find shapes reliably and robustly whatever the value of any parameter that can control the appearance of a shape. As a basic invariant, we seek immunity to changes in the illumination level: we seek to find a shape whether it is light or dark. In principle, as long as there is contrast between a shape and its background, the shape can be said to exist, and can then be detected. It is clear that, any computer vision technique will fail in extreme lighting conditions; you cannot see anything when it is completely dark. Then, we often seek to find a shape irrespective of its rotation (assuming that the object or the camera has an unknown orientation): this is usually called rotation- or orientation invariance. Then, we might seek to determine the object at whatever size it appears, which might be due to physical change, or to how close the object has been placed to the camera. This requires size- or scale-invariance. These are the main invariance properties we shall seek from our shape extraction techniques. However, nature tends to roll balls under our feet: there is always noise in images. Also since we are concerned with shapes, note that there might be more than one in the image. If one is on top of the other, it will occlude, or hide, the other, so not all the shape of one object will be visible. But before we can develop image analysis techniques, we need techniques to extract the shapes. Extraction is more complex than detection, since extraction implies that we have a description of a shape, such as its position and size, whereas detection of a shape merely implies knowledge of its existence within an image [24]. In order to extract a shape from an image, it is necessary to identify it from the background elements. This can be done by considering the intensity information or by comparing the pixels against a given template. In the first approach, if the brightness of the shape is known, then the pixels that form the shape can be extracted by classifying the pixels according to a fixed intensity threshold. Alternatively, if the background image is

known, then this can be subtracted to obtain the pixels that define the shape of an object superimposed on the background. Template matching is a model-based approach in which the shape is extracted by searching for the best correlation between a known model and the pixels in an image.
There are alternative ways to compute the correlation between the template and the image. Correlation can be implemented by considering the image or frequency domains. Additionally, the template can be defined by considering intensity values or a binary shape.

Wang and Archer [26] have introduced ultrafuzzy sets for modeling decision-making under conflict, using a modified version of backpropagation. In case of ultrafuzzy sets, the membership function takes on fuzzy values. Ultrafuzzy interval of certainty factor is modeled as the consequent of a rule. Two fuzzy membership functions termed as participation and moderation functions, falling in the ultrafuzzy interval, are developed based on the well-known plausibility and belief functions [27]. The concept of plausibility and belief functions is used to construct conflict measures, which help in explaining the compromise phenomena observed in decision-making. This fuzzy decision-making model is capable of cumulating human knowledge and is claimed to be useful for maintaining consistency while making decisions. According to [28], It is appropriate to use FL when:

1. one or more of the variables are continuous and are not easily broken down into discrete segments;
2. a mathematical model of the process does not exist, or exists but is too difficult to encode;
3. a mathematical model of the process exists but is too complex to be evaluated fast enough for real-time operation;
4. high ambient noise levels are expected in the input signals; and/or
5. engineering interpretations become highly subjective and context dependent.

Engineering interpretations becomes highly subjective and context dependent when considering the additional information such as historical usage trends, weather, and system/component reliability data. Generally the rules and the membership functions used by the fuzzy logic for solving the classification problem are formed from the experience of the human experts. With an increasing number of variables, the possible number of rules for the system increases exponentially, which makes it difficult for experts to define a complete rule set for good system performance.

In fuzzy inferencing and rule generation approaches, the fuzzy classification rule described by Ishibuchi et al. [29], the partitioning is uniform, i.e., the regions continue to be split until a sufficiently high certainty of the rule, generated by each region, is achieved. Ishibuchi et al. extended this work later [30] by using an idea of sequential partitioning of the feature space into fuzzy subspaces until a predetermined stopping criterion is satisfied and studied its application for solving various pattern classification problems. Wang and Mendel [31] developed a slightly different method for creating a fuzzy rule base, made up of a combination of rules generated from numerical examples and linguistic rules supplied by human experts. The input and output domain spaces are divided into a number of linguistic subspaces. Human intervention is sought to assign degrees to the rules and conflicts are resolved by selecting those rules yielding the maximum of a computed measure corresponding to each linguistic subspace. Rovatti and Guerrieri [32] have attempted to identify the correct rule structure of a fuzzy system when the target input–output behavior is sampled at random points. The assumption that a rule can either be included or excluded from the rule set is relaxed, and degrees of membership are exploited to achieve good approximation results. In [33], the proper fuzzy rule base for gray image extraction possessed with the help of correct rule structure. In the rule generation phase, different existing thresholding methods are used to build membership functions. Defuzzification methodologies are then used to extract well-behaving crisp rule sets. Symbolic minimization is carried out to obtain a compact structure that captures the high-level characteristics of the target behavior. For other details, one may refer to [35]–[36]. Dietterich et. al. [37] suggests a Multiple Classifier Systems that introduce a new way for building more accurate classifiers. He suggests three types of reasons namely, statistical, representational and computational, explaining why a classifier ensemble can be better than a single classifier. There are two approaches for making a classifier out of multiple classifier systems namely, classifier fusion and classifier selection [38]. In classifier fusion each classifier is supposed to know the whole data points in feature space, whereas in classifier selection each ensemble member is supposed to know one part of the feature space well and be responsible for objects in this part. In the selection approach we select one or more classifiers to label a new input. Some of the more famous methods for classifier fusion are Majority vote, Weighted Majority vote, Naive Bayes Combination, Multinomial Methods and Probabilistic Approximation [39]. The most commonly used method is assigning a competence to each classifier for the current input and choosing the most competent one. Kuncheva et. al. [38] shows that if we select the best classifier for each region in feature space, regardless of how we partition feature space, the resulting classifier is at least as good as the best classifier in the ensemble.

The theory of rough sets [39] has recently emerged as another major mathematical tool for managing uncertainty that arises from granularity in the domain of discourse, i.e., from the indiscernibility between objects in a set. The intention is to approximate a rough (imprecise) concept in the domain of discourse by a pair of exact concepts, called the lower and upper approximations. These exact concepts are determined by an indiscernibility relation on the domain, which, in turn, may be induced by a given set of attributes ascribed to the objects of the domain. The lower approximation is the set of objects definitely belonging to the vague concept, whereas the upper approximation is the set of objects possibly belonging to the same. These approximations are used to define the notions of discernibility matrices, discernibility functions, reducts, and dependency factors, all of which play a fundamental role in the reduction of knowledge.

3 Present work

It is interesting that all methods invariably performed poorly for at least one or two instances. Thus it was observed that any single algorithm could not be successful for all noisy image types, even in a single application domain. To obtain the robustness of the thresholding method, we explored the combination of more than one thresholding algorithm based on the conjecture that they could be complementary to each other. The combination of thresholding algorithms can be done at the feature level or at the decision level. At the feature level, we use, for example, some averaging operation on the maximum values obtained from individual algorithms; on the decision level, we have fusion of the foreground-background decisions, for example, by taking the majority decision. Thus it will help us on creating membership envelops in the proposed system.

The algorithm for the proposed work is as follows:

Step 1. Read a noisy image as input

Step 2. Identify the Region of Interests of the image by different thresholding values

Step 3. Extract the image information in terms of pixel attributes and threshold values for future use.

Step 4. Construct the different membership envelops of the input image.

Step 5. Generate fuzzy rules based on the numerical data obtained from the input image corrupted by noise. The fuzzy rule generation consists following steps:

a. Discern Input and Output spaces into fuzzy regions
b. Generate fuzzy rules from the given data
c. Map the threshold values obtained from different methods in the corresponding fuzzy region
d. Create a combined fuzzy rule base Determine a mapping on the basis of this combined fuzzy rule base.

Step 6. Approximate the value obtained in Step 5.

Step 7. Display the image constructed thus.

Fuzzy image processing is the collection of all approaches that understand, represent and process the images, their segments and features as fuzzy sets. Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. Building classifiers involves capturing the similarity among the training patterns and assigning labels for the group of similar patterns. Capturing the similarity among patterns becomes complicated when a training pattern belongs to more than one class, i.e., the output classes are overlapping. Thus fuzzy uncertainty appears in form of similarity and overlap. Due to the lack of details, two input patterns may appear similar whereas the class labels may not be same. The complexity and limitations of previous mechanisms are largely due to the lacking of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases. On the contrary, fuzzy classification assumes the boundary between two neighboring classes as a continuous, overlapping area within which an object has partial membership in each class. This viewpoint not only reflects the reality of many applications in which categories have fuzzy boundaries, but also provides a simple representation of the potentially complex partition of the feature space. Both neural networks and fuzzy systems are dynamic, parallel processing systems that estimate input–output functions. They estimate a function without any mathematical model and learn from experience with sample data. A fuzzy system adaptively infers and modifies its fuzzy associations from representative numerical samples. In brief, we use fuzzy IF-THEN rules to describe a classifier. The representation and processing depend on the selected fuzzy technique and on the problem to be solved. A fuzzy system is comprised of five basic elements, as shown in Figure 2. A fuzzifier is responsible for mapping the crisp inputs from the system into fuzzy sets modeling the inputs. The second element is the knowledge base, which incorporates the required knowledge about the system in the form of fuzzy If-Then rules. The rules are governed by the relationships between the inputs and the way that they combine to produce the desired output. The third element is the fuzzy model, which is the group of fuzzy sets describing each of the input and output variables. The fuzzy sets partition the universe of discourse of a given input or output variable into a group of overlapping fuzzy sets. The fourth element is the fuzzy inference system, which is the reasoning process through which the fuzzified inputs are used to activate the relevant rules. The last element is the defuzzifier, which is the mechanism by which the fuzzy input set is converted into a single output value or control parameter.

The fuzzification and defuzzification steps are particularly important because of absence of any fuzzy hardware at our disposition. Therefore, the coding of image data (fuzzification) and decoding of the results (defuzzification) are steps indispensible that make possible to process images with fuzzy techniques. The main power of fuzzy image processing lies in the effective use of the middle step (modification of membership values). Wang et al. [25] have used a fuzzy logic rule-based system to first determine a good feature set for the recognition of Escherichia coli O157:H7, a cause of serious health problems. Fuzzy membership functions are defined for each term set of each linguistic variable in the rules. The human inspired features of this reduced rule set are then incorporated in a multiple neural network fusion approach. The fuzzy integral is utilized in the fusion of the networks trained with different feature sets. Unfortunately, most of the available literature on rule generation does not provide such rigorous assessment on their pros and cons. There is also a preponderance of specific purpose techniques that are designed to work with a particular architecture. This limits the scope of comparing the various techniques in a single framework.

4 Results and Analysis

The goal of this paper is to describe a generic system using a Mamdani rule base. Specifically, we are modeling the relationship among the images, its extracted counterpart and the fuzzy rule base system using as many as 15 well known thresholding methods. In pattern recognition and mage processing, feature extraction is a special form of dimensionality reduction. Feature extraction is a general term for methods for constructing combinations of the variables, but still describes the data sufficiently accurately. All images of different categories can be distinguished via their homogeneousness or feature characteristics. All the thresholding methods are generally based on the characteristics of one or some features, which will help us to build an adaptive mechanism guided by some already established methods. We use Lena images having 256X256 and 512X512 dimensions with Gaussian and Salt and Pepper noise respectively. We are using different noise levels and use all the existing techniques and our proposed technique to extract images. The comparisons are listed in the TABLE-1 and TABLE-2. We evaluated all possible to measure of how well the rule described the actual system behavior over the domain where its antecedent was true. In this paper, we take proper care about how well a Mamdani rule base can be put to model the system, using rules that have high correctness.

For Gaussian noise, the corrupted image, subsequent result obtained by well-known methods and proposed fuzzy rule base method is depicted in Figure 3, Figure 4 and Figure 5 respectively and the same for the salt and pepper noise are depicted in Figure 6, Figure 7 and Figure 8 respectively. The comparison among different PSNR values of Gaussian and Salt and Pepper noises are illustrated in Figure 9 and Figure 10 respectively.

5 Conclusion

The main features and advantages of this approach are:

1. It provides us a general method to combine measured numerical information into a common framework- a combined fuzzy rule base that theoretically entertains both numerical and linguistic information

2. It is a simple and straightforward single pass buildup procedure and hence is devoid of any time consuming iterative training as it happens in a comparable neural network or in a neuro-fuzzy approach

3. There is a lot of freedom in choosing the membership domains in the said design. In fact, this happens to be one of the fundamental challenges

4. This can be viewed as very general model free integrated fuzzy system for a wide range of image processing problems where “model free” means no mathematical model is required for the problem; “integrated” means the systems integrates all the reported threshold values that are integrated with the systems for finding ROIs and that can help to design adaptive fuzzy regions; and, “Fuzzy” denotes the fuzziness introduced into the system by linguistic fuzzy rules, fuzziness of data, etc.

There are two criteria used in assessing the quality of images. They are subjective criterion and objective criterion. The subjective criterion relies on human beings’ individual judgment and interpretation. Naturally, it is shrouded with the possibility of inconsistency and lacks repeatability, it is also time consuming and expensive. One of the standard ways of subjective measurement is called Mean Opinion Score (MOS), it is very tedious, costly and could not be feasible in real time. It has five scales ranging from ‘impairment is not noticeable’ (best) to ‘impairment is extremely objectionable’ (worst). On the other hand, the objective criterion available relies on the result of computing some of the following statistical error based methods dependent on pixels difference. Overall image mean absolute error (MAE), overall image mean square error (MSE), signal-to-noise ratio (SNR), or peak signal-to-noise ratio (PSNR) figure this list. The smaller the MAE (or MSE) or the larger the SNR (or PSNR) is, the higher is the quality of the signal. It is fast and repeatable.

There is no universal theory on image segmentation yet that may be universally applicable in all types of images. This is because image segmentation is subjective in nature and suffers from uncertainty. All the existing image segmentation approaches are, in the main, ad hoc. They are strongly application specific. In other words, there are no general algorithms vis-à-vis color spaces that are uniformly good for all color images. An image segmentation problem is fundamentally one of psychophysical perception and it is essential to supplement any mathematical solutions by a priori knowledge about the image. The fuzzy set theory has attracted more and more attention in the area of image processing because of its inherent capability of handling uncertainty. Fuzzy set theory provides us with a suitable tool, which can represent the uncertainties arising in image segmentation and can model the relevant cognitive activity of the human beings. Fuzzy operators, properties, mathematics, inference rules have found more and more applications in image segmentation. Despite the computational cost, fuzzy approaches perform comparable to or better than their crisp counterparts. The more important advantage of a fuzzy methodology lies in that the fuzzy membership function provides a natural means to model the uncertainty prevalent in an image scene. Subsequently, fuzzy segmentation results can be utilized in feature extraction and object recognition phases of image processing and subsequent computer vision. Fuzzy approach also provides a promising means for color image segmentation.

REFERENCES

[1]. L. A. Zadeh, "Fuzzy logic, neural networks, and soft computing," Communication ACM, vol. 37, pp. 77–84, 1994.

[2]. L.A. Zadeh, "Fuzzy Sets", Information and Control, 1965.

[3]. L.A. Zadeh, "Outline of A New Approach to the Analysis of Complex Systems and Decision Processes", 1973.

[4]. L.A. Zadeh,"Fuzzy algorithms," Info. & Control, Vol. 12, 1968, pp. 94-102.

[5]. Bezdek J C, Kellar J, Raghu K, Pal N H, "Fuzzy models and algorithms for pattern recognition and image processing" Kluwar Academic Publishers, Boston 1999.

[6]. IEEE Computer, Special issue on Content Based Image Retrieval, 28, 9, 1995.

[7]. K. S. Fu and J.K. Mui, "A Survey on Image Segmentation", Pattern Recognition, 13, 3-16, 1981.

[8]. R. M. Haralick, L. G. Shapiro, "Image Segmentation Techniques", Computer Vision, Graphics and Image Processing, 29, 100-132, 1985.

[9]. P. K. Sahoo et. al., "A Survey of Thresholding Techniques", Computer Vision, Graphics and Image Processing, 41, 233-260, 1988.

[10]. L. Spirkovska, "A Summary of Image Segmentation Techniques", NASA Technical Memorandum, 104022, June 1993.

[11]. S.K. Pal et. al. "A Review on Image Segmentation Techniques", Pattern Recognition, 29, 1277-1294, 1993.

[12]. E. M. Riseman and M. A. Arbib, "Computational Techniques in the Visual Segmentation of Static Scenes", Computer Vision, Graphics and Image Processing, 6, 221-276, 1977.

[13]. W. Skarbek, A. Koschan, "Colour Image Segmentation – A Survey", Technical Report, Tech. Univ. of Berlin, Oct. 1994.

[14]. W. Power and R. Clist, "Comparison of supervised learning techniques applied to color segmentation of fruit image", Proceedings of SPIE, Intelligent Robots and Computer Vision XV: Algorithms techniques, Active Vision and Materials Handling, 370-381, Nov. 19-21, 1996, Boston, Massachusetts.

[15]. G.A. Hance, S. E. Umbaugh, R. H. Moss and W. V. Stoecker, "Unsupervised color image segmentation with application to skin tumor borders", IEEE Engineering in medicine and biology, 104-111, January/February, 1996.

[16]. J. Hu, H. Yan, A. N. Chalmers, " Color image segmentation using fuzzy clustering and supervised learning", Journal of Electronic image, 3(4), 397-403, Oct. 1994.

[17]. K. B. Eom, "Segmentation of monochrome and color texture using moving average modeling approach", Image Vision Computing, 17(1999), 233-244.

[18]. G. D. Guo, S.Yu and S. D. Ma, "Unsupervised Segmentation of Color Images", IEEE International Conference on Image Processing, 299-302, 1998.

[19]. S. Bhattacharyya, P. Dutta, U. Maulik, "Binary object extraction using bi-directional self-organizing neural network (BDSONN) architecture with fuzzy context sensitive thresholding", International Journal on Pattern Analysis and Applications, Springer-Verlag, 2010.

[20]. D. E Goldberg, 1989, "Genetic Algorithm in Search, Optimization and Machine Learning", Addison-Wesley Reading, Massachusetts.

[21]. B. Bhanu, S. Lee, "Genetic Learning for Adaptive Image Segmentation", Kluwar Academic Press, 1994.

[22]. D. Nauck, F. Klawonn, and R. Kruse, Foundations of Neuro–Fuzzy Systems. Chichester, U.K.: Wiley, 1997.

[23]. Mark S. Nixon, Alberto S. Aguado, "Feature extraction and Image Processing" Newnes, Reed Elsevier plc. Group, 2002.

[24]. R. C. Gonzalez, R. E. Woods, and S. L. Eddins, Digital Image processing using MATLAB. Upper Saddle River, N. J.: Pearson Prentice Hall, 2004.

[25]. D. Wang, J. M. Keller, C. A. Carson, K. K. McAdoo-Edwards, and C.W. Bailey, "Use of fuzzy-logic-inspired features to improve bacterial recognition through classifier fusion," IEEE Trans. Syst., Man, Cybernetics, vol. 28, pp. 583–591, 1998.

[26]. S. Wang and N. P. Archer, "A neural network based fuzzy set model for organizational decision making," IEEE Trans. Syst., Man, Cybernetics, vol.28, pp. 194–203, May 1998.

[27]. G. Shafer, A Mathematical Theory of Evidence. Princeton, NJ: Princeton Univ. Press, 1976.

[28]. E. Cox, "Fuzzy fundamentals," IEEE Spectrum, vol. 29, no. 10, pp. 58-61, Oct. 1992.

[29]. H. Ishibuchi, K. Nozaki, and H. Tanaka, "Distributed representation of fuzzy rules and its application to pattern classification," Fuzzy Sets System, vol. 52, pp. 21–32, 1992.

[30]. H. Ishibuchi, K. Nozaki, and H. Tanaka, "Efficient fuzzy partition of pattern space for classification problems," Fuzzy Sets Syst., vol. 59, pp. 295–304, 1993.

[31]. L. Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," IEEE Trans. Syst., Man, Cybernetics, vol. 22, pp. 1414–1427, 1992.

[32]. R. Rovatti and R. Guerrieri, "Fuzzy sets of rules for system identification," IEEE Trans. Fuzzy Syst., vol. 4, pp. 89–102, 1996.

[33]. Koushik Mondal, Paramartha Dutta, Siddhartha Bhattacharyya,"Gray image extraction using fuzzy Logic" IEEE Second International Conference on Advanced Computing & Communication Technologies, pp.289-296,2012.

[34]. S. Abe and M. S. Lan, "Fuzzy rules extraction directly from numerical data for function approximation," IEEE Trans. Syst., Man, Cybernetics, vol. 25, pp. 119–129, 1995.

[35]. T. Hong and C. Lee, "Induction of fuzzy rules and membership functions from training examples," Fuzzy Sets Syst., vol. 84, pp. 33–37, 1996.

[36]. "Special issue on fuzzy diagnosis," Artificial Intelligence Med., vol. 16, no. 2,1999.

[37]. T. G. Dietterich, "Ensemble methods in machine learning," In J. Kittler and F. Roli, editors, Multiple Classifier Systems, volume 1857 of Lecture Notes in Computer Science, Cagliari, Italy, 2000, Springer, pp. 1–15.

[38]. Ludmila I. Kuncheva, Combining Pattern Classifiers: Methods and Algorithms, John Wiley & Sons, 2004, ISBN 0-471-21078-1.

[39]. Z. Pawlak, Rough Sets, Theoretical Aspects of Reasoning about Data. Dordrecht, The Netherlands: Kluwer, 1991.

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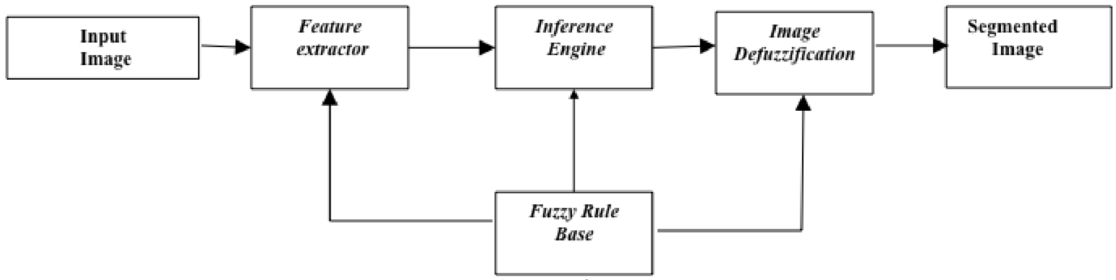

Figure 2: Schematic diagram of Fuzzy Image Processing

TABLE 1: COMPARISON OF GAUSSIAN NOISE REDUCTION WITH THE HELP OF DIFFERENT THRESHOLDING METHOD AND OUR PROPOSED METHOD

PSNR Calculation for Gaussian Noise					
Threshold method/Sigma	**15**	**30**	**45**	**60**	**75**
Default	18.7977	18.3826	17.8666	17.3449	16.9336
Huang	18.6423	18.3849	17.8578	17.3449	16.9263
Iso Data	18.9834	18.6435	17.4262	17.2113	16.9321
Li	18.6785	18.3245	17.8166	17.2354	16.8386
Max Entropy	18.7496	18.6748	17.4992	17.3166	16.9392
Mean	18.6342	18.3242	17.6822	17.3166	17.1336
Min Error	18.9321	18.3449	17.9321	17.8866	16.9336
Minimum	18.2435	18.1262	17.4221	17.3971	16.9491
Moments	18.9213	18.6314	17.8578	17.6314	16.937
Otsu	18.9932	18.6808	17.5817	17.4262	16.9336
Percentile	18.9213	18.6314	17.4213	17.3376	16.9321
RenyiEntropy	18.9491	18.6718	17.6166	17.4262	16.9392
Shanbhag	18.7661	18.2381	17.9932	17.7977	17.6166
Triangle	8.998	8.6314	7.7262	7.3216	5.4422
Yen	18.4262	18.2166	17.7143	17.4132	16.9402
Proposed method	**29.6435**	**29.3126**	**28.9962**	**28.7143**	**28.6166**

Figure 3: Image corrupted by Gaussian Noise

Figure 4: Image extracted by proposed method

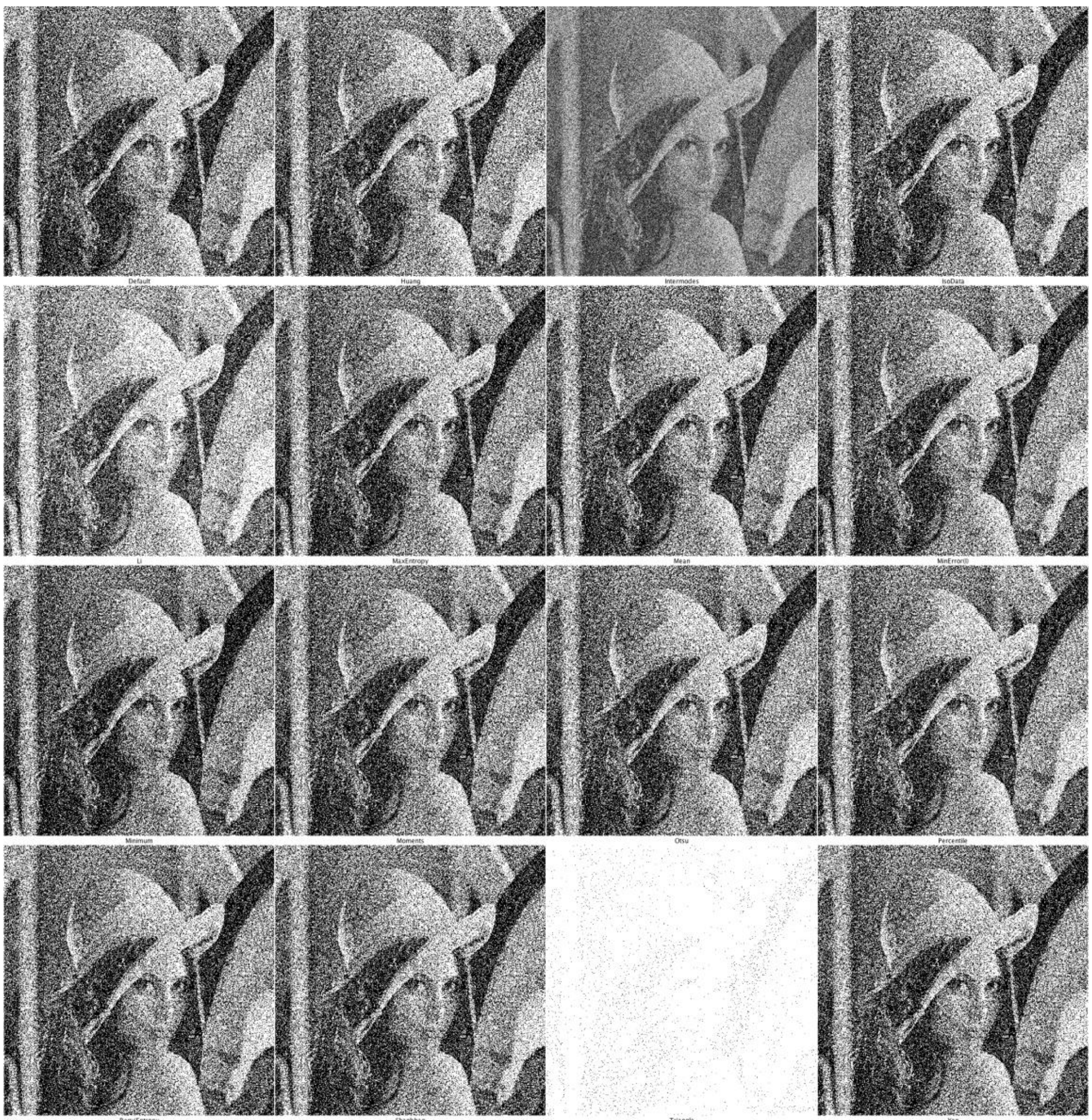

Figure 5: Image extraction by different thresholding methods

TABLE 2: COMPARISON OF SALT AND PEPPER NOISE REDUCTION WITH THE HELP OF DIFFERENT THRESHOLDING METHOD AND OUR PROPOSED METHOD

PSNR Calculation for Salt and Pepper Noise						
Threshold method/%	**10**	**20**	**30**	**40**	**50**	**60**
Default	18.7933	18.4693	18.1202	17.7935	17.4915	17.2249
Huang	17.1179	16.5558	16.0381	16.2808	15.9843	15.8381
Iso Data	18.5741	18.4853	18.1272	17.792	17.4915	17.2249
Li	17.7779	17.4125	17.0988	16.7947	16.6229	16.4197
Max Entropy	19.0767	18.4389	17.9857	17.6086	17.324	17.0689
Mean	18.5855	18.2576	17.927	17.6422	17.3936	17.1514
Min Error	15.4763	14.4525	14.452	14.5692	14.5671	14.6786
Minimum	15.7978	15.802	15.8024	15.8438	16.6312	16.5642
Moments	19.009	18.5407	18.1272	17.7814	17.4832	17.2228
Otsu	18.8227	18.4853	18.1377	17.7922	17.4869	17.2168
Percentile	18.4624	18.0417	17.6974	17.4219	17.1763	16.952
RenyiEntropy	18.9433	18.3988	17.946	17.6086	17.324	17.0847
Shanbhag	18.6629	18.23	17.8106	17.5152	17.2395	17.0081
Triangle	8.385	8.0863	5.811	5.2963	5.4104	5.5636
Yen	18.7309	18.1383	17.7587	17.4427	17.1979	16.9721
Proposed method	**23.7809**	**23.6086**	**23.2963**	**22.9447**	**22.5481**	**22.4017**


Figure 6: Image corrupted by Salt and Pepper Noise


Figure 7: Extracted image by Proposed Technique

The extracted images of 40% Salt and Pepper noise using different techniques are as follows:

Figure 8: Image extraction by different thresholding methods

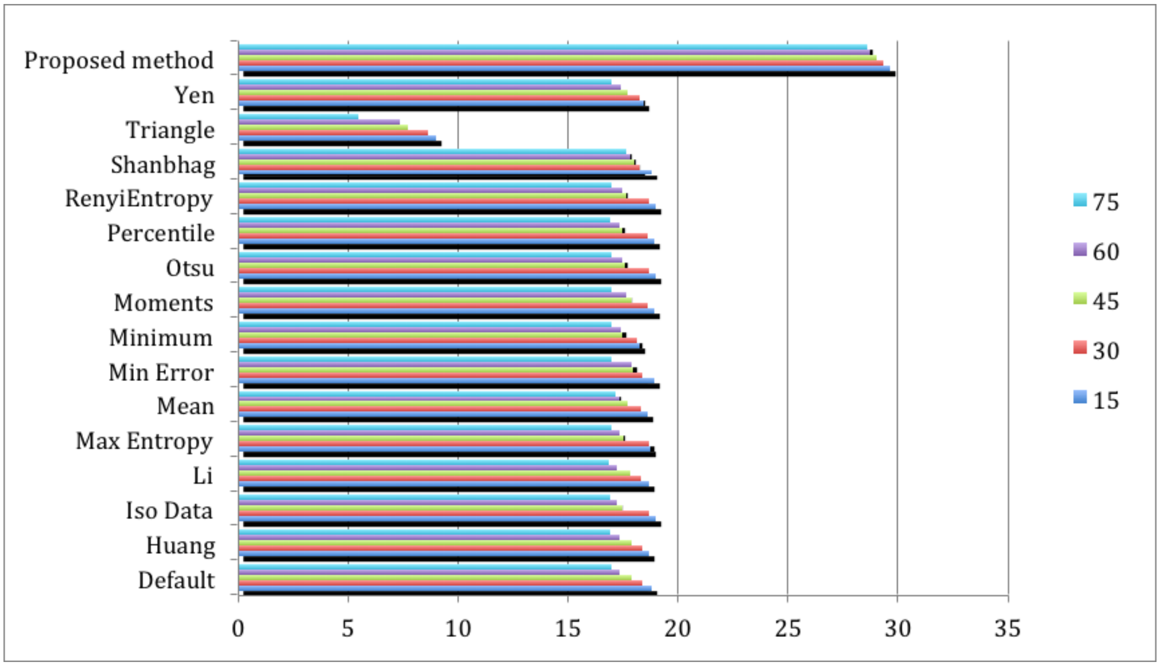

Figure 9: PSNR Calculation for Gaussian Noise

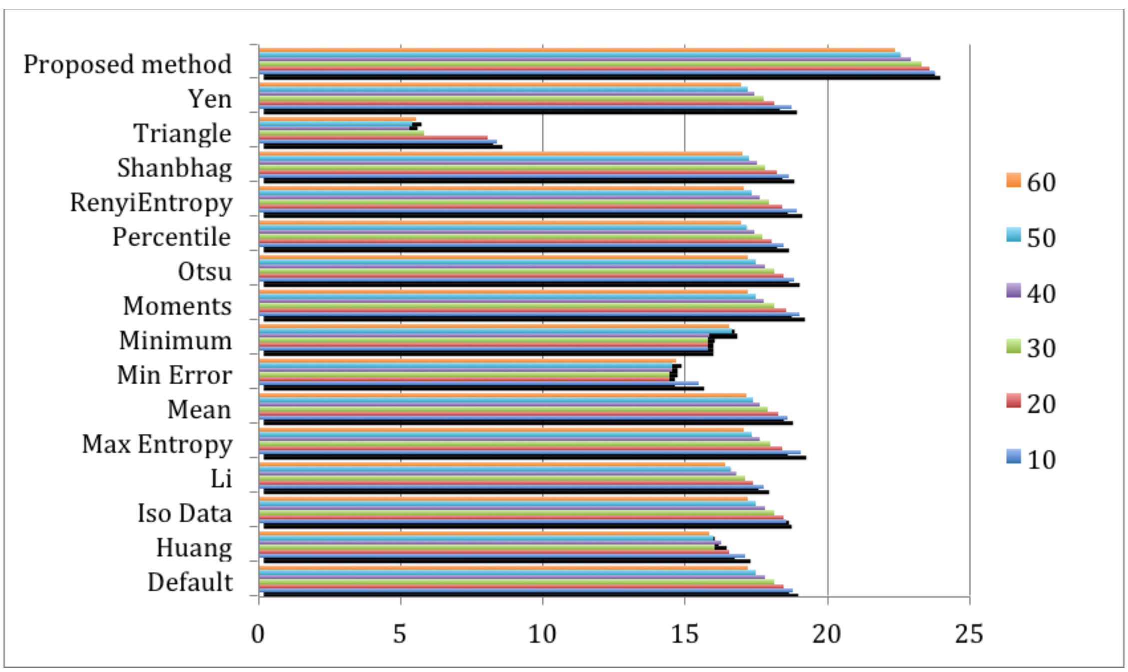

Figure 10: PSNR Calculation for Salt and Pepper noise