Rough Sets: An Overview, Hybridization and Applications

Amit Saxena, Leeladhar Kumar Gavel, Madan Madhaw Shrivas

Abstract - Rough set theory has emerged as a useful mathematical tool to extract conclusions or decisions from real life data involving vagueness, uncertainty and impreciseness and is therefore applied successfully in the field of pattern recognition, machine learning and data mining. This paper presents basic concepts and terms of rough set theory. The paper also presents hybridization approach of rough sets with various other established techniques along with developments from time to time.

Keywords— Pattern recognition, rough sets, hybridization of rough sets, neural networks, fuzzy sets.

I. INTRODUCTION

Rough set theory proposed by Pawlak [1],[2], has become a well-established theory to resolve problems related to vagueness, uncertainty and incomplete information in variety of applications related to pattern recognition and machine learning. The problems belonging to these areas widely include classification [3], [4], [5], feature selection [6], [7], [8], [9], [10], [11], clustering [12], [13], [14], data mining, knowledge discovery [15], Image processing [16], and prediction [17]. The theory of rough sets can be described in two ways: constructively and algebraically (axiomatically) [18]. The constructive approach is found suitable for practical applications of rough sets, while the algebraic approach is appropriate for studying the structures (theory) of rough set algebras. Subsequently a new extension of rough set theory, called α –RST [19], presented a suitable framework to deal with vague data and for quantifying fuzzy concepts. Two new operators introduced for the rough set theory [20] can be used to convert two inequalities into equalities. Hence, many properties in rough set theory can be improved and in particular, the union, the intersection, and the complement operations can be redefined based on these two equalities. A new roughness measure of a fuzzy set based on the notion of the mass assignment of a fuzzy set and its α-cuts are proposed by Huynh et al. [21]. It is shown that this roughness measure inherits interesting properties of Pawlak's roughness measures of a crisp set. The Variable Precision Rough Set (VPRS) model extends the basic rough set theory to incorporate probabilistic information [22].

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A non-parametric modification of the VPRS model called the Bayesian Rough Set (BRS) model tends to serve well for data mining applications whereas the predictive model is suitable for primary importance. Knowledge acquisition using rough set theory in the systems having incomplete information is proposed in literature [15]. Two kinds of partitions, lower and upper approximations, are formed for the mining of certain and association rules in incomplete decision tables. As a result one type of *optimal certain* and two types of *optimal association* decision rules is generated. Definable concepts are very important in investigating properties of various generalized rough set models [23]. The rough set concept has led to its various generalizations approach to multi-criteria decision making for synthesis and analysis of concept approximations in the distributed environment of intelligent agents [24]. Based on rough membership and rough inclusion functions [25], Bayesian decision-theoretic analysis is adopted to provide a systematic method for determining the precision parameters by using more familiar notions of costs and risks. JingTao Yao [26] presented a list of decision types based on rough set regions created by two models viz. Pawlak and probabilistic. A general framework is formed for the study of fuzzy rough sets which uses both approaches (constructive and axiomatic) and classical representation of Interval Type 2 (IT2) fuzzy [27] and rough approximation operators. The association between special IT2 fuzzy relations and IT2 fuzzy rough approximation operators is investigated [28]. The composite rough set model for composite relations was developed to deal with attributes of multiple different types simultaneously [29]. Multigranulation rough set (MGRS) theory provides a new perspective for decision making analysis based on the rough set theory. The new model based on MGRS and decision-theoretic rough sets together is called a multigranulation decision theoretic rough set model [30]. Jia etal. [31] proposed an optimization representation of decision-theoretic rough set model to minimizing the decision cost.The MGRS model based on the decision strategy *Seeking common ground while eliminating differences* (SCED), also called pessimistic rough set model was proposed in literature [32]specifying the relationship between optimistic and pessimistic multigranulation rough sets. Susmaga [33] introduced the constructs in a uniform definition framework of Dominance-based Rough Sets Approach (DRSA) which isa collection of twenty four reduced attribute subsets. The DRSA systematically discusses the basic theory of the probabilistic rough fuzzy set.Subsequently the 0.5-probabilistic rough fuzzy set model, variable precision probabilistic rough fuzzy set model and Bayesian rough fuzzy set model are defined [34]. It has been observed that every technique performs well under certain parameters, in other words, every technique

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also has certain limitations and it fails to perform that well under that condition. The hybridization process combines a technique with another to take advantages of both techniques to cover up all limitations. This paper presents most common hybridizations of rough sets with other bench mark techniques or tools. This paper introduces basic terms associated to rough sets in Section II, hybridization of rough sets with fuzzy, neural and others in Section III. Further, some important applications of rough sets to feature selection, classification and some other general applications with the state of art are provided in Section IV followed by conclusions.

II. ROUGH SET THEORY: BASIC DEFINITIONS

Rough set theory was developed by Zdzislaw Pawlak [1], [2]. It deals mainly with classification analysis of data tables. The main goal of the rough set analysis is to synthesize approximation of concepts from the acquired data which contains vagueness, missing values or redundancy of features. In this section, some terms which are frequently used in rough sets are defined.

A. Information and decision systems

A data set is represented as a table where each row represents a case, an event, a pattern or simply an object. Every column represents an attribute (a variable, an observation, a property, a feature) that can be measured for each object; the attribute may also be supplied by a human expert or user. This table is called an information system. More formally, it is a pair $I= (U, A)$ where$U$ is a non-empty finite set of objects called Universe and A is a non-empty finite set of attributes such that $a: U \rightarrow V_a$ for every $a \in A$. The set V_a is called the value set of a. In many applications, the class of the attribute of several patterns (or objects) is known in advance. This set of patterns is called training data.The class of an unknown pattern (also called test data), can be predicted from the priory knowledge of the training data; this process is known as supervised learning. Information systems of this typeare called decision systems. Mathematically a decision system is any information system of the form $D=(U,A\cup\{d\})$, where $d \notin A$ is the decision attribute. The element of A are called condition attributes or simply conditions.

Table. 1

AN EXAMPLE DATASET

$x \in U$	a	b	c	d	⇒	e (class)
0	S	R	T	T		R
1	R	S	S	S		T
2	T	R	R	S		S
3	S	S	R	T		T
4	S	R	T	R		S
5	T	T	R	S		S
6	T	S	S	S		T
7	R	S	S	R		S

An example of a decision system can be found in Table I. The table consists of four conditional features *(a, b, c, d)*, a decision feature *(e)* also called class, and eight objects (or patterns). A decision system is consistent if for every set of objects whose attribute values are the same, the corresponding decision attributes are also identical.

B. Indiscernibility

A decision system (i.e. decision table) represents the knowledge about the model. This table may be redundant in at least two ways. The same or indiscernible objects may be represented several times or even some of the attributes may be superfluous. As we know, for a binary relation $R \subseteq X \times X$to be an equivalence relation, it should be reflexive (i.e. an object is in relation with itself xRx), symmetric (if xRy thenyRx) and transitive (if xRy and yRz then xRz) is called an equivalence relation. The equivalence class of an element $x \in X$ consists of all objects $y \in X$ such that xRy.

Let $I=(U,A)$ be an information system, then with any $B \subseteq A$, there is associated an equivalence relation $IND_I(B)$.

$$IND_I(B) = \{(x, x') \in U^2 \mid \forall a \in B\, a(x) = a(x')\} \quad (1)$$

$IND_I(B)$ is called the B-indiscernibility relation.

If $(x, x') \in IND_I(B)$, then object x and $x'$are indiscernible from each other by attributes from B. The equivalence classes of the B-indiscernibility relation are denoted $[x]_B$.

For the illustrative example, if $B=\{b, c\}$ then object 1,6,7(values S S) and objects 0,4 values (R T) are indiscernible; $IND_I(B)$ creates the following partition of U.

$$U/IND_I(B)=\{\{0, 4\}, \{1, 6, 7\}, \{2\},\{3\},\{5\}\}$$

C. Lower and upper approximation

Let $I=(U,A)$ be an information system and let $B \subseteq A$ and $X \subseteq U$. We can approximate X using only the information contained in B by constructing the B-lower and B-upper approximations of X, denoted $\underline{B}(X)$and$\overline{B}(X)$respectively.

$$\underline{B}(X) = \{x \in U : [x]_B \subseteq X\} \quad (2)$$

$$\overline{B}(X) = \{x \in U : [x]_B \cap X \neq \emptyset\} \quad (3)$$

D. Positive, negative and boundary regions

Let P and Q be sets of attributes including equivalence relations over U, then the positive, negative, and boundary region are defined as

$$POS_P(Q) = \bigcup_{X \in U/Q} \underline{P}X \quad (4)$$

$$NEG_P(Q) = U - \bigcup_{X \in U/Q} \overline{P}X \quad (5)$$

$$BND_P(Q) = \bigcup_{X \in U/Q} \overline{P}X - \bigcup_{X \in U/Q} \underline{P}X \quad (6)$$

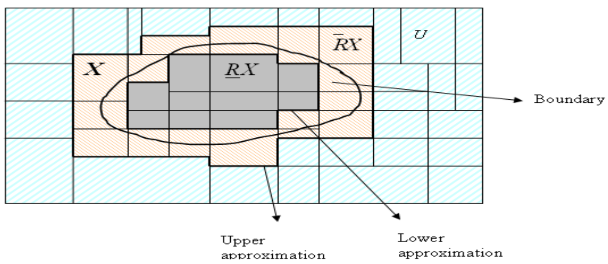

Fig. 1 A Rough set

The positive region comprises all objects of U that can be classified to classes of U/Q using the information contained within attributes P. The boundary region, $BND_P(Q)$, is the set of objects that can possibly, but not certainly, be classified in this way. The negative region,$NEG_P(Q)$, is the set of objects that cannot be classified to classes of U/Q.

For example, let $P=\{b,c\}$ and $Q=\{e\}$, then

$$POS_P(Q) = \cup\{\emptyset, \{2, 5\}, \{3\}\} = \{2, 3, 5\}$$

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$$NEG_P(Q) = U - \cup \{\{0,4\},\{2,0,4,1,6,7\ 5\},\{3,1,6,7\}\} = \emptyset$$

$$BND_P(Q) = \cup \{\{0,4\},\{2,0,4,1,6,7\ 5\},\{3,1,6,7\}\} - \{2,3,5\} = \{0,1,4,6,7\}.$$

This means that objects 2, 3 and 5 can certainly be classified as belonging to a class attribute e, where considering attributes b and c. The rest of the objects cannot be classified as information that would make them discernible is absent.

E. Dependency of attributes

Another important issue in data analysis is discovering dependencies between attributes. Intuitively, a set of attributes Q depends totally on set of attributes P, denoted by $\Rightarrow Q$, if all values of attribute from Q are uniquely determined by values of attributes from P. Formally, dependency can be defined in the following way. Let P and Q be subsets of A.

We will say that Q depends on P in a degree k $(0 \le k \le 1)$, denoted$P \Rightarrow_k Q$, if

$$k = \gamma(P,Q) = \frac{|POS_p(Q)|}{|U|} \quad (7)$$

Where

$$POS_P(Q) = \bigcup_{X \in U/Q} \underline{P}X$$

Called positive region of the partition *U/Q* with respect to *P*, is the set of all elements of *U* that can be uniquely classified to block of the partition *U/Q*, by means of *P*.

Obviously

$$\gamma(P,Q) = \sum_{x \in U/Q} \frac{|\underline{P}X|}{|U|} \quad (8)$$

If *k=1* we say that *Q* depends totally on *P* and if *k <1*, we say that *Q* depends partially on *P*. Again

For example, if *P={a, b, c}* and *Q={e}* then

$$\gamma_{\{a,b,c\}}(\{e\}) = \frac{|\{2,3,5,6\}|}{8} = 4/8$$

$$\gamma_{\{a,b\}}(\{e\}) = \frac{|\{2,3,5,6\}|}{8} = 4/8$$

$$\gamma_{\{b,c\}}(\{e\}) = \frac{|\{2,3,5\}|}{8} = 3/8$$

$$\gamma_{\{a,c\}}(\{e\}) = \frac{|\{2,3,5,6\}|}{8} = 4/8$$

F. Reducts and Core

In several application problems, the information system is unnecessarily large due to existence of repeated objects or redundant features. One way to reduce the dimensionality is to search for a minimal representation of the original dataset. For this reason, concept of a reduct is introduced and defined as minimal subset R of the initial attribute set *C* such that for a given set of attributes *D*, $\gamma_R(D) = \gamma_C(D)$. *R* is a minimal subset if $\gamma_{R-\{a\}}(D) \neq \gamma_R(D)$ for all $a \in R$. This means that any attribute removed from the subset will affect the dependency degree. Hence a minimal subset by this definition may not be the *global* minimum (areduct of smallest cardinality). A given dataset may have many reduct sets, and the collection of all reducts is denoted by

$$R_{all} = \{X | X \subseteq C, \gamma_X(D) = \gamma_C(D); \gamma_{X-\{a\}}(D) \neq \gamma_X(D), \forall a \in X\} \quad (9)$$

The intersection of all the sets in R_{all} is called the core, denoted by CORE(C).

$$CORE(C) = \cap RED(C) \quad (10)$$

Where RED(C) is the set of all reducts of C.

G. Discernibility matrix

Many applications of rough sets make use of discernibility matrices for finding rules or reducts. A discernibility matrix of a decision table $(U, C \cap D)$ is a symmetric $|U| \times |U|$ matrix with entries defined by

$$c_{ij} = \{a \in C | a(x_i) \neq a(x_j)\}, \quad i,j = 1,\dots,|U| \quad (11)$$

Each c_{ij} contains those attributes that differ between objects *i* and *j*.

For finding reduct, the decision-relative discernibility matrix is of more interest. This matrix considers only those object discernibilities that occur when the corresponding decision attributes differ [35]. The decision-relative discernibility matrix is produced as shown in Table II. For example, it can be seen from the table that objects 0 and 1 differ in each attribute. Although some attributes in objects 1 and 3 differ, their corresponding decisions are the same, so no entry appears in the decision-relative matrix. Grouping all entries containing single attributes forms the core of the dataset (those attributes appearing in every reduct). Here, the core of the dataset is {d}. From this matrix, the concept of discernibility functions can be introduced. This is a concise notation of how each object within dataset may be distinguished from the others. A discernibility function f_D is a Boolean function of m Boolean variables $a_1^*, \dots, a_m^*$ (corresponding to the membership of attributes $a_1 \dots a_m$ to a given entry of the discernibility matrix), defined as follows:

Table. 2

DECISION-RELATIVE DISCERNIBILITY MATRIX

x ∈ U	0	1	2	3	4	5	6	7
0								
1	a, b, c, d							
2	a, c, d	a, b, c						
3	b, c		a, b, d					
4	d	a, b, c, d		b, c, d				
5	a, b, c, d	a, b, c		a, b, d				
6	a, b, c, d		b, c		a, b, c, d	b, c		
7	a, b, c, d	d		a, c, d			a, d	

$$f_D(a_1^*, \dots, a_m^*) = \wedge \{\vee c_{ij}^* | 1 \le j \le i \le |U|, c_{ij} \neq \phi\} \quad (12)$$

Where $c_{ij}^* = \{a^* | a \in c_{il}\}$ .The notation $\vee\{a,b,c,d\}$ and $\wedge\{a,b,c,d\}$ denote $a \vee b \vee c \vee d$ and $a \wedge b \wedge c \wedge d$, respectively. By finding the set of all prime implecants of the discernibility function, all the minimal reducts of a system may be determined. From Table II, the decision-relative discernibility function is (with duplicates removed)

$$f_D(a^*,b^*,c^*,d^*) = (a^* \vee b^* \vee c^* \vee d^*) \wedge (a^* \vee c^* \vee d^*) \wedge (b^* \vee c^*) \wedge (d^*) \wedge (a^* \vee b^* \vee c^*) \wedge (a^* \vee b^* \vee d^*) \wedge (b^* \vee c^* \vee d^*) \wedge (a^* \vee d^*)$$

Further simplification can be performed by removing those clauses that are subsumed by others:

$$f_D(a^*,b^*,c^*,d^*) = (b^* \vee c^*) \wedge (d^*)$$

The reducts of the dataset may be obtained by converting the expression above from conjunctive normal form to disjunctive normal form (without negation). Hence the minimal reducts are *{b, d}* and *{c, d}*. After a brief introduction of rough sets, we are now ready to explore some of the research issues based on rough set theory. There have been several areas where intensive research is being

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carried out including following [3], [4], [5],[6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16],[17].

Some of the research directions on Rough Sets are as follows-

- Feature selection
- Dimensionality reduction
- Rough set based clustering
- Rough sets and noisy data
- Rough sets and relational databases
- Rough sets and inductive reasoning
- Rough set based approach based on neighbourhood (uncertainty) functions and inclusion relation. In particular, variable precision rough set model.

III. HYBRIDIZATION OF ROUGH SETS WITH OTHER TOOLS

In order to improve its performance, rough sets have been combined with other well established tools such as neural networks, fuzzy sets or evolutionary techniques from time to time. This section describes the hybrid approaches of rough sets with others to achieve various applications.

A. Rough set and fuzzy set

The fuzzy set theory [36] is similar to rough set theory in many aspects and is commonly used for solving problems due to vague and uncertain data. We know that the real word data can be imprecise, noisy or vague containing uncertainty due to which decision making becomes inconsistent. For the same attributes, many times the decisions are different. To overcome this problem, rough sets and fuzzy sets are used in a combination. In classical set theory, elements could belong fully (i.e. have a membership of 1) or not at all (a membership of 0) to a set. This theory is also known as crisp set theory and a computer deals successfully with all operations including decision making, mathematical calculations etc using crisp set theory. A Fuzzy set theory on the other hand, relaxes this restriction by allowing membership to take values in the range [0, 1]. A fuzzy set can be defined as a set of ordered pairs $A=\{x, \mu A(x)\}$. The function $\mu A(x)$ is called the membership function for A, mapping each element of the universe U to a membership degree in the range [0, 1]. The universe may be discrete or continuous. A fuzzy set containing at least one element which membership degree of 1 is called normal fuzzy set. The various applications of rough and fuzzy sets hybridized together are summarized in Table III. Rough set theory allows for obtaining a linguistic description of the function whereas the fuzzy logic theory allows to generate numerical values of the function starting from it's linguistic description. Jagielska et al. [37] studied neural network and genetic algorithms. Fuzzy rule induction system have been developed and applied to three classification problems. Rule induction software based on rough set theory was also used to generate and test rule bases for the same data. A comparison of these approaches with the C4.5 inductive algorithm was also carried out. The research to date indicated that based on the evaluation criteria used, the genetic/fuzzy approach compares favourably with the neuro/fuzzy and rough set approaches. Shen and Chouchoulas [38] presented an approach which integrates a potentially powerful fuzzy rule induction algorithm with a rough set-assisted feature reduction method. Unlike transformation-based techniques, this approach maintains the underlying semantics of the feature set. This is very important to ensure that the resulting models are readily interpretable by the user. Through the integration, the original rule induction algorithm (or any other similar technique that generates fuzzy rules), which is sensitive to the dimensionality of the set of feature patterns, becomes usable on patterns involving a moderately large number of features

Table III

An overview of hybridization of rough and fuzzy sets

Sl.No.	Author Name	Description
1.	Bhatt and Gopal [7]	Modified fuzzy-rough sets model using fuzzy t-norm and t-conorm properties of fuzzy set, on compact computational domain, which is then utilized to improve the computational efficiency of FRSAR algorithm.
2.	P et al. [9]	Proposed novel algorithm based on fuzzy- rough sets for the feature selection and classification of datasets with multiple features, with less computational efforts..
3.	Jagielska et al. [37]	Compared various data mining techniques for rule identification.(iris species, heart disease, credit approval dataset are used for testing)
4.	Shen and Chouchoulas [38]	Presented an approach that integrates a potentially powerful fuzzy rule induction algorithm with a rough set-assisted feature reduction method.
5.	Roy and Pal [39]	Developed hybrid model base on fuzzy (discrtization of feature) and Rough Set (classifier) for overlapping data set.
6.	Tsai et al. [40]	Proposed a new fuzzification technique called Modified Minimization Entropy Principle Algorithm (MMEPA) to construct membership functions of fuzzy sets of linguistic variables.
7.	Sarkar [41]	Proposed a new method, each training pattern is considered neighbour to the test pattern with varying degree, and hence we do not need to determine the appropriate value of K.
8.	Shen and Jensen [42]	Presented an overview of the rough set theory and its extensions, supported with a brief discussion of a number of representative application of these theories

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Sl.No.	Author Name	Description
9.	Chen et al [43]	Proposed Gaussian kernel based fuzzy rough sets and introduces parameterized attribute reduction with the derived model of fuzzy rough sets.
10.	Hu et al. [44]	Proposed a new model of fuzzy rough called soft fuzzy rough sets, and design a robust classification algorithm based on the model.
11.	Parthalain and Jensen [46]	Presented two different approaches for unsupervised feature selection based on fuzzy-rough set methods.
12.	Cheng [47]	Proposed forward and backward approximations in fuzzy rough sets based on a granulation order.
13.	Qian [48]	Proposed forward approximation theoretic frameworks based on rough set theory which can be used to accelerate algorithms of heuristic attribute reduction.
14.	Meher [67]	Proposed an explicit rough-fuzzy model for pattern which is explores and provides the synergistic integration of the merits of both fuzzy and rough sets.
15.	Sarkar [73]	Proposed to characterize a medical time series by quantifying the ruggedness of the time series. The presence of two close data points on the time axis implies that these points are similar along the time axis.
16.	He et al. [74]	Proposed new algorithm with general fuzzy rough sets from the theoretical viewpoint and define inconsistent fuzzy decision system and its reductions.
17.	Pal et al. [75]	Proposed a new rough-fuzzy model for pattern classification based on granular computing.
18.	Murakidharan and Sugumaran [76]	Proposed a hybrid model, feature are extracted using discrete wavelets, number of rules generated using rough set theory and classified using fuzzy logic algorithm (99.84% accuracy).

Roy and Pal [39] explained a concept of fuzzy discretization of feature space for a rough set theoretic classifier. Fuzzy discretization is characterised by membership value, group number and affinity corresponding to an attribute value, unlike crisp discretization which is characterised only by the group number and observed its effectiveness in a multilayer perceptron in which case raw (non-discretizes) data is considered as input, in addition to discretized ones. Tsai et al. [40] proposed a new fuzzification technique called Modified Minimization Entropy Principle Algorithm (MMEPA) to construct membership functions of fuzzy sets of linguistic variables. This technique was combined with variable precision rough set (VPRS) model to form an entropy-based fuzzy-rough classification approach. Sarkar [41] enhanced the classification efficiency of the conventional K-nearest neighbour (K-NN) algorithms by exploiting fuzzy-rough uncertainty. Unlike the conventional one, the proposed algorithm does not need to know the optimal value of K, moreover, the generated class confidence values, which are interpreted in term of fuzzy-rough ownership values, do not necessarily sum up to one. Consequently, the proposed algorithms can distinguish between equal evidence and ignorance, and thus the semantics of the class confidence values become richer. Shen and Jensen [42] explained the outline of three such approaches, including variable precision rough sets, tolerance rough sets and fuzzy rough sets. These extensions allow the ability of the original rough set theory in handling discrete and nominal data, which is assumed to be maximized to cope with numerical and other contextual aspects of real world data. He et al. [43] defined inconsistent fuzzy decision system and their reductions, and developed discernibility matrix-based algorithms to find reducts. Finally, two heuristic algorithms are developed and compared with the existing algorithms of attribute, found effective and also deal with decision systems with numerical conditional attribute values and fuzzy decision attributes rather than crisp sets. Hu et al. [44] introduced a robust model of fuzzy rough sets called soft fuzzy rough sets and discussed the connection between the soft fuzzy rough set model and other models and design a soft fuzzy rough classifier based on the model. Dai [45] proposed an extended rough set model, i.e. tolerance-fuzzy rough set model to deal with this type of data characterized with numerical attributes and missing values, that is, incomplete numerical data. Discernibility matrices and discernibility functions for incomplete numerical information systems and incomplete numerical decision systems are defined to compute reducts or relative reducts. Finally, uncertainty measurement is also investigated which suggests that the tolerance- fuzzy rough set model provides an optional approach to incomplete numerical data. Parthalain and Jensen [46] presented two different approaches for unsupervised feature selection. Both approaches use fuzzy-rough sets to select features for inclusion or removal from the final candidate subset. The UFRFS algorithm utilises a simple but nevertheless effective backwards elimination method for search, whilst dUFRFS uses a greedy forward selection method. Cheng [47] proposed two algorithms based on forward and backward approximations, namely, mine rules based on the forward approximation (MRBFA) and mine rules based on the backward approximation (MRBBA), for rule extraction. Both MRBFA and MRBBA achieved better classification performances than other methods based on attribute reduction. Qian [48] proposed an

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accelerator, called forward approximation, which combines sample reduction and dimensionality reduction together. The strategy can be used to accelerate a heuristic process of fuzzy-rough feature selection. Through the use of the accelerator, three representative heuristic fuzzy-rough feature selection algorithms have been enhanced. The modified algorithms are much faster than their original counterparts and performance of the modified algorithms becomes more visible when dealing with larger data sets.

B. Rough set and neural network

A neural network is a technique that seeks to build an intelligent system using models that simulate the working network of the neurons in the human brain [49], [50]. A neuron is made up of several protrusions called dendrites and long branches called the axons. A neuron is joined to other neurons through the dendrites. The dendrites of different neurons meet to form synapses, the area where messages pass. The neurons receive the impulses via the synapses. If the total of the impulses received exceeds a certain threshold value, then the neuron sends impulses down the axon where the axon is connected to other neurons through more synapses. The synapses may be excitatory or inhibitory in nature. An excitatory synapse adds to the total of the impulses reaching the neuron, whereas an inhibitory neuron reduces the total of the impulses reaching the neuron. In a global sense, a neuron receives a set of input impulses and sends out another pulse that is a function of the input pulses. The hybridizations of rough set and neural network are summarized in Table IV.

Table IV
An overview of rough set and neural network hybridization

Sl.No.	Author Name	Description
1.	Jensen and Cornelis [5]	Proposed FRNN, a new nearest neighbour classification and prediction approach that exploits the concept of lower and upper approximations from fuzzy-rough set theory.
2.	Ahn et al. [17]	Developed hybrid intelligent system that predicts failure of firms based on the past financial performance.
3.	Swiniarksi and Hargis [51]	Described an application of rough sets method to feature selection and reduction as a front end of neural-network-based texture images recognition.(selected reduct were used to trained a neural network with 18 hidden layer neuron, get 94.64% accuracy)
4.	Ganivada et al. [55]	Proposed a new granular neural network model in natural computing framework by integrating the concept of fuzzy rough sets with a multilayer perceptron (MLP) using a back-propagation algorithm.
5.	Valdes et al [56]	Proposed model as a combination of neural networks and rough set techniques, used for constructing virtual reality spaces for visual data mining suitable for representing data and symbolic knowledge.
6.	He et al. [57]	Presented a new approach for fault classification in extra high volt age (EHV) transmission line using a rough membership neural network (RMNN) classifier.
7.	Li and Wag [69]	Presented hybrid model of integrating rough set and Artificial Neural Networks to mine classification rules from large data sets.

Ahn et al. [17] proposed a hybrid intelligent system that predicts the failure of firms based on the past financial performance data, combining rough set approach and neural network. The reduced information table, which implies that the number of evaluation criteria such as financial ratios and qualitative variables with no information loss, through rough set approach and then, this reduced information was used to develop classification rules and train neural network to infer appropriate parameters. The rules developed by rough set analysis shows the best prediction accuracy if a case does match any of the rules. Swiniarksi and Hargis [51] described an application of rough sets method to feature selection and reduction as a front end of neural-network-based texture images recognition. The methods applied include singular-value decomposition (SVD) for feature extraction, principal components analysis (PCA) [52], [53] for feature projection and reduction, and rough sets methods for feature selection and reduction. For texture classification the feed-forward back-propagation neural networks were applied. Li and Wang [54] presented a hybrid approach of integrating rough sets and neural networks to mine classification rules from large data sets. They also proposed a new algorithm for finding a reduct and a new algorithm for rule generation from a decision table based on a binary discernibility matrix. The reduct was obtained using rough set theory and the neural network was applied to delete noisy data. Again the rough set theory was applied to obtain rules or patterns. This hybrid approach generated a more concise and accurate rules than traditional neural network based approach and rough set -based approach. Ganivada et al. [55] introduced a fuzzy rough granular neural network (FRGNN) model based on the multilayer perceptron using a back-propagation algorithm for the fuzzy classification of patterns. The

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development strategy of the network mainly based upon the input vector, initial connection weights determined by fuzzy rough set theoretic concepts, and the target vector. While the input vector is described in terms of fuzzy granules, the target vector is defined in terms of fuzzy class membership values and zeros. Crude domain knowledge about the initial data is represented in the form of a decision table, which is divided into sub tables corresponding to different classes. The data in each decision table is converted into granular form that automatically determines the appropriate number of hidden nodes, while the dependency factor from all the decision tables are used as initial weights. Valdes et al [56] combined neural networks and rough set techniques for constructing visual data mining with virtual reality space for the representation of data and symbolic knowledge. High quality structure-preserving and maximally discriminative visual representations can be obtained using a combination of neural networks (SAMANN and NDA) and rough sets techniques, so that a proper subsequent analysis can be made. He et al. [57] presented a new approach for fault classification in extra high voltage (EHV) transmission line using a rough membership neural network (RMNN) classifier. To reduce the training times of the neural network, the rough neurons are used as input layer neurons, and the fuzzy neurons are utilized in hidden and output layer in each RMNN and the Back Propagation (BP) algorithm is employed for determining the optimal connection weights between neurons of the different layers in the RMNN.

C. Rough set and metaheuristic algorithms

A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems. In other words, a metaheuristic can be seen as a general purpose heuristic method designed to guide an underlying problem specific heuristic toward promising regions of the search space containing high quality solutions. A metaheuristic therefore is a general algorithmic framework, which can be applied to different optimization problems with relatively few modifications to make them, adapted to a specific problem. The use of metaheuristic has significantly increased the ability of finding very high-quality solution to hard, practically relevant combinatorial optimization problems in a reasonable time. This is particularly true for large and poorly understood problems. The metaheuristic algorithms with rough sets are presented in Table V. Khoo et al. [58] presented an integrated approach that combines rough set theory, genetic algorithms and Boolean algebra, for inductive learning and developed a prototype system (R Class-Plus) that discovers rules. The RClass-Plus is able to combine the strengths of rough set theory and the GA-based search algorithm to deal with rule induction under uncertainty.

Table V

An overview of metaheuristic algorithms

Sl. No.	Author Name	Description
1.	Kim [4]	Proposed Tolerant rough set, based on similarity threshold value which is determined to measure between two data set using distance function.
2.	Khoo et al. [58]	Presents an integrated approach that combines rough set theory, genetic algorithms and Boolean algebra, for inductive learning (R Class-Plus) that discovers rules from inconsistent empirical data.
3.	Jensen and Shen [60]	Proposed a new feature selection mechanism based on ant colony optimization (ACO). Compared with the original fuzzy-rough method, an entropy-based feature selector, and a transformation-based reduction method, PCA. Comparisons with the use of a support vector classifier are also included.
4.	Ke et al. [62]	Proposed an ACO-based algorithm (ACOAR) based on rough set theory for attribute reduction.
5.	He et al. [63]	Proposed a novel compromise-based ant colony algorithm (CACA) for simultaneously solving attribute discretization and reduction.
6.	Huang [64]	Proposed a method, designated as the GRP-index method, for the classification of continuous value datasets in which the instances do not provide any class information and may be imprecise and uncertain.
7.	Lingras [77]	Suggested a rough set approach to both SVM binary classification and SVM multi-classification.
8.	Verbiest et al. [78]	Proposed a new Prototype Selection method, FRPS and designed to only retain instances with good predictive ability.

Kim [4] proposed a new data classification method based on the tolerant rough set based on similarity threshold value which is determined to measure between two data sets using distance function and optimized by using genetic algorithm (GA))[59]. After finding the optimal similarity threshold value, a tolerant set of each object is obtained and the data set is grouped into the lower and upper approximation set depending on the coincidence of their classes. Jensen and Shen [60] proposed a new feature selection mechanism based on ant colony optimization (ACO)[61].The method was applied to the problem of finding optimal feature subsets in the fuzzy-rough data reduction process and compared with the original fuzzy-rough method, an entropy-

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based feature selector, and a transformation-based reduction method, PCA. Ke et al. [62] proposed an ACO-based algorithm, called ACOAR, to deal with attribute reduction in rough set theory. Proposed algorithm has the following features: (a) it updates the pheromone trails of the edges connecting every two different attributes of the best-so-far solution; (b) pheromone values are limited between the upper and lower trail limits; (c) it uses a rapid procedure to construct candidate solutions. ACOAR has the ability to find solutions with very small cardinality rapidly. He et al. [63] proposed a bi-objective optimization problem which is constructed for simultaneous attribute discretization and reduction. A novel compromise-based ant colony algorithm (CACA) for simultaneously solving attribute discretization and reduction was also proposed, which adopts a distance metric to stepwise approach the ideal solution. Huang [64] proposed a method consisting of a genetic algorithm (GA) and an FRP-index method, designated as the GRP-index method, for the classification of continuous value datasets in which the instances do not provide any class information and may be imprecise, uncertain and discretizes the values of the individual attributes within the dataset and achieved both the optimal number of clusters and the optimal classification accuracy.

IV. FEATURE SELECTION, CLASSIFICATIONUSING ROUGH SETS AND APPLICATIONS

Rough sets are efficiently used for feature selection and classification. This section summarizes on application of rough sets for feature selection and classification. This section also briefs few other applications of rough sets.

A. Feature Selection, Classification:

Feature selection process refers to selecting the significant subsets of attributes (features) from the set of all attributes. The classification [65] is the process of separating the objects on the basis of some criteria. On many occasions, the class of each object is given in advance then it becomes easy to group the objects in to their classes. This type of classification is called supervised classification. On the other hand, many times there is no class attached to any object and we have to group them on the basis of some similarity based criteria like color, size or similar attributes. Such type of classification is called unsupervised.There has been an extensive research work in the area of feature selection and classification using rough sets.The purpose of the feature selection is to identify the significant features, eliminate the irrelevant or dispensable features. This will reduce the burden on learning models and as a result it will help in building better learning model. The benefits of feature selection are two folds: it considerably decreases the computation time of the induction algorithm and secondly increases the accuracy of the resulting mode. Feature selection has been studied intensively in the past one decade [3], [6], [16]. Khoo et al. [3] proposed a novel approach for the classification and rule induction of inconsistent information systems. Swiniarski and Skowron [6] presented an application of rough set method for feature selection in pattern recognition. They proposed a new feature selection method to the result of principle component analysis (PCA [52], [53]) used for feature projection and reduction. Fen et al. [66] proposed new incremental rule-extraction algorithms to solve the dynamic database problem. When a new object is added-in the information system, it is unnecessary to re-compute rule sets from the very beginning. Some more work in this area can be seen in [14] [27] [34] [47] [67].

B. Applications:

Rough set theory has been successfully applied in almost all the fields. The major drawback of traditional rough set models in real life application is the inefficiency to compute reducts and generate cores attributes. To improve the efficiency of computing core attributes and reducts, many novel approaches have been developed [22], [25], [28],[29], [30], [32], [34], [40]. Some more applications of rough sets in areas like medical images [16], breast cancer [68], texture classification [51] and [55], [57], [69], [70], [71], [72] can be seen.

V. CONCLUSION

In several real life databases, the information collected in the form of patterns (or objects) to represent various decisions along with attributes contains vagueness. Further, for few identical objects; decisions (or the class) differ with each other. Rough set theory has emerged as a powerful tool to handle such vagueness. This paper presents an overview of the rough set theory, terms used in the rough sets with examples. Rough sets can be applied to several applications in real life. On several instances, it is observed that a single tool is not so suitable to perform for certain problem due to some of its limitations. However by combining the tool with some other tool which can excel against that limitation can give better results. On this concept, various hybridizations of rough sets with other tools are devised. The hybridizations of rough sets with fuzzy sets, neural networks and evolutionary algorithms have been described in this paper with various developments reported time to time. A few applications of rough sets to feature selection and classification are briefed in the paper. Further, applications of rough sets are countless due to their capability to deal and solve problems related to vagueness or uncertainty, some of the applications are summarised in the paper with references. The available literature in rough sets opens a promising domain towards future research directions in many other complex areas including big data, communications, computational intelligence, data mining, business etc.

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