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A Review on Rough Set Theory in Medical Images.

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ABSTRACT

The accurate representation of sets in crisp set is known as rough set. The knowledge is obtained by considering every data as objects with its discourse to extract associated information. There are many applications that used the advent of traditional rough set approach. A rough set handles the uncertainties in the medical images. It monitors tasks such as feature identification, dimensionality reduction, pattern classification and image segmentation. It provides various algorithms to discover the knowledge from finding patterns in data, data reduction, validating the data significance and framing the rules from the known information. This paper intends to help the study on Rough Set Theory (RST) especially focused in medical images.
Keywords: Rough set theory, Medical images, feature identification, dimensionality reduction and image segmentation

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INTRODUCTION

Nowadays, a vast amount of data has been created. The investigation on these data becomes a trivial task. There are many efficient data mining algorithms were created by various researchers. Though, there is a lack of efficient mining of the data in perspectives of the Rough Sets Theory (RST) [1] [2] [4]. The concept of Rough Set Theory (RST) was introduced by Pawlak in 1980s. It is purely based on the perceptibility of objects. The uncertainties of the objects were handled by the Rough Set Theory. If any idea generated is not clear, then the rough set works on to provide an ‘approximate’ knowledge. In the view of medical systems, the key-value boundaries are usually undefined [3].

The universe objects and its discourse are used as the philosophy of the rough sets. For instance, if objects are patients experiencing an illness, the illness symptom’s structures the data about patients [6]. The objects may display some similar information in view of known information. So, indiscerniblity occurs that leads to the mathematical foundation of RST. In RST, the indiscerniblity referred as the attributes of the given function [5]. The propagation of set theory is the Rough Set Theory. A core concept in the RST is the reduction of attributes.

ROUGHT SET THEORY BASIC TERMS AND DEFINITIONS

The uncertainties of the data were investigated by Rough sets. The features of objects were determined with the advent of rough sets and develop the upper and lower approximate of object sets. In the aspect of computational point, the data are immense in volumes which are difficult to manage it [7]. The goal of rough sets is to lessen the data size and maintain the inconsistency in data.The basic concepts in rough sets are discussed below:

Information Table

The information is stored in a table format. Each object is denoted by a single row or tuple. The tuple in the table saves the related information about the object. The column denotes the attribute of an object. This table is called as information system. It is denoted as IS= (U, A) where U= {x1, x2, x3…x_n) is a non-empty sets of objects and A= {a1, a_2, a_3…a_n} is non-empty set of attributes [18]. The value of set a is represented by U-> V_a. The attributes is of two types namely, condition attributes and decision attributes. The condition attributes represents the metric of object’s features whereas decision attributes denotes an empiric results of classification.

Indiscerniblity Relation

The beginning point of rough set theory is the indiscerniblity relation. Unknown information about the objects is measured by indiscerniblity relation. The knowledge cannot be determined from the available information and this leads to indiscern of the objects. It is also a form of data redundancy [19]. The indiscerniblity relation is given by:

$$IND_B(U) = \{(x, y) \in U^2 \mid \forall_{a \in B} a(x) = a(y)\} \quad (2.1)$$

If $(x, y) \in IND_{IS}$, then objects x and y are indiscernible from each other by attributes from B. This leads to another relation known as equivalence relation. The set is said to be equivalence if the class division and union of these sets acquires universal sets.

Equivalence Relation

Let us consider that R be an equivalence relation over universal set U [22]. The class of R is represented by U/ R. The category in R contain an element a then it is denoted by $[a]_R$.

Approximation of rough sets

The aim of rough sets is to create upper and lower approximation set of objects. The lower and upper approximation of the sets is given by:

$$\underline{B}X = \{x \in U : [x]_B \subseteq X\} \quad (2.2)$$

$$\bar{B}X = \{x \in U : [x]_B \cap X \neq \varnothing\} \quad (2.3)$$

The approximation of rough sets is given by:

$$\mathrm{BN}_B(\mathrm{X}) = \bar{B}X - \underline{B}X \quad (2.4)$$

Where $\underline{B}X$ and $\bar{B}X$ is known as B-lower and B-upper approximation. Based on the lower and upper approximation, it is divided into three regions known as positive (pos) region, negative (neg) region and boundary (bnd) region.

$$POS(\mathrm{X}) = \underline{apr}(x) \quad (2.5)$$

$$\mathrm{NEG(X)} = \overline{apr}(x) \quad (2.6)$$

$$\mathrm{BND(X)} = \overline{apr}(x) - \underline{apr}(x) \quad (2.7)$$

Rough Membership function

This function depicts the conditional probability of the sets [25]. The conditional probability of sets is given by:

$$\mu_X^R : U \rightarrow < 0,1 > \quad (2.8)$$

$$\mu^R x^{(x)} = \frac{|\mathrm{X} \cap \mathrm{R(x)}|}{|\mathrm{R(x)}|} \quad (2.9)$$

Where |X| denotes the cardinality of X.

Reducts and Core

It alludes to a subset of properties which can, without anyone else's, completely portray the information in the database which implies that it can evacuate some pointless information from data framework while maintaining its essential properties. A reduct can be considered as an adequate set of attributes to its category structure.Let $C, D \subseteq A$ be sets of condition and decision attributes successfully. If C' is a minimal subset of C, then D is reduct of C. The intersection of all D-reducts is known as D-core. The core is necessary in case of category attributes [34].

Functional Dependency

The functional dependence of D on C in A is given by IND (C) $\subseteq$IND (D). The degree of the dependencies is also estimated.

Decision systems and rules

A decisionsystem is a tuple A^d= (U, A, d), where (U, A) is an informationsystem with the set A of condition attributes, and the decision(attribute) d: U→V_d, where d∉A. In case A → d holds in A^d,we say that the decision system $A^d$is deterministic and thedependency A→ d is A^d–exact [12]. Then, for each class $[x]_A$thereexists a unique decision d(x) throughout the class. Otherwise,the dependency A→ d in A^dholds to a degree [89]. A decision rulein $A^d$is any expression ∧{a=v_a: a∈A and v_a ∈V_a}→d=v whered is the decision attribute and v∈V_d.

Definable and rough concepts

The class of B is treated as B-definable. The B is said to be definable iff $[y]_a \subseteq$ U or

$[y]_b \cap$ X= $\emptyset$.

Rough Mereology

More mind boggling data granules are characterized recursively utilizing effectively characterized data granules and their measures of incorporation and closeness. Data granules, for example, classifiers [32] or estimate spaces can have complex structures. Calculations on data granules are performed to find pertinent data granules, e.g., examples or estimation spaces for complex idea approximations.

LITERATURE SURVEY

The modalities of the medical images were the Magnetic Resonance Imaging (MRI) [14], Computed Tomography (CT), ultrasound etc. The segmentation of the medical images is trivial task in the medical diagnosis systems. The causes of the segmentation leads to low image contrast that leads to lose or collision of the tissue boundaries [1] [5] [8]. The segmentation process acts as a predecessor to the subsequent analysis [2][3][5][10]. The rough set is an essential tool for analyzing the knowledge. This survey is based on three approaches namely

i) Feature selection
ii) Clustering
iii) Rule Induction

Rough Set Theory in Feature Selection

Feature selection is a crucial part in data mining. The important features of objects are extracted and the remaining irrelevant features are discarded. Based on constraints of an object, the optimal features are grouped together to form a relevant subset. The relevant subsets are defined as follows:

- Noisy variables are inconvenient to the speculation of learning systems, as the systems grow computational hardness in preparing low signal to noise ratios.
- Deceptive variables which leads to generalizing over the misunderstood concepts.

Feature Selection has two objectives:

a) Enhance the information content using the relevant subsets.
b) Reduce the cardinality of subset.

Filters: These are everlasting preprocessors. They depend on assessing the data substance of variables, and in this way draw vigorously from Data Theory. Filters are exceptionally non specific; however utilize no knowledge of the grouping properties of the information [31]. However the channel methodology is ineffectual in managing the highlight excess. Few learning systems in Filter approach systems are Relief,Focus [4], Las Vegas Filter (LVF)[, Selection Construction Ranking utilizing Attribute Design (SCRAP), Entropy-Based Reduction (EBR), Fractal Dimension Reduction (FDR) .

Wrappers: It works in blend with a classifier. They focus the nature of subsets of variables on the premise of how proficiently those variables arrange the samples. Wrappers are more exact methodology than the filters.A Wrapper's approach routines are LasVegas Wrapper (LVW) and neural system based systems.

The idea of reducts in the feature selection and decrease of traits has been considered and utilized by different experts [3, 24]. Rough sets have been broadly utilized for feature selection. Their utilization has been proposed in different commitments [9,10]. The primitive methodology is to focus the center subset for discrete property dataset, which contains firmly significant elements and reducts, likewise a subset of center and feebly significant elements, so that each reduct is adequate to focus the ideas depicted in information set. Reducts can be further utilized for highlight determination for instance an insignificant reduct would be a reduct containing a negligible arrangement of traits. Idea of nonstationary reducts was proposed by [9, 10].

Numerous great routines for figuring reducts have been created, some of them depend on genetic learning systems, which permits the computation of reducts with an worthy computational cost and others based on heuristic methods[12, 27,28 ,29].Another developmental approach for feature selection in light of RST proposed by Caballero et al.[23]. Two learning systems were proposed using evolutionary methods namely epigraph 2 and epigraph 3. Another RST based feature schemewas given by Zhang and Yao in particular PASH(Parameterized Average Support Heuristic). The core set of rules are fully extracted from this schemes. In support to that, the level of approximations was also studied.

Rough Set Theory in Clustering

A group of similar facts are clustered into single form is known as clustering which is vital task in data mining systems. This systems is applied in various fields namely, unsupervised learning, data summation and data segmentation. The homogenous subsets are grouped together and managed easily. Many researchers have worked on the various clustering techniques. The latest development is rough clustering which is based on the rough set theory. This provides the solution to cluster many objects in a parallelized manner.

Clustering based on Rough set hypothesis can be accomplished by mapping the grouping dataset to the information table. The core concept of set as lower and upper approximations of rough sets can be utilized as a part of a more extensive connection.Rough clustering has been utilized effectively in forestry, medicine imaging, web mining, supermarkets and movement designing applications. Rough sets are utilized to create proficient heuristics looking for significant resistance relations that permit extricating objects in information. Rough sets are utilized to create proficient heuristics looking for significant resistance relations that permit removing articles in information. A feature oriented rough schemes lessens the computational multifaceted nature of learning forms and wipes out the insignificant or immaterial attributes. It is also used for solving the overlapping clusters. It requires special rules than the traditional sets. Thus, in this way the uncertainty is handled using the membership of the objects.

Mazlack et al.have proposed rough set procedure for selecting a group quality. They have given two procedures, Bi-clustering and Total Roughness (TR) procedure which depend on the bi-valued quality and greatest aggregate harshness in every quality set. Another effective rough set based clustering method given by Parmar et al. is MMR(Minimum-Minimum Roughness). This procedure depends on lower and upper approximation of sets. Another system Maximal Properties Dependency (MADE) was proposed by Herawen et al. Later on hierarchical clustering was framed by Chen et al [26]. Based on RST, the consistent degree and summation degree of grouping were estimated. The Euclidean distance is estimated by the similarity of clusters.

Upadhyaya, Arora and Jainhave proposed indiscerniblity relation using the Rough Set Theory. Based on the degree of similarity, the clusters are discovered. Hakim, Winarko and Winarko [36] have proposed a strategy for grouping parallel information in view of the mix of confusion and its incongruity level [38].Partitive Algorithm incorporates information transformation models where the groups are represented by the capacities of objects. Peters and Lampartproposed rough kmedoids and Peters additionally proposed rough information systems. Other related methodologies incorporated Genetic Algorithm Based Rough Grouping. There are three variants of the GA based on rough clustering, initial one proposed by Lingras, another by Mitra et.al, and a developmental k-medoid by Peters et al. Kohonen Network Based Rough Clustering fuses rough sets into the Kohonen learning which requires lower and upper approximation of sets. Peter and Weber proposed dynamic grouping where the parameters are grouped to the environments. A few further ways to deal with rough clustering have been proposed [30].

Rough Set Theory in Rule Induction

The data mining algorithms that applied decision rules were ID3, C4.5, Bayesian approach, back propagation, neural networks, rough set framework and evolutionary algorithms. Agarwal et al [1], Agrawal andSrikant[2], Zaki and Han et al.[37] framed association rules using Rough set theory. Only the parameters support and confidence are inclusively used and metric of interest and significance using association rules.Based on the variables, the deep relations between average and strong rules were framed. A strong association rules was also framed [9][13]. An inductive learning methods was also used to form decision rules in attributes tables. Anyhow, an uncertainty among the data was established and it is recovered using automated reasoning of rule oriented systems [35]. A mathematical approach to resolve vagueness and uncertainty was recovered using indiscerniblity relation and its association in. Then the analysis was done in ‘reduct’ and ‘core’ set of condition-decision data records without the use of available knowledge.

Hu et al., figured the essentialness of features utilizing heuristic thoughts from perceptibility frameworks and proposed a heuristic lessening systems (DISMAR). Hugave rough set lessening systemsutilizing a positive locale based important attributes as a measure. Wang and Li added to a restrictive data entropy lessening systems (CEAR). Law and Au exhibited a methodology which included rough based classification, data framework, data elimination anddecision rulesto generate novel framework using numeric and non-numeric data. A data driven based fuzzy rule set called Rough Set Attribute Reduction (RSAR) was framed in. An incremental learning was studied in[33]. A gravitational based incremental clustering [27] was used to control the quality of sub clusters. There are additionally various studies including incremental rough set hypothesis. For instance, Blaszczynski and Slowinski[21] proposed another RST technique for incremental principle prompting, called DomAprioriUpp, which is a procedure of post-handling of decision sets. Asharaf et al.[8] proposed a novel RS-based incremental way to deal with clustering information. Bazan et al.[11] indicated how among equations utilized for classifier development from choice principles can be need to look for new examples significant for the incremental idea estimation of unpleasant set hypothesis.

Richards and Compton depicted Ripple-Down Rules (RDR) and its way to deal with check and approval, concentrating especially on late augmentations which utilize Rough Set Theory for check and Formal Concept Analysis for approval. Guo et al.[40] proposed a novel incremental guidelines extraction calculation called ''RDBRST'' (Rule Derivation Based On Rough sets and Search Tree) [40]. Shan and Ziarko proposed an incremental RS learning calculation, in spite of the fact that it does not bolster conflicting information. To take care of this issue, Bian[20] exhibited enhanced systems on considering Shan's learning systems.Thevast majority of the above examined methods find abnormal state in the structure of framing Production Rules (PRs) (If Premise Then Decision). Despite the fact that PRs areeasy to decipher and actualize approximate reasoning. The above insufficiencies of PRs have been applied in Censored Production Rules (CPRs), Hierarchical Production Rules (HPRs), Hierarchical Censored Generation Rules (HCPRs) and Hierarchical Censored Generation Rules with Fuzzy Hierarchy (CPRFHs) [5,15, ,16,17,18,19].

SUMMARY

This paper surveyed the research conducted in Rough Set Theory. The various experts proposed various techniques with the advent of Rough Sets. The rough sets have been applied in various data mining techniques. We focused on three approaches namely, Feature Selection, Clustering and Rule Induction. From this survey, we can infer that there is still lack of solving uncertainty and vagueness among the data exists. In medical applications, the exact potentialities of the rough sets were not utilized. The decision making process in medical images are not clear, still it is vague.

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