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Local Rough Set: An Overview

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Abstract:
Local rough set (LRS) is one of the effective tool to enhance the limitations of classical rough set theory. In recent years many scholars interested to focused on LRS. At present there is no specific literature reviews of this LRS and applications. This review paper first explores a summary of current LRS from three basic aspects, such as basic models, local fuzzy rough sets and other applications. This review, lists about the distinct promising issues of LRS which are helpful to the future works.
***Key Word**: Rough Set, LRS, Local Fuzzy Rough Set, Attribute reduction.*

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I. Introduction

Pawlak [20] originated a new concept named as rough set theory (RST). The advantage of this concept is to solve uncertainty problems. Many researchers spent their interest to deal with RST. It is established with many fields like Fuzzy sets (FS), intuitionistic FS, Neutrosophic sets, similarity measure, decision making, multigranulation, soft set, covering etc. Yuhua Qian [17] reconstructed a classical rough set defined as LRS, which overcome the drawbacks of classical rough sets. LRS is helpful to control the limited labeled data, computational ineffective and overfitting in attribute reduction.

As stated in the existing works of LRS can be segregated them in the following three classifications.

1. LRS in terms of basic models: LRS model is combined with the concept of classical rough set and the decision theoretic RS introduced by Yuhua Qian [17]. In the LRS framework, two algorithms were introduced, first one is to calculate the target concept of a local lower approximation. The second algorithm is to find a local attribute reduction of a target concept. The LRS have some extension as local neighbourhood RS [7,9]. Double LRS by [4]. Local multigranulation RS [5, 10 ,11,12 ,14] and covering based LRS [21]. Consequently, the basic models are investigating through LRS.
2. LRS in terms of fuzzy sets: Fuzzy sets, due to Xie L L, Lin G P [15] was proposed to handle indermination and inaccuracy in data analysis. Xie L L, Lin G P [6] initiated the attribute reduction to the LFRS model for two universes. It motivated the development of handling the complex data.
3. LRS in terms of other applications: For the past few years LRS theory demonstrate its distinctive capabilities in many fields, like data analysis, disease diagnosis, decision making and classification [1,17]. The applications of the real-world problems are important research in LRS models.

In recent years the concept of LRS is one of the emerging research areas. This paper aims to provide a systematic review of recent works in LRS and illustrate future research for better development of LRS.

II Preliminaries

Rough Set (RS)

Before defining the concept of RS, the information system allows a framework to describe several objects corresponding to their attributes [20]. RST is computed with the equivalence relation. The equivalence relation is a fairly strict requirement in the practical application, which restricts the use of rough sets. For this consideration, the equivalence relation replaced with Fuzzy relation, similarity relation, covering and tolerance relation etc [2,8,18,19].

Definition 1:[20]

Let Q be a non-zero set, C be a equivalence relation on Q. For some non-zero subset P of Q.

$\overline{C}P = \cup\{p: [p]_C \cap P \neq \emptyset\}$

$\underline{C}P = \cup\{p: [p]_C \subseteq P\}$

called the upper and lower approximations respectively on P. Here (Q, C) called an approximation space and C is an indiscernibility relation. The two $(\overline{CP}, \underline{C}P)$ called as RS on P.

III LRS in terms of the basic models

Definition 2:[17]
Let (C, Q) be approximation space, D be an including degree on $S(C) \times S(C)$. Any subset $P \subseteq C$, α- lower and β- upper approximations defined by,

$$\underline{Q}_{\alpha}(P) = \{p | D\ (P/\ [q]_p\ \geq\ \alpha\ , p\ \epsilon\ P\ \},$$
$$\overline{Q}_{\beta}(P) = \{p | D\ (P/\ [q]_p >\ \beta\ , p\ \epsilon\ P\ \}.$$

This pair $(\underline{Q}_{\alpha}(P), \overline{Q}_{\beta}(P))$ is defined as LRS.

Apply $\alpha = 1$and $\beta = 0$ to the above-mentioned definition, it will degenerate to the classical (Pawlak's) rough set. Here Yuhua Qian [17] calculated target concept of information granules, it is possibly to reduce the computation time for concept approximation. Also, Yuhua Qian provide four algorithms to calculate approximation and attribute reduction of a target concept by dividing it into two parts. The LLAC and LLAD algorithms is to calculate local lower approximation and LARC and LARD algorithms is to compute local attribute reduction of the target concept. Also, they discussed the similarity measure and accuracy of LRS. The authors provided a theoretical and experimental analysis in a brief way.

Definition 3:[7]
Let (Q, N) be a neighborhood approximation, D be an inclusion degree in $P(Q) \times P(Q)$. For any $G \subseteq Q$, α– lower, β- upper approximations are

$\underline{N}_{\alpha}(G) = \{g | D\ (G/\ [q]_Q\ \geq\ \alpha\ , g\ \epsilon\ G\ \}$,
$\overline{N}_{\beta}(G) = \{g | D\ (G/\ [q]_Q >\ \beta\ , g\ \epsilon\ G\ \}$.

Where $\delta(g) = \{p\ |\Delta(g, p) \leq \delta\}$, Δ is an distance function. $D(G/\delta(g) = \frac{|\ G \cap \delta(g)|}{|\ \delta(g)|}$ defined by degree of inclusion. This pair $(\underline{N}_{\alpha}(G), \overline{N}_{\beta}(G))$ called as local neighborhood rough set. The boundary is defined by $BN_N(G) = (\underline{S}_{\alpha}(G) - \overline{S}_{\beta}(G)$.

Yuhua Qian [7] introduced local neighbourhood rough sets (LNRS). He was the first to establish the depth of local neighbourhood rough set and to inspect its properties and measures. LNRS is able to solve local lower/upper approximation and attribute reduction of a target concept. Also, he verified the LNRS algorithm with experimental results. Zhang Y [9] introduced dynamic algorithms using LNRS. It is used to analyze the local approximation when the object set is decreased. given the dynamic algorithm to get the local approximation approximations. Also, it is used to verify the algorithm through experiments using datasets.

In a classical RST the multigranularity decision theoretic RS model [MDTRS] proposed in the information system. Using fundamental function to compute the probability measure through dominance relation. Xiaoyan Z [5] introduced local multigranulation rough set in 2019. It is effective tool to overcome uncertain problems. Also apply this concept is applied in decision making problems for large scale dataset. MDTRS constructed the probability measure. Using lower & upper fusion function to calculate the multigranulation approximations.

Definition 4[5]
Let (Q, AT, G) is ordered information system (OIS), $R_K^{\geqq}(K = 1,2, \ldots n)$ be dominance relation on OIS. $[z]_{R_K}^{\geqq}$ be a dominance class on $R_K^{\geqq}$. For any $Z \epsilon Q$, the parameters α, β satisfies the relation $0 \leq \beta < \alpha \leq 1$. The local optimistic multigranulation of upper and lower approximations established on a dominance relation $R_K^{\geqq}$ defined as $\underline{\sum_{K=1}^{n} R_K^{\geqq^O}}(Z) = \left\{z\ |\ \bigvee_{K=1}^{n}(P(Z\ |\ h\ (\ [z]_{R_K}^{\geqq})) \geq \alpha, z \epsilon Z\right\}$

$\overline{\sum_{K=1}^{n} R_K^{\geqq^O}}(Z) = \bigcup_{K=1}^{n}\left\{z\ |\ \bigwedge_{K=1}^{n}(P(Z\ |\ h\ (\ [z]_{R_K}^{\geqq})) > \beta, z \epsilon Z\right\}$

Here$(P(Z\ |\ h\ (\ [z]_{R_K}^{\geqq}))$ be a conditional probabilistic equivalence class $l([z]_{R_K^{\geqq}})$ on Z.

Then, local optimistic multigranulation negative, positive and boundary on Z.

$$Pos^O(Z) = \underline{\sum_{K=1}^{n} R_K^{\geqq^O}}\ (Z)$$

$$neg^O(Z) = Q - \overline{\sum_{K=1}^{n} R_K^{\geqq^O}}\ (Z)$$

$bnd^{O}(Z) = \overline{\sum_{K=1}^{n} R_K^{\geq O}}(Z) - \underline{\sum_{K=1}^{n} R_K^{\geq O}}(Z).$

Definition 5[5]

Let (Q, AT, G) is an OIS, $R_K^{\geq}(K = 1,2, \dots n)$ be dominance relation on OIS. $[z]_{R_K}^{\geq}$ be a dominance class on $R_K^{\geq}$. For any $Z \epsilon Q$, the parameters α, β satisfies the relation $0 \leq \beta < \alpha \leq 1$. The local pessimistic multigranulation of upper and lower approximations established on a dominance relation $R_K^{\geq}$ defined as

$\underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = \left\{z \mid \bigwedge_{K=1}^{n}(P(Z \mid h\,([z]_{R_K}^{\geq})) \geq \alpha, z\epsilon Z\right\}$

$\overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = \bigcup_{K=1}^{n} \overline{hpr_{R_K}}$

Here$(P(Z \mid h\,([z]_{R_K}^{\geq}))$ be a conditional probabilistic equivalence class $l([z]_{R_K^{\geq}})$ on Z.

Then, local pessimistic multigranulation negative, positive and boundary on Z.

$$Pos^{P}(Z) = \underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z)$$

$$neg^{P}(Z) = Q - \overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z)$$

$bnd^{P}(Z) = \overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) - \underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z).$

Definition 6[12]

Let (Q, AT, G) is an OIS, $R_K^{\geq}(K = 1,2, \dots n)$ be dominance relation, for every $P \epsilon Q$. The upper and lower approximations established on Q by a dominance relation $R_K^{\geq}$ defined as

$\underline{\sum_{K=1}^{n} R_K^{\geq O}}(P) = \left\{p \mid \bigvee_{K=1}^{n} ([p]_{R_K}^{\geq} \subseteq P), p\epsilon P\right\},$

$$\overline{\sum_{K=1}^{n} R_K^{\geq O}}(P) = \bigcap_{K=1}^{n} \overline{R_K^{\geq}}$$

Here $\underline{\sum_{K=1}^{n} R_K^{\geq O}}(P)$ denoted as intersection of upper approximation under granularity.

$R_K^{\geq} = \bigcup\left\{\left[[p]_{R_K}^{\geq} \,\middle|\, [p]_{R_K}^{\geq} \cap P \neq \emptyset, p\epsilon P\right\}.$

Define the positive, negative and boundary for optimistic local multigranulation in OIS.

$$Pos(P) = \underline{\sum_{K=1}^{n} R_K^{\geq O}}(P) = \left\{p \mid \bigvee_{K=1}^{n}([p]_{R_K}^{\geq} \subseteq P),\ p\epsilon P\right\},$$

$$neg(P) = \sim \overline{\sum_{K=1}^{n} R_K^{\geq O}}(P) = U - \bigcap_{K=1}^{n} \overline{R_K^{\geq}}$$

$bnd\,(P) = \overline{\sum_{K=1}^{n} R_K^{\geq O}}(P) - \underline{\sum_{K=1}^{n} R_K^{\geq O}}(P).$

Definition 7[12]

Let (Q, AT, G) is an OIS, $R_K^{\geq}(K = 1,2, \dots n)$ be dominance relation, for every $Z \epsilon Q$. The upper and lower approximations established on Q by a dominance relation $R_K^{\geq}$ defined as

$\underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = \left\{z \mid \bigwedge_{K=1}^{n}([z]_{R_K}^{\geq} \subseteq Z), z\epsilon Z\right\},$

$$\overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = \bigcup_{K=1}^{n} \overline{R_K^{\geq}}$$

Here $R_K^{\geq} = \bigcup\left\{\left[z\right]_{R_K}^{\geq} \,\middle|\, [z]_{R_K}^{\geq} \cap Z \neq \emptyset, z\epsilon Z\right\}$, denoted as local upper approximation under granularity.

Define the positive, negative and boundary for pessimistic local multigranulation in OIS.

$$Pos(Z) = \underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = \left\{z \mid \bigwedge_{K=1}^{n}([z]_{R_K}^{\geq} \subseteq Z)\ z\epsilon Z\right\},$$

$$neg(Z) = \sim\overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) = U - \bigcup_{K=1}^{n} \overline{R_K^{\geq}}$$

$$bnd\ (Z) = \overline{\sum_{K=1}^{n} R_K^{\geq P}}(Z) - \underline{\sum_{K=1}^{n} R_K^{\geq P}}(Z).$$

Weihua xu [10] initiated local generalized multigranularity based neighbourhood RS. Jirong Li [14] proposed multigranulation on interval valued hesitant fuzzy information system.

Zhouming Ma [21] proposed variable precision covering RS on the boundary region. He was the first to initiate CVPRS model, it is evaluating the existing covering in the boundary region. Main work of this model describes the pair of boundary operators and pair of approximations operators with some threshold value. This theoretical model is verified by numerical experiments.

Table no 1 provides literature papers in the field of basic models.

S.No	Authors	Year	Study Contribution
1	Yuhua Qian et al. [17]	2018	Developed four algorithms to solve local lower approximation and attribute reduction of a target concept and gave a brief experimental works.
2	Yuhua Qian et al. [7]	2018	Established the depth of LNRS and inspected its properties and measures.
3	Jia Zhang et al. [5]	2019	Developed a local multigranulation decision theoretic rough set model in IOS. This model is effective to handle large dataset & it minimize the computation time.
4	Eric C.C. T [16]	2019	Introduced local logical disjunction double quantitative RS (LLDDRS) method. This method is an efficient tool for decision making and discovering knowledge to a huge data set. Also studied its important properties, decision rules and optimal computation of RS. Also, presented an experimental works to verify this model.
5	X. Yang et al. [13]	2020	Introduced S3WGrC by the prospect of temporal spatial multigranularity learning, which can be represented by dynamic data & parameter of temporality & spatiality of three-way decision. He also proposed local neighbourhood trisecting model for S3WGrC and presented local sequential model for three-way granular computing and comparative experimental work can be conducted.
6	Xiaoyan Zhang et al. [14]	2021	Introduced a dynamic updating approximation to produce attribute variation of MG-IVHFIS. Studied four algorithms for updating approximations of optimism, pessimism in dynamic MG-IVHFIS.
7	Tianrui Li et al. [4]	2021	Proposed local equivalence class & local membership functions. Using double LRS, a quick attribute reduction model is proposed and applied the model to the experimental analysis.
8	Wentao Li et al. [12]	2021	Introduced two kinds of local multigranulation rough approximation on OIS, those are optimistic & pessimistic LMRS model in OIS. Discussed the comparison of classical and LMRS model in OIS with static & dynamic conditions.
9	Zhouming Ma et al. [21]	2022	Developed CVPRS model in the boundary region is based on covering based RS model. Used CVPRS model to compute attribute reduction for covering based decision information system.
10	Weihua Xu et al. [10]	2022	Constructed local generalized multigranulation neighbourhood RS model by using the definition of support & inclusion function.
11	ZHANG Yanlan et al. [9]	2023	Initiated dynamic updating algorithm of LNRS model. It is effective tool to handle approximation operators of dynamic numerical data. This algorithm makes to avoid a repeated calculation and comparative experimental work can be conducted.

As stated in the concept of LRS, it is simple to identify the significant contribution of LRS and it open a new direction of research. The future direction of this study is listed below.

1. Extend LRS to several binary relations, rough classifiers and attribute reduction and its applications.
2. Extend double DLRS with attribute significant measures, increment learning technique and etc.
3. To overcome the change of optimal fusion on data and parameters.

IV LRS in terms of local fuzzy rough sets (LFRS)

Definition 8[15]

Let (Q, C) is fuzzy information system, z_λ is fuzzy point, $z\epsilon Q, \lambda\epsilon[0,1]$ and $0 \leq \beta < \alpha \leq 1$, for some target concept $\tilde{Z}\epsilon F(Q)$, is α- local lower approximations and β local upper approximation respectively.

$$\underline{L\tilde{C}_{(\alpha,\beta)}}(\tilde{Z}) = \bigcup\{ z_\lambda |\ \tilde{D}(\tilde{Z}/[z_\lambda]_{\tilde{C}}^{T})\} \geq \alpha\ , z\epsilon Z\}$$

$\overline{L\tilde{C}_{(\alpha,\beta)}}(\tilde{Z}) = \bigcup\{ [z_{Z(z)}]^T_{\tilde{C}} \mid \tilde{D}(\tilde{Z}/[z_\lambda]^T_{\tilde{C}})\} > \beta , z\epsilon Z\}$

Here the inclusion degree is $\tilde{D}$,

$$\tilde{D}(\tilde{Z}/[z_\lambda]^T_{\tilde{C}}) = \frac{\sum_{y\epsilon Q}([z_\lambda]^T_{\tilde{C}}(y) \wedge \tilde{Z}(y))}{\sum_{y\epsilon Q}([z_\lambda]^T_{\tilde{C}}(y)}$$

The two $(\underline{L\tilde{C}_{(\alpha,\beta)}}(\tilde{Z}), \overline{L\tilde{C}_{(\alpha,\beta)}}(\tilde{Z}))$ called the LFRS on $\tilde{Z}$.

Definition 9[6]

Let $(Q, V, \tilde{C})$ be an fuzzy approximation space in two universe, for some $\epsilon[0,1]$, $z\epsilon Q$ and $0 \leq \beta < \alpha \leq 1$, z_λ be a fuzzy unique point set, for some $\tilde{Z}\epsilon F(Q)$, the ρ- local fuzzy lower approximations and L- local fuzzy upper approximation operators on $\tilde{Z}$ defined as

$\underline{\tilde{C}_{\alpha\rho}}(\tilde{Z}) = \bigcup\{ z_\lambda | \tilde{D}(\tilde{Z}/[z_\lambda]^L_{\tilde{C}})\} \geq \alpha , \lambda > \in, [z_\lambda]^L_{\tilde{C}} \neq \emptyset\}$

$\overline{\tilde{C}_{\beta L}}(\tilde{Z}) = \bigcup\{ z_\lambda | \tilde{D}(\tilde{Z}/[z_\lambda]^L_{\tilde{C}})\} > \beta , \lambda > \in, [z_\lambda]^L_{\tilde{C}} \neq \emptyset\} \bigcup \{z_\lambda \mid [z_\lambda]^L_{\tilde{C}} = \emptyset\}$

The two $(\underline{\tilde{C}_{\alpha\rho}}(\tilde{Z}), \overline{\tilde{C}_{\beta L}}(\tilde{Z}))$ called LFRS on $\tilde{Z}$. Particularly if $\underline{\tilde{C}_{\alpha\rho}}(\tilde{Z}) = \overline{\tilde{C}_{\beta L}}(\tilde{Z})$, then $\tilde{Z}$ called definable on V.

Introducing the framework of LFRS by Xie LL [15] in 2021, LFRS theory motivates to handle complex data. Also, LFRS described in two universes [6] also analyzes its decision rules and properties.

Table no 2 provides a literature paper in the field of LFRS.

S.No.	Authors	Year	Study Contribution
1	Xie LL, Lin G petal et al. [15]	2021	Proposed to handle indetermination & inaccuracy in data analysis.
2	Guoping Lin et al. [6]	2023	Initiated the attribute reduction to LFRS model for two universes. It is effective to handle the complex data and proposed experimental works to validate this model.
3	Guoping Lin [3]	2023	Proposed local double quantitative fuzzy RS (FRS) model on two universes. Discussed its properties and decision rules of local double quantitative FRS model. Improved the applicability of this model with efficient reduction method & experimental works also conducted.

In the information system, there are having numerous features and objects, but the need based on upper and lower approximation classification ability on the LFRS on two universes cannot be changed, and thus the new reduction model was proposed by Xie L L, Lin G P [6]. The future work of this study is given below.

1. To combine the reduction algorithm with other models.
2. Develop multigranularity LFRS model over two universes.

V LRS in terms of other applications:

In preceding sections, we revisited the idea of LRS, LRS in terms of the basic models, local fuzzy rough sets. Our aim in the present section is discussed other applications of LRS. i.e., Data analysis, disease diagnosis and some detailed information is listed below.

1. **Data Analysis:** A Fatih Ozean A F [1] proposed a concept on classification of LRS. He also examined the students who addicted to the social media. The selected numerical data was compared with RS and LRS. LRS theory gives more real and exact information when compared with RST. Yuhua Qian [17] investigated mushroom data set with the use of LRS. For future extension of LRS to construct the algorithms for other data sets, risk analysis, decision making, etc.
2. **Disease Diagnosis:** Guoping Lin [6] introduced the LLAC algorithm, its uses to diagnosis the patient's illness. Tianrui Li [13] proposed a local neighborhood-based temporal-spatial S3WGRC model, applying this model to the data set of Wisconsin diagnosis breast cancer, diabetic retinopathy Debrecen and etc.

VI Conclusion

LRS theory is a effective tool for handling limited labeled data, overfitting and computational problems. As a way to construct comprehensive overview of LRS theory, the work focus on three perspectives of existing works, i.e., Basic models, Local Fuzzy rough sets and other applications. In the presented conversation, LRS achieved a substantial development in distinct research areas.

In the future direction, still there is a lot of work to be enhance the analysis of LRS in other considerable aspects of LRS models, such as uncertainty measure, decision making, etc. Furthermore, the growth of novel LRS is a considerable attention, such as LRS in terms of various attribute reduction, LRS in terms of semi supervised rough classifiers, LRS with the extension of Fuzzy sets. It is significant to expand the realistic applications with the proposed models.

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