A Precise and Adaptive Graph Regularized Low Rank Representation Model for Recognizing Oil-bearing

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Abstract: The recognition of oil-bearing formation is an important part in oil exploration, and recognition technology influences the predictive accuracy and efficiency. Low rank representation (LRR) has aroused much attention in the field of data mining. As a modified version, the low rank representation with adaptive graph regularization (LRR-AGR) exploits the global and local information of data for graph learning, and it simultaneously integrates distance regularization term, non-negative constraint and a rank constraint into the framework of LRR. However, how to balance these regularization terms according to the data greatly limits its clustering performance. To adaptively balance these regularization terms according to the data and further improve the clustering performance, we propose a novel model named low-rank representation with adaptive parameters and graph regularization (LRR-APGR) in this paper. Firstly, a novel parameter optimization model is formulated and designed based on the framework of LRR-AGR and the feedback mechanism. Secondly, two global intelligent optimization algorithms, which can effectively solve the parameter optimization problem are presented based on particle swarm optimization (PSO) in multi-dimensional continuous space. Experimental results on the data oilsk81, oilsk83 and oilsk85 wells of Jianghan oil fields in China show that the proposed method can significantly improve the clustering performance and the predictive accuracy.

Keywords: Low rank representation, graph regularization, rank constraint, particle swarm optimization .

1. INTRODUCTION

The recognition of oil-bearing formation is the process of recognizing the characters of each layer in the well. These characters include dry layer, water layer, inferior oil layer, and oil layer (Guo et al., 2011). In the fields of pattern recognition, based on whether label information is used or not, data analysis technologies can be divided into three groups, i.e., supervised learning, unsupervised learning and semi-supervised learning (Jain., 2010). In order to obtain a good predictive accuracy, which is the main task in the recognition of oil-bearing formation, it is necessary to appropriately use the correlative information of the data and data analysis technologies.

The multidimensionality and heterogeneity of well log data is a very challenging problem in recognizing oil-bearing formation. It is found that reservoirs expand over hundreds to thousands of miles spatially in thin layers resulting in huge multidimensional data collection at well locations (Syed et al., 2022). In addition, unconventional reservoirs are found to be complex and highly heterogeneous that are commonly characterized by their ultra-tight permeability. Finding an accurate model and designing an appropriate control strategy constitute a challenging task (Mitrica et al., 2021).Therefore, different well log features and recognizing models are selected to deal with well log data. Self-organizing feature map neural network (SOM) model and six feature parameters were selected to identify the unconventional reservoir (Fu et al., 1999), i.e., resistivity (RT), porosity (POR), permeability (PERM), shale content (Vsh), water saturation (Sw), and acoustic time

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(AC). Back propagation (BP) neural network model based on fuzzy approach degree and four parameters i.e., POR, Sw, AC and induction well log value (COND),were used to identify the reservoir oil and gas properties (Feng., 1999). Genetic algorithms (GA) and fuzzy c-means (FCM) were used to reduce well log features, and construct a model through BP neural network optimized by GA to predict the value of optimal feature subset (Guo et al., 2010; Li et al., 2012). Obviously, the acquisition of relevant features and the establishment of appropriate models are two critical steps in recognizing oil-bearing formation. It can be known that it is meaningful and beneficial for label information to construct predictive model and optimize feature selection. However, it is difficult to obtain the label information, and there are some issues to overcome, such as the lack of logging analyst's experience, and lower efficiency in interpretation. How to automatically manage these well log data into different natural groups is a challenging problem. Data clustering is the most favored technique to deal with this challenge for discovering the natural groups without any label information (Jain., 2010).Clustering algorithms is the process of splitting the dataset in smaller parts under a specific criterion, which is involved in the optimal division of the dataset set by appropriate optimization problem(s) (Borlea, et al,2022; Pehlivan, et al,2021).It is necessary and beneficial to find an accurate clustering model and design an appropriate strategy to control parameters.

As a subspace clustering technology, low-rank representation (LRR),has attracted great interest in pattern analysis and signal processing communities (Yin et al., 2015), because of pleasing efficacy in exploring low-dimensional subspace structures embedded in data. LRR can better capture global structure of data and preserve the membership of the samples that belong to the same subspace, simultaneously partition data into different clusters with each cluster corresponding to a subspace (Liu et al., 2010; Liu et al., 2012). Even if the data with noise and outlier in dealing with high dimensional data, it is robust and widely used in image classification and clustering (Wang et al., 2018; Fu et al., 2021; Chen et al.,2022), data recovery (Zhou et al., 2020), dimensionality reduction (Syed et al., 2022), anomaly detection (Zhang et al., 2021; Miao et al., 2020) and other fields. Non-negative and sparse constraints added to the representation coefficient matrix in LRR, a non-negative low-rank and sparse (NNLRS) model was proposed (Zhuang et al., 2012), which can enhance physical interpretation for real data and capture the local dim linear relationships of data. By introducing the hypergraph Laplacian regularization term into the NNLRS model, the non-negative sparse hyper-Laplacian regularized low-rank representation (NSHLRR) model was proposed (Yin et al., 2015), in which the intrinsic non-linear geometry information in data is further captured. According to spectral theory and prior cluster information, i.e., the number of clusters embedded in data, rank constraint is imposed on the Laplacian matrix in LRR model (Lu et al., 2018; Feng et al., 2014), in which the learned graph is forced to have exactly connected components corresponding to clusters embedded in data. A non-negative weighted sparse distance constraint and a rank constraint were integrated into the framework of LRR model (Wen et al., 2018), low-rank representation with adaptive graph regularization (LRR-AGR) model was proposed. LRR-AGR not only simultaneously captured the local structure and global structure of data, but also learned an optimal graph with clearly clustering structure. Two-moon synthetic dataset and some real datasets, including four non-image datasets from UCI machine repository and six image datasets, were selected to prove the effectiveness of LRR-AGR. In fact, it is essential to exploit the intrinsic structure of data for data clustering task. And it can be an appropriate and accurate model in the recognition of oil-bearing.

In real world applications, the clustering performance of LRR-AGR model is dependent on these different regularization terms, i.e., distance constraint term, low-rank constraint term, and rank constraint term. These regularization terms make the LRR-AGR model to learn an ideal graph by capturing the intrinsic structure of data (both local structure and global structure). The affect of these regularization terms in the model are tuned by three parameters. Actually, these parameters balance the above terms in LRR-AGR model. How to adaptively balance these regularization terms in LRR-AGR model is an open problem (Wen et al., 2018). However, adaptively balance these regularization terms, i.e., adaptively select optimal parameters for a dataset, can reduce the sensitivity and improve the clustering performance. Designing an appropriate control strategy and an optimization method is the main task of tuning parameters to adaptively balance multiple reguarization terms for LRR-AGR. As a result, aiming at well log data, a new approach which can adaptively select optimal parameters for LRR-AGR model to improve the clustering performance, is proposed in this paper. Inspired by the reference (Lazzus et al., 2020; He et al., 2007), i.e., heuristic algorithms optimize the parameters in Lotka-Volterra system, we optimize the parameters of LRR-AGR model based on particle swarm optimization (PSO) algorithm. We propose a model named low-rank representation with adaptive parameters and graph regularization (LRR-APGR) in this paper. A mathematic model about the optimization problem and an effective method based on metaheuristic optimization techniques are presented in this study. Firstly, parameter estimation for LRR-AGR is modeled as a multidimension optimization problem based on the framework of LRR-AGR model and the feedback mechanism between parameter values and clustering performance evaluation. Secondly, an effective searching strategy based on MPSO algorithm is presented to solve the optimization problem in multidimensional continuous space. The optimal parameters searched by PSO algorithm, matching with LRR-AGR model, are selected adaptively for each well log data. In summary, designing an appropriate control strategy for LRR-AGR by optimizing tuning parameters is the main feature in this work, and our main contribution lies in the following three aspects:

(1) A modified LRR-AGR model with optimal parameters named LRR-APGR is proposed and applied successfully in oil-bearing recognition.

(2) Instead of parameters of LRR-AGR model selected in a candidate range set, we model the parameter estimation as a multidimension continuous optimization problem based on the framework of LRR-AGR model and the feedback mechanism between parameter values and clustering

performance evaluation. Moreover, an effective algorithm based on PSO algorithm for searching optimal solution in multidimension continuous space is designed to solve the optimization problem.To the best of our knowledge, few contributions address the problem of designing optimal tuning parameters for LRR-AGR.

(3) The proposed model has good interpretability and adaptability, in which the recognition ability in oil-bearing formation is mainly achieved by capturing various structures information through the combination of regularization terms and their interactions tuned by these parameters among various regularization terms.

The rest of this paper is organized as follows. In section 2, we give a brief description to several related works. Section 3 presents the proposed model about the parameter estimation of LRR-AGR and the mechanism in solving the optimization problem about this model. Section 4 analyzes the result of experiment based on data oilsk81, oilsk83, oilsk85, wells of Jianghan oil fields in China. Section 5 offers the conclusion of the paper and the next research direction.

2. RELATED WORKS

2.1 LRR model

According to the assumption that data in a high-dimensional space actually lie on the union of several linear subspaces, LRR model is proposed, aiming at finding the lowest-rank representation of all data for data clustering (Liu et al., 2010; Liu et al., 2012). It has been shown that LRR model is an effective tool for subspace clustering because it is better at capturing the global structure of data. For the given data X, the LRR model is defined as rank minimization problem and solved by a following convex optimization problem through a good surrogate for rank function.

$$\begin{aligned} &\min_{Z,E} \|Z\|_* + \lambda\|E\|_1 \\ &s.t. X = XZ + E \end{aligned} \tag{1}$$

where $\|Z\|_*$ is the nuclear norm of representation matrix Z, calculated as $\|Z\|_* = \sum_i^n \delta_i$. δ_i is the i-th singular value of matrix Z, n is the number of samples in data, and E is the error matrix term used to model different noises, $\|E\|_1$ is the l_1 norm, defined as the sum of absolutes of all entries, and λ is a penalty parameter for balancing the rank function and the l_1 norm.
Several methods have been proposed for solving the problem (1), such as augmented Lagrange multiplier method (ALM) (Liu et al., 2010), and linearized alternating direction method with adaptive penalty (LADMAP) (Lin et al., 2011). After obtaining an optimal solution Z^*, each column of Z^* is normalizes as $z_i = z_i/\|z_i.\|_\infty$. Then the similarity graph matrix $W = |Z| + |Z^T|$ is calculated. Each element w_{ij} denotes the similarity degree between samples x_i and x_j, and then applies the spectral clustering algorithm to cluster data into different subspaces.

2.2 LRR-AGR model

LRR model is better at capturing the global data structures (such as multiple clusters and subspaces). However, it may fail to discover the intrinsic geometric and discriminating structures of data (Yin et al., 2015), which is essential to actual application. A model which well preserves the locality and similarity of data, has the potential to convey more discriminative information. In addition, if the representation coefficient value is negative, it will lead to the lack of physical interpretation in the real-world applications. By introducing the distance constraint, low-rank constraint, non-negative constraint and a rank constraint, LRR-AGR is proposed to learn an ideal graph (Wen et al., 2018). The LRR-AGR model is formulated as follows

$$\begin{aligned} &\min_{Z,E} \sum_{i,j}^n \|x_i - x_j\|_2^2 z_{ij} + \lambda_1\|Z\|_* + \lambda_2\|E\|_1 \\ &s.t. X = XZ + E, diag(Z) = 0, Z \geq 0, \\ &rank(L_z) = n - c \end{aligned} \tag{2}$$

where $\sum_{i,j}^n \|x_i - x_j\|_2^2 z_{ij}$ is the distance constraint, if Z is non-negative, adaptively selecting a few nearest neighbor samples for representation, which enables the model to guarantee the locality and sparsity, and the non-negative constraint on Z aims to guarantee that each data point is in the middle of its neighbors, which can enhance physical interpretation for real data and embody the dependency among data points than otherwise, c is the number of connected components in optimal graph corresponding to the clusters embedded in data, rank constraint $rank(L_z) = n - c$, as a prior information, is imposed on the Laplacian matrix L_z which is defined as $L_z = D - (Z + Z^T)/2$, where D is a diagonal matrix and its i-th diagonal element $D_{ii} = \sum_j (z_{ij} + z_{ji})/2$, λ_1, λ_2 are positive penalty parameters for balancing the low-rank term, the weighted distance regularization term and the error term.
As the Laplacian matrix L_z is positive semi-definite (Nie et al., 2016) and the facilitation of Theorem (Fan., 1949), the minimization optimization problem (2) is converted into the following equivalent optimization problem:

$$\begin{aligned} &\min_{Z,E} \sum_{i,j}^n \|x_i - x_j\|_2^2 z_{ij} + \lambda_1\|Z\|_* + \lambda_2\|E\|_1 + \\ &2\lambda_3 \sum_{i=1}^c Tr(F^T L z F) \\ &s.t. X = XZ + E, diag(Z) = 0, Z \geq 0, \sum_j z_{ij} = 1, \\ &F^T F = I \end{aligned} \tag{3}$$

where $F = [f_1^T, f_2^T, \cdots, f_n^T]^T \in R^{n\times c}$ is the set of c eigenvectors corresponding to the first the c smallest eigenvalues of L_z, $Tr(\cdot)$ is the trace operator, and λ_3 is also a positive penalty parameter used to balance the regularization term in the model. And the optimization problem (3) has been solved by alternating direction method (ADM) through constructing the augmented Lagrangian function (Wen et al., 2018).

2.3 PSO algorithm and MPSO algorithm

PSO is an evolutionary computation technique (Eberhart et al., 1995). Due to its simplicity of implementation and its ability to quickly converge to a reasonably acceptable

solution, PSO has been successfully applied to solve non-convex or combinatorial optimization problems that arise in many science and engineering domains (Lazzus et al., 2020; He et al., 2007; Clerc et al., 2002; Shi et al., 1999). As a swarm intelligent search algorithm, PSO aims to find the optimal solution by interacting and sharing information with neighbor particles. The information shared in PSO is obtained by the best positions visited earlier by itself and by any particle in the population so far, named as $pbest_i$ and $gbest$, respectively. Each particle i of the swarm has a current position in search space as x_i and a velocity v_i. So, in the standard PSO algorithm, for each iteration t, the velocity and position update equation are described as follows.

$$\begin{aligned} &v_{ij}(t+1) = w_{ij}v_i(t) + c_1r_1(pbest_{ij}(t) - x_{ij}(t)) + \\ &c_2r_2(gbest_{ij}(t) - x_{ij}(t)) \\ &x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \end{aligned} \tag{4}$$

where w_{ij} is the inertial weight,c_1 and c_2 are acceleration positive constants, r_1, r_2 are random numbers in the range of [0,1] drawn from a uniform distribution, j is the j-th dimension in solution space. To guarantee the search from global to local, inertia weight starts with a value close to 1 and linearly decreases to 0.4.

To solve the local optimum or stagnation problem in the standard PSO algorithm, a modified version of PSO (MPSO), which adds another behavioral term to the swarm, is implemented to solve the parameters optimization problem of Lotka-Volterra system (Lazzus et al., 2020; He et al., 2007). The formula of MPSO algorithm is updated as follows.

$$\begin{aligned} &v_{ij}(t+1) = w_{ij}(t)v_i(t) + c_1r_1(pbest_{ij}(t) - x_{ij}(t)) + \\ &c_2r_2(gbest_{ij}(t) - x_{ij}(t)) + c_3r_3(prand_{ij}(t) - x_{ij}(t)) \\ &x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \end{aligned} \tag{5}$$

where c_3 is also an acceleration positive constant, r_3 is the elements with random sequences in range [0,1]. *prand* is a random position in swarm. To diversify and improve the search capability in the swarm, a new random term provided by *prand* is added. The random particle's information can weaken the attraction of the *gbest* position, and move the particles to a better location.

3. LOW RANK REPRESENTATION WITH ADAPTIVE GRAPH REGULARIZATION AND ADAPTIVE PARAMETERS

LRR-AGR learned an ideal graph with intrinsic structure of data because of integrating distance constraint, low-rank constraint and rank constraint into the framework of LRR. These constraints in LRR-AGR were balanced by three parameters, i.e., λ_1, λ_2 and λ_3. Depending on the application and the characteristics of the problem, tuning all these parameters properly may lead to better results. It is necessary to balance these regularization terms adaptively in the recognition of oil-bearing formation. Thus, a parameter optimization model is formulated based on the framework of LRR-AGR and the feedback mechanism aiming at different well log data. Meanwhile, an optimal algorithm based on PSO and MPSO is implemented to solve the optimization problem.

3.1 The model of parameter optimization for LRR-AGR

As mentioned in formula (3), assuming the optimal matrix of Z^* and E are given, there are three parameters, i.e., λ_1, λ_2 and λ_3 affecting the performance of LRR-AGR. To obtain the best clustering performance, we need to optimize these parameters. In this paper, we introduce the feedback theory of a system to precisely control these parameters and regularization terms for aimed well log data. The LRR-AGR model is regarded as a recognition system. Clustering performance is considered as a state under the input of these parameters. The process of obtaining and evaluating the optimal representation matrix Z is regarded as the executing agency. Fig.1 is the schematic diagram of obtaining optimal parameters to precisely control different regularization terms for LRR-AGR model.

In the following, we describe quantitatively the model of parameter optimization in mathematical form according to above analysis, so as to achieve optimal parameters. Denote c as the clusters of data, X_0 is initial input matrix calculated by data X, vector $\mathbf{p}$ is a parameter combination of $\lambda_1, \lambda_2, \lambda_3$. Actually, $c, \mathbf{p}$ and X_0 are pre-programmed or calculated in LRR-AGR model, for a given data X, then the optimal representation matrix Z^* is obtained through solving the problem (3) by ADM in LRR-AGR model. We denote this process as $Z^* = F(X, X_0, c, \mathbf{p})$. To evaluate the optimal graph Z^* the two metrices function, i.e., clustering accuracy (ACC) and normalized mutual information (NMI) (Yin et al., 2022; Wen et al., 2018;Yin et al., 2015), defined as following formula (8) and (9), are selected to evaluate the clustering result achieved by spectral clustering. We denote the evaluation and quantization process as $y = G(Z^*)$ where y is the evaluation value. In a word, under a given initial input, after obtaining an optimal graph Z^*, for a data X, the clustering evaluation value y can be obtained and summarized as

$$y = G(F(X, X_0, c, \mathbf{p})) \tag{6}$$

Simultaneously, the parameter optimization problem is the inverse problem of (6), i.e., the following formula

$$\mathbf{p}^* = \arg\max_{\mathbf{p}}(G(F(X, X_0, c, \mathbf{p}))) \tag{7}$$

3.2 Solution of the model of parameter estimation

Parameter estimation is a process to obtain the parameter values of a mathematical model using sample data of a given system (Lazzus et al., 2020; He et al., 2007). As an optimization method, the three parameters, i.e., λ_1, λ_2 and λ_3 are chosen in a candidate parameter range set of $\left\{10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 10^1, 10^2\right\}$ (Wen et al., 2018). According to the sensitivity of parameters to the clustering ACC, parameter λ_3 is firstly fixed, and then perform the LRR-AGR model to find the optimal λ_1 and λ_2 in a candidate domain. Then by similar strategy, parameters λ_1 and λ_2 are fixed, and then perform LRR-AGR method to find the optimal parameter λ_3 in a candidate domain. Lastly, the optimal combination of these parameters can be obtained in the 3D candidate space which is composed by the three candidate domains of parameters.

In fact, the above method is a discretization method and the optimal parameters may not exist in the 3D candidate

space. It is targeted at specific dataset corresponding research optimal method. In the recognition of oil-bearing formation, we propose an effective method to optimal parameters in a multi-dimensional continuous space. At first, we consider **p** as the variable and detection signal, and change its value in 3-dimensional continuous space. Then, the clustering evaluation value y is regarded as state feedback describing the state information of recognition system under the detection signal of **p**. So, a feedback mechanism between **p** and y is established, as shown in Fig.1, which is an effective measure to utilize state information to tune the detection signal **p**. As we know, under the above assumptions, there exists a y value corresponding with **p**, whichever the evaluation function is ACC or NMI.

PSO is a swarm intelligent search algorithm based on particles's historical information (i.e., *pbest* and *gbest*). The information of its own individual extremum and global extremum is shared among all particles and used to adjust new particle's position and velocity. Therefore, we explore the standard PSO algorithm and the MPSO algorithm to search optimal parameters. Fig.1 is a schematic diagram of obtaining an optimal parameter for LRR-AGR model based on the feedback mechanism and PSO algorithm. Fig.2 shows the flowchart for MPSO algorithm in solving the optimization problem. Here, the fitness function $f(\cdot)$ is a composition function of F and G, formulated as (7), c is the clusters of data X.

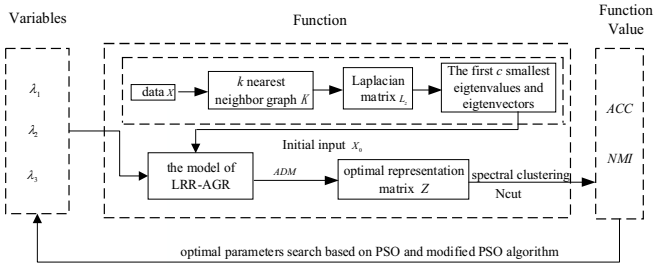


Fig. 1. A schematic diagram of obtaining an optimal parameter for LRR-AGR model based on the feedback mechanism and PSO search algorithm

4. THE APPLICATION OF THE PROPOSED MODEL IN OIL-BEARING OF RESERVOIR RECOGNITION

In this section, we conduct several experiments on the real data oilsk81, oilsk83, oilsk85 wells of Jianghan oil fields in China, to evaluate the model of LRR-AGR with optimal parameters. All experiments are performed on the software Matlab R2016b and Windows 10 system, hardware Intel Core i5-1135G7, 16GB ram.

4.1 Description of data and parameters setting in searching algorithm

Experiments are performed on three well log data from Jianghan oil fields in China. Table 1 shows the description of the real used data. There are six well log features and four class information when recognizing oil-bearing formation, i.e. acoustic travel time (AC), compensated neutron logging (CNL), resistivity (RT), porosity (POR), oil saturation (SO), permeability (PERM). Class information

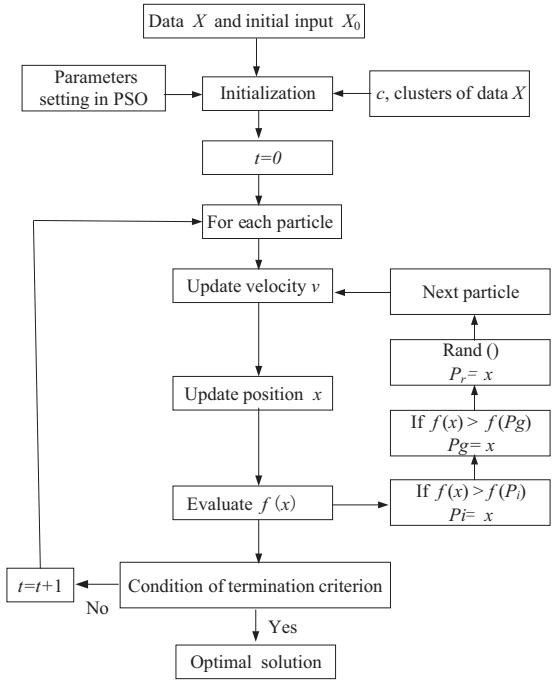


Fig. 2. Flowchart of MPSO algorithm in solving the parameter optimization problem

is dry layer, water layer, oil layer, and inferior oil layer. The quality of data is good without any missing values. In PSO and MPSO algorithm, we denote the population size, initial weight, acceleration constants and maximum iteration as m, w, (c_1, c_2, c_3), $t_{\max}$, respectively. Table 2 shows the parameters setting in PSO and MPSO algorithm. Fig.2 shows the flowchart for MPSO algorithm in solving parameter optimization problem.

Table 1. Statistic description on the well-logging datasets

Dataset	Variables	Classes	Total number of samples
oilsk81	6	4	31
oilsk83	6	4	50
oilsk85	6	4	34

Table 2. Parameter setting in PSO and MPSO algorithms

Algorithm	m	w	(c_1, c_2, c_3)	$t_{\max}$
PSO	150	0.7	$(0.5, 0.5, 0)$	40
MPSO	150	$0.7 - 0.4t/t_{\max}$	$(0.5, 0.5, 0.6)$	40

4.2 Evaluation metrics

In this paper, we use two metrics, i.e., clustering accuracy (ACC) and normalized mutual information (NMI) to evaluate the clustering performance of different algorithms. Moreover, ACC is also selected as fitness function in PSO and MPSO, which can evaluate the match between the three parameters and the LRR-AGR model. For a dataset X with n samples, ACC is calculated as follows:

$$ACC = \frac{\sum_{i}^{n} \delta(y_i, map(r_i))}{n} \tag{8}$$

Table 3. Optimal parameters searched by PSO and MPSO for three oilsk data (Part)

	oilsk81		oilsk83		oilsk85	
	PSO	MPSO	PSO	MPSO	PSO	MPSO
λ_1	0.3641415	0.0964888	0.2572347	0.5910087	0.4452192	0.9916791
λ_2	0.1279067	0.0111202	0.1462713	0.3038111	0.3982446	0.5919352
λ_3	0.0624397	0.0149865	0.1440339	0.1907449	0.2774069	0.3200301

where r_i and y_i denote the cluster label obtained by clustering algorithm and the true label of sample x_i, respectively. Under the condition of $x = y$, then $\delta(x, y) = 1$, otherwise, $\delta(x, y) = 0$. $map(\cdot)$ is a permutation mapping function, used to map each prediction cluster label r_i to the equivalent label according to the distribution of the true label (Yin et al., 2022; Wen et al., 2018;Yin et al., 2015).

When the predicted cluster label K' is obtained and the true label K is given, NMI is defined as follows (Yin et al., 2022; Wen et al., 2018;Yin et al., 2015).

$$NMI(K, K') = \frac{MI(K, K')}{\max(H(K), H(K'))} \tag{9}$$

where $H(K), H(K')$ denote the entropy of labels K and K', respectively. Mutual information $MI(\cdot)$is calculated as follows

$$MI(K, K') = \sum_{s \in K} \sum_{t \in K'} p(s, t) \log_2 \left(\frac{p(s, t)}{p(s)p(t)} \right) \tag{10}$$

where $p(s, t)$ denotes the joint probability distribution of s and t, $p(s)$ and $p(t)$ are the marginal probability of s and t, respectively. Both ACC and NMI are in the range of [0,1], and the larger value of ACC or NMI is, the better the clustering performance is.

4.3 Optimal parameters and clustering result

Aiming at three well log data oilsk81, oilsk83 and oilsk85 wells of Jianghan oil fields in China (see Tables 9-11), optimal parameters in LRR-AGR model is searched by PSO and MPSO, respectively. Since the recognizing accuracy is strongly expected in recognizing oil-bearing formation in PSO or MPSO algorithm, we select the ACC metric as fitness function to search optimal parameters. To facilitate statistical results, we reorder the well log data which is listed in Tables 9-11, respectively. The samples which belong to the same cluster are ordered in sequence. Meanwhile, the clusters are displayed as follows: dry layer, oil layer, inferior oil layer, and water layer. Table 3 shows the optimal parameters corresponding to each dataset. Table 4 shows the statistic result of clustering performance by ACC metric with the model of LRR-APGR. Experiments are performed 20 times. We observe the best, the average and the worst result to compare their matching performance. According to the matching results, we determine the optimal parameters between the two sets of optimal parameters searched by PSO and MPSO.

Firstly, from Table 3, we can find that different well log data has different optimal parameters and each data can have various optimal parameters. Simultaneously, it is difficult to obtain optimal parameters for a dataset in a given candidate parameter range set. It is meaningful and necessary to adaptively select optimal parameters for a given dataset. Secondly, from Table 4, we can find the clustering performance is different for different optimal parameters. The clustering performance with the optimal parameters searched by MPSO is more significant. MPSO algorithm has advantages over PSO algorithm in searching global optimal solution due to adding random particle information to the population. It is the reason that it can move the particles to a better location and weaken the attraction of the P_g position to local minima in the search space. However, all results show that MPSO or PSO algorithm can be a useful and powerful technique for parameter optimization of LRR-AGR model with an accurate performance, fast convergence process, and very low deviations. Above all, adaptively balancing these regularizations, i.e., global structure constraint, local structure constraint, and prior structure constraint, can significantly improve clustering performance in recognition of oil-bearing formation.

Table 4. Comparison of clustering performance (ACC) with different optimal parameters

	MPSO			PSO		
Dataset	Best	Average	Worst	Best	Average	Worst
oilsk81	1	1	1	1	1	1
oilsk83	0.96	0.954	0.94	0.94	0.916	0.90
oilsk85	1	0.989	0.9705	1	0.9823	0.9705

To extensively demonstrate the effectiveness of the LRR-APGR model in recognizing the oil-bearing formation, we select some related clustering methods for comparison, i.e. K-means (Kanungo et al., 2002), Normalized cut clustering method (Ncut) (Shi et al., 2000),LRR (Liu et al., 2010), NNLRS (Zhuang et al., 2012), latent low-rank representation for subspace segmentation and feature extraction (LatLRR) (Liu et al., 2011), Laplacian regularized LRR(LapLRR) (Liu et al., 2014), NSHLRR (Yin et al., 2015), LRR-AGR (Wen et al., 2018), LRR with adaptive dictionary learning (ALRR) (Chen et al., 2021),and a hierarchical weighted low-rank representation (HWLRR) (Fu et al., 2021). The two metrics of clustering performance are ACC and NMI. Parameters setting are listed in Table 5. In LRR-APGR, we mainly use two procedures to get optimal parameters and perform LRR-AGR. To get the optimal parameters, the maximum iteration is 4 in MPSO algorithm. Besides, the optimal representation matrix is calculated via solving the LRR-AGR model with alternating direction method (ADM), and the maximum iterations are 80 times. The maximum iterations are adopted as same as initial setting in others referred algorithms. The result of recognition in oil-bearing for oilsk81, oilsk83, oilsk85 well-logging data are listed in Table 6 and 7, respectively.

From Table 6, we can firstly find that LRR and its improved version have a better clustering performance than Ncut in most cases. It is inappropriate to cluster

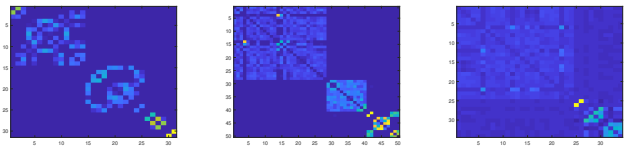
Table 5. Parameters setting in related algorithms

Algorithm	Symbols	Meaning	Value
Ncut	σ	scale parameter	0.5
LRR	λ	Penalty parameter	0.31
LatLRR	λ	Penalty parameter	0.5
NNLRS	λ_1	Regularized parameter	10
	λ_2	Regularized parameter	0.2
LapLRR	λ_1	Penalty parameter	0.7
	λ_2	Penalty parameter	1.26
NSHLRR	λ	Penalty parameter	0.01
	β	Penalty parameter	0.001
	γ	Penalty parameter	0.1
ALRR	λ	Penalty parameter	15
	α	Penalty parameter	3
HWLRR	β_1	Balance parameter	0.5
	β_2	Balance parameter	0.5
LRR-AGR	λ_1	Penalty parameter	0.7
	λ_2	Penalty parameter	0.7
	λ_3	Penalty parameter	0.7

original data directly because it contains many redundant features even noises. It is beneficial to capture the intrinsic structure relationships of data for improving the clustering performance. Then, LapLRR, NSHLRR can obtain better clustering performance than LRR, LatLRR. By integrating Laplacian term into LRR model, the local structure of data is captured, which can guide model to learn a better graph. It is the reason that local structure contains sufficient discriminative information for data clustering. As another local structure constraint, distance constraint is added into the LRR-AGR model. Experiment results show that it is more effective than Laplacian term. By integrating distance constraint, non-negative constraint, rank constraint into the LRR model, the LRR-AGR model has potential to learn an ideal graph. Meanwhile, the results show that the intrinsic geometric structure of data and the prior connected structure are more suitable and necessary for the clustering task. In brief, LRR-AGR is an accurate model to recognize the oil-bearing formation.As shown in Table 7, the proposed method LRR-APGR is much better than LRR-AGR. This clearly demonstrates that optimal parameters adaptively balance these constraints according to the data which are exploited in LRR-AGR model helpful for recognizing the oil-bearing formation. Therefore, the proposed mathematic model is appropriate and search strategy is effective. An accurate model with an appropriate control strategy is beneficial to perform the perform the task of recognizing oil-bearing formation.

Fig.3 is the visualization of optimal matrices obtained from LRR-APGR. As shown in Fig.3, we can see the optimal matrix obtained by LRR-APGR model has a relatively distinct block-diagonal structure, which is helpful for data clustering. The illustration of optimal matrices, (a) and (c) in Fig.3 are permuted according to the order of four true clusters as shown in Table 9 and Table 11. Meanwhile, only two samples which belong to inferior oil are wrongly clustered into the water layer, as shown in (b), while the remaining data are exactly consistent with true clusters as shown in Table 10.

Besides, we compare the LRR-APGR method with the previous work which is a classification model (Guo et al., 2011). In that work, AC and SO are two optimal features



(a) (b) (c)

Fig. 3. Illustration of optimal matrix produced by LRR-APGR for different well log data.

selected by genetic algorithm (GA) and fuzzy c-means algorithm (FCM). Then some classification algorithms are used to evaluate the accuracy of recognition in oil-bearing, such as FCM, K-means, Support vector machine (SVM), self-organizing maps (SOM). Accuracy (ACC), as a common evaluation metric, is selected to distinguish the difference. The comparison results are displayed in the following Table 8. Compared with the published work, the LRR-APGR has at least as good as previous work.

As above analysis, it is critical and useful to use the prior structure and capture the intrinsic structure of data, i.e., both local and global structure in recognizing the oil-bearing formation task. Meanwhile, we find that it is necessary to adaptively adjust parameters which are used to balance these regularizations describing corresponding structure information in real world applications. Therefore, the mechanism of parametric modeling and the optimization method are applicable and effective, and the proposed method LRR-APGR is more suitable for recognizing the oil-bearing formation.

5. CONCLUSIONS

The recognition of oil-bearing in reservoir is a process that restores well log data to geological information about the reservoir category. It is a stage to reflect the achievements of logging interpretation, and it can improve recovery efficiency significantly and minimize uncertainties. A novel model LRR-APGR is proposed based on MPSO for high-dimensional and low-rank logging data, which is an improved version of LRR-AGR with optimal parameters. The parameters in the model of LRR-AGR is optimized by MPSO in continuous space for the well log data of oilsk81, oilsk83, and oilsk85. Experimental results on well log data show that the model of LRR-APGR has a higher accuracy in recognition and a stronger robustness than other models.

Although the results presented here are extremely encouraging, there is an issue that deserves in-depth study in the future. The optimal parameters used here only are found by MPSO according to different well log data. Therefore, the rules of the optimal parameter distribution are worth of studying. A mechanism that obtains the optimal parameters automatically should be investigated.

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Table 6. Clustering result comparison on oilsk81, oilsk83 with mean ACC and NMI and their standard deviations. Note: bold numbers denote the best results.

	oilsk81		oilsk83		oilsk85	
Metrics	ACC	NMI	ACC	NMI	ACC	NMI
Ncut	59.35 ± 3.97	42.64 ± 1.44	52.00 ± 0.00	28.67 ± 0.00	52.94 ± 0.00	36.51 ± 0.00
LRR	74.19 ± 0.00	53.89 ± 0.00	66.20 ± 4.63	60.84 ± 1.72	71.18 ± 2.05	60.51 ± 0.80
LatLRR	75.32 ± 5.26	59.66 ± 2.61	68.10 ± 4.65	61.11 ± 2.37	73.55 ± 0.00	61.62 ± 0.00
NNLRS	76.24 ± 4.25	58.77 ± 2.65	75.12 ± 4.32	62.22 ± 1.23	80.79 ± 2.78	62.45 ± 0.49
LapLRR	80.64 ± 0.00	52.74 ± 0.00	76.00 ± 0.00	60.14 ± 0.00	63.97 ± 2.31	49.54 ± 0.43
NSHLRR	79.03 ± 2.87	59.31 ± 3.78	80.00 ± 0.00	64.85 ± 0.00	81.91 ± 1.08	57.94 ± 0.15
ALRR	70.97 ± 0.00	66.80 ± 0.00	56.00 ± 0.00	59.95 ± 0.00	50.00 ± 0.00	51.09 ± 0.00
HWLRR	64.52 ± 0.00	57.20 ± 0.00	58.00 ± 1.24	56.31 ± 0.00	47.06 ± 0.00	42.38 ± 0.00
LRR-AGR	$\mathbf{92.58 \pm 4.33}$	$\mathbf{81.39 \pm 2.94}$	$\mathbf{88.00 \pm 0.00}$	$\mathbf{69.68 \pm 0.00}$	$\mathbf{85.29 \pm 0.00}$	$\mathbf{75.14 \pm 0.00}$

Table 7. Clustering result comparison between LRR-AGR and LRR-APGR on oilsk81, oilsk83 with mean ACC and NMI and their standard deviations. Note: bold numbers denote the best results.

	oilsk81		oilsk83		oilsk85	
Metrics	ACC	NMI	ACC	NMI	ACC	NMI
LRR-AGR	92.58 ± 4.33	81.39 ± 2.94	88.00 ± 0.00	69.68 ± 0.00	85.29 ± 0.00	75.14 ± 0.00
LRR-APGR	$\mathbf{100.00 \pm 0.00}$	$\mathbf{100.00 \pm 0.00}$	$\mathbf{96.00 \pm 0.00}$	$\mathbf{91.00 \pm 0.00}$	$\mathbf{100.00 \pm 0.00}$	$\mathbf{100.00 \pm 0.00}$

Table 8. Comparison between LRR-APGR and other models

Algorithm	oilsk81	oilsk83	oilsk85
FCM	100%	96%	93.85%
SOM	80.65%	86%	89.23%
K-means	87.10%	82%	90.77%
SVM	100%	96%	92.31%
LRR-APGR	100%	96%	100%

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Table 9. Log explanation of oilsk81 well

Layer	AC	CNL	RT	POR	SO	PERM	Conclusion
1	195	7.5	13.0	6.0	0	0	Dry
2	225	10.0	7.3	11.0	0	0	Water
3	230	14.0	5.5	12.0	0	0	Water
4	220	9.0	25.0	9.0	56	1.3	Oil
5	225	8.0	30.0	9.0	58	2.3	Oil
6	210	7.0	26.0	6.0	0	0	Dry
7	220	8.0	26.0	10.0	60	2.4	Oil
8	225	9.0	30.0	10.0	62	2.5	Oil
9	195	4.0	36.0	5.5	0	0	Dry
10	220	9.0	30.0	9.0	61	1.7	Oil
11	217	7.5	50.0	8.0	55	1.1	Oil
12	210	6.0	130.0	7.0	48	0.7	Inferior oil
13	195	4.0	100.0	5.0	0	0	Dry
14	195	4.0	70.0	5.0	0	0	Dry
15	200	6.0	90.0	6.0	0	0	Dry
16	200	4.0	130.0	6.0	0	0	Dry
17	200	4.0	90.0	5.0	0	0	Dry
18	215	9.0	25.0	9.0	54	1.6	Oil
19	195	4.0	70.0	4.0	0	0	Dry
20	200	6.0	55.0	6.0	0	0	Dry
21	200	4.0	100.0	5.0	0	0	Dry
22	240	13.5	12.0	12.0	40	2.4	Oil
23	212	8.0	36.0	8.0	60	1.5	Oil
24	197	6.0	50.0	6.0	0	0	Dry
25	202	6.0	55.0	7.0	52	0.8	Inferior oil
26	195	4.5	50.0	6.0	0	0	Dry
27	203	5.0	45.0	7.0	46	0.6	Inferior oil
28	195	6.0	50.0	6.0	0	0	Dry
29	210	7.5	20.0	8.0	57	1.2	Oil
30	201	6.0	16.0	7.0	40	0.4	Inferior oil
31	213	9.5	12.0	9.0	61	2	Oil

Table 10. Log explanation of oilsk83 well

Layer	AC	CNL	RT	POR	SO	PERM	Conclusion
1	225	10	4	10	0	0	Water
2	226	10	5	10.5	0	0	Water
3	220	8.5	6.6	9.5	0	0	Water
4	235	12	8.8	10	32	0.4	Inferior oil
5	226	13	8	9	35	0.2	Inferior oil
6	202	10	11	7	0	0	Dry
7	209	12	30	3	0	0	Dry
8	198	8	46	4	0	0	Dry
9	178	0.8	600	1.5	0	0	Dry
10	220	9	35	10	52	1.8	Oil
11	205	6	58	8	36	0.5	Inferior oil
12	216	8.3	40	10	55	2.6	Oil
13	197	3.5	120	4	0	0	Dry
14	236	11	17	9	51	1.2	Oil
15	213	6	40	5	0	0	Dry
16	235	10	30	9.5	52	2.5	Oil
17	202	6	60	5	0	0	Dry
18	206	7	40	8	50	1.6	Oil
19	192	4	130	3	0	0	Dry
20	210	8	40	7.6	53	2.2	Oil
21	205	7.5	50	7	36	0.7	Inferior oil
22	208	5	18	7	35	0.8	Inferior oil
23	225	7	15	9	50	1.2	Oil
24	190	2	53	3	0	0	Dry
25	212	5	30	7	30	0.5	Inferior oil
26	200	4	40	2	0	0	Dry
27	201	4	46	2.9	0	0	Dry
28	195	3.5	100	3	0	0	Dry
29	199	11	40	1	0	0	Dry
30	188	3.8	400	2	0	0	Dry
31	197	6	280	3	0	0	Dry
32	200	6	105	5	0	0	Dry
33	196	6	190	3	0	0	Dry
34	210	11	60	8.5	62	2.6	Oil
35	209	9	48	8	52	1.6	Oil
36	185	1.6	70	1	0	0	Dry
37	188	4	70	2	0	0	Dry
38	203	8	27	7	40	0.8	Inferior oil
39	192	5.5	98	3	0	0	Dry
40	190	4	100	2	0	0	Dry
41	191	4.3	105	3	0	0	Dry
42	188	5	70	2	0	0	Dry
43	210	8.3	30	8	60	4	Oil
44	185	3.9	85	1	0	0	Dry
45	190	5	23	4	0	0	Dry
46	211	9.5	10	7.5	61	4.3	Oil
47	199	5.2	14	2	0	0	Dry
48	205	8	12	4	0	0	Dry
49	200	5	18	3	0	0	Dry
50	211	8.5	9	7.5	50	5	Oil

Table 11. Log explanation of oilsk85 well

Layer	AC	CNL	RT	POR	SO	PERM	Conclusion
1	225	15.1	10.5	10.7	0	3.2	Water
2	224	13.4	16	10.5	0	2.9	Water
3	200	11.9	23	4.8	0	0	Dry
4	230	13	8.5	11.3	0	3.5	Water
5	245	15.7	12	14.8	48	8.1	Inferior oil
6	230	17.5	0	11.3	0	3.8	Water
7	203	7.2	18	5.2	0	0	Dry
8	201	8.1	20	4.8	0	0	Dry
9	208	6.6	16	6.8	35	1	Inferior oil
10	205	9	36	6.1	39	0.9	Inferior oil
11	200	8.1	33	5	0	0	Dry
12	195	9.8	34	3.8	0	0	Dry
13	175	12.4	360	0.1	0	0	Dry
14	190	11.1	100	0.3	0	0	Dry
15	200	14	50	5	0	0	Dry
16	195	12.9	90	3.8	0	0	Dry
17	199	11.5	100	4.7	0	0	Dry
18	190	16.6	100	2.7	0	0	Dry
19	180	8.9	300	0.5	0	0	Dry
20	230	13	40	11.8	59	3.5	Oil
21	200	14.6	160	4.9	0	0	Dry
22	215	12.1	80	8.4	60	2.2	Oil
23	188	8.6	90	2.3	0	0	Dry
24	188	11.3	150	2.3	0	0	Dry
25	200	11.5	165	5	0	0	Dry
26	190	9.5	180	2.7	0	0	Dry
27	198	10.8	60	4.5	0	0	Dry
28	195	9.8	90	3.8	0	0	Dry
29	193	9.4	35	3.4	0	0	Dry
30	195	10	32	3.8	0	0	Dry
31	195	11.6	390	3.8	0	0	Dry
32	197	8.8	100	4.3	0	0	Dry
33	207	8.6	60	6.6	46	1.8	Inferior oil
34	185	10.3	100	1.6	0	0	Dry