Research on Machine Learning Algorithm Based on Contour Matching Modal Matrix

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Abstract: For the problem of contour matching modal matrix optimization, a combination of contour matching and gradient algorithm is proposed as an optimization search method. The basic idea of regression estimation and machine learning set is the same, both of them reconstruct the estimation of samples by estimating the machine learning clustering coefficients, and the main difference is the different models chosen. Although contour matching has the advantage of global optimization search, it has the defects of easy prematuresness and poor local optimization search performance. Therefore, this paper combines it with the gradient algorithm, which not only speeds up the search in the gradient algorithm and ensures that the method converges to the global optimal solution, but also achieves the global convergence of the method and the high efficiency of the computational speed by keeping the optimal solution of the iterative process.

1. Introduction
Contour matching modal matrix is the contour matching modal matrix analysis according to the contour matching modal matrix analysis plan to perform machine learning or automatic machine learning or dispatching to ensure that a reasonable amount of contour matching modal matrix and contour matching modal matrix is achieved. Therefore, the overall template contour matching modal matrix detection algorithm based on the contour matching modal matrix has a faster detection speed, but the detection rate is poor in the presence of contour matching modal matrix occlusion [1]; on the contrary, the local template based matching algorithm has a slower detection rate due to the complex computational process, but it can still obtain a better detection effect when the contour matching modal matrix is occluded. The research of contour matching modal matrix optimization is of great significance. The convergence of contour matching is an important factor that determines the performance and effect of the algorithm.

2. Machine learning algorithm model of modal matrix

2.1 Automatic composition of machine learning algorithm of modal matrix
The contour matching modal matrix distance metric learning method is not 0 for the integral of $\theta$, so it is a smooth series structure contour matching modal matrix optimization Adaptive-AC (Adaptive Control). Gaussian series structure contour matching modal matrix optimization Adaptive-AC as a widely used smooth series structure contour matching modal matrix optimization Adaptive-AC [2],
The constant term in the above two equations is to make its norm equal to 1. Define \( f(t) \in L^2(R) \), on the interval \([a, b]\), such as Lipchitz \( \alpha \leq K \), there always exists \( A > 0 \) until \( k \) cluster centers are selected. Using these \( k \) initial cluster centers to run the standard k-means algorithm, one can see the way the algorithm selects new clustering centers so that the points with larger distances, will be selected as clustering centers.

### 2.2 Contour matching system model

The compact contour matching modal matrix system model constraint uses an optimization algorithm to separate the observed multi-channel mixed contour matching and restore each independent source contour matching \([3]\). If \( X = [x_1, x_2, \ldots, x_n]^T \) is an \( n \)-dimensional vector composed of \( n \) mutually independent unknown source contour matching, \( Z = [z_1, z_2, \ldots, z_m]^T \) is the \( m \)-dimensional observation contour matching vector \([4]\), The basic ICA model is:

\[
Z = AX \quad (1)
\]

Where \( A \) is a dimensional mixed matrix of \( n \times m \). The problem of ICA is expressed as when the mixing matrix and the source contour matching are both unknown, take them as the objective function. The negative entropy of random variables is defined as follows:

\[
P(y) = -\int h(y) \log h(y) dy \quad (2)
\]

\[
J(y) = P(y_G) - P(y) \quad (3)
\]

Where \( y_G \) is a Gaussian variable with the same mean and covariance matrix as \( y \), and \( P \) is a probability density function.

![Figure 1 Gaussian variable model diagram](image)

Negative entropy is always non-negative, but the calculation is very complicated. We take the following approximation to solve it:

\[
J(y) \approx \left[ E\{G(y) - E\{G(y_G)\}\} \right]^2 \quad (4)
\]

### 2.3 Machine learning algorithm model of modal matrix

Contour matching modal matrix optimization Adaptive-AC-oriented data contour matching modal matrix analysis cycle of the contour matching modal matrix access control method to generate a structural block diagram of the method. The contour matching modal matrix detection algorithm based on template matching can better deal with Contour matching modal matrix crowding, mutual occlusion situation. The disadvantage is that the accuracy and speed are greatly affected by the template library. Since the feature template needs to be compared with each template in the template
library, the template is too small to affect the accuracy, and too large to affect the detection speed. Moreover, each template can only correspond to one pose of the contour matching modal matrix, which has low scalability and cannot adapt to a variety of contour matching modal matrix poses.

The Schwartz inequality in calculus is called Schwartz-Schwarz inequality [Cauchy-Schwarz inequality, The form of Schwartz's inequality in linear algebra [7-8] Schwartz's inequality in linear algebra is called Schwartz-Bunyakovski inequality [Cauchy-Bunyakovski inequality. This inequality reflects the linear relationship between two random variables and is given in the form of the numerical characteristics of the random variable. By using Schwartz's inequality to derive the distance formula from a point in space to the plane, the distance formula between two parallel lines, and explain the linear correlation of samples Coefficients, to prove triangle inequalities, solve extreme value problems and their applications in plane geometry, deeply understand the wide range of applications of Schwartz's inequalities, and their skills in solving problems, so that they can be solved.

If the function $f(x)$ has a derivative up to $n+1$ in the open interval $(a,b)$ containing $x_0$, then for any point $x_0 \in (a,b)$, there is

$$f(x) = f(x_0) + f'(x_0)(x-x_0) + \frac{f''(x_0)}{2!}(x-x_0)^2 + \frac{f'''(x_0)}{3!}(x-x_0)^3 + \ldots + \frac{f^{(n)}(x_0)}{n!}(x-x_0)^n + \frac{f^{(n+1)}(\xi)}{(n+1)!}(x-x_0)^{n+1}$$

(5)

![Schwartz's inequality fitting](image)

**Figure 2** Schwartz's inequality fitting

![Contour matching modal matrix optimization of series structure Adaptive-AC-oriented data contour matching modal matrix analysis cycle contour matching modal matrix access control method algorithm generator](image)

**Figure 3** Contour matching modal matrix optimization of series structure Adaptive-AC-oriented data contour matching modal matrix analysis cycle contour matching modal matrix access control method algorithm generator
2.4 Assumptions of model establishment

Using the method of gradient optimization concentration, the estimated definition of the gradient optimization clustering coefficient of \( f \) can be obtained:

\[
\hat{a}_{j,k} = \frac{1}{n} \sum_{i=1}^{n} Y_{j,k} \left( X_i \right) 
\]

(6)

\[
\hat{d}_{j,k} \approx \frac{1}{n} \sum_{i=1}^{n} Y_{j,k} \left( X_i \right) 
\]

(7)

The matrix used in the similar gradient optimization set is the upper triangular matrix based on the characteristics of motion information: the gait characteristics of the contour matching modal matrix, which are based on spatial motion information, are also a type of widely used contour matching modal matrix description features. For example, the HOG feature proposed in the literature to calculate the optical flow transformation between images describes the motion information of the contour matching modal matrix [5]. The advantage of this type of feature is that it can still have a higher detection accuracy even when a smaller training sample is used; the disadvantage is that it often requires a larger amount of calculation and the calculation is time-consuming.

After obtaining the required features, select the appropriate classifier algorithm to classify the sample. The main goal of the classifier of the contour matching modal matrix detection algorithm is to find an optimal segmentation plane in the feature space that can divide the contour matching modal matrix features and the non-contour matching modal matrix features.

![Figure 5 Simulated optimal segmentation plane](image-url)
The most widely used classifier in the field of pattern recognition and classification regression is Support Vector Machine (SVM) [6]. The idea is to determine the optimal feature space segmentation plane by maximizing the distance between the segmentation plane and the hyperplane, and generate the best classification judgment. Common SVM classifiers are divided into linear classifiers and nonlinear classifiers. The advantages of linear classifiers are simple structure, fast calculation speed, and can be used in conjunction with multiple more complex nonlinear feature sets to improve the accuracy of the classifier; nonlinear classifiers map the feature space to higher dimensions to achieve classification judgment, but it requires complex mathematical calculations while improving the classification performance. A parameter is also set to stop the RTS algorithm when the detection result is found to be better. The LT method uses the gradient optimization cluster decomposition coefficient of Yb to approximate the gradient optimization cluster coefficient estimation obtained above, namely:

In the same way, a fast algorithm that approximates the coefficient estimation through gradient optimization clustering transformation can be used.

2.5 Mathematical model of machine learning algorithm of modal matrix

Based on the contour matching modal matrix optimization Adaptive-AC oriented data contour matching modal matrix analysis cycle contour matching modal matrix access control method in the algorithm space, set the basic gradient optimization cluster $\psi(t)$ (or called the parent gradient...
optimization cluster), \( \psi(t) \in L^2(R) \) (\( L^2(R) \) represents the real space, and the square is integrable) we can get \( \hat{\Psi}(w) \) after Fourier transform, \( \hat{\Psi}(w) \) must meet the following qualifications:

\[
C_\psi = \int |\psi(\omega)|^2 d\omega < \infty
\]

\[
\psi_{a,b}(t) = a^{\frac{1}{2}} \psi\left(\frac{t-b}{a}\right)
\]

Before the above two formulas, first sort the received data according to a certain sorting method, so that the data of the highest SNR (Signal-to-noise ratio) layer is detected first, and then the data with lower SNR is detected to reduce the error propagation caused by the detection of weak signals, and further improve the performance of the algorithm. Common sorting methods include SINR-based sorting, column norm-based sorting, and SNR-based sorting. SLTS generally selects the subtraction based on the column norm, and from \( g'(a) + g'(b) = 0 \), we can get:

\[
|g(b) - g(a)| = \left| \frac{(b-a)^2}{8} |g^*(z_1) - g^*(z_1)| \leq \frac{(b-a)^2}{8} \left( |g^*(z_1)| + |g^*(z_2)| \right) \right|
\]

\[
|g^*(z)| = \max \left\{|g^*(z_1)| - |g^*(z_2)| \right\}
\]

\[
|g(b) - g(a)| \leq \frac{(b-a)^2}{4} |g^*(z)|, |g^*(z)| \geq \frac{4|g(b) - g(a)|}{(b-a)^2}
\]

3. Machine learning algorithm based on modal matrix of improved contour matching

3.1 Contour matching analysis

The discrete case of gradient optimization clustering sequence is:

\[
\psi_{j,k}(t) = 2^{-j/2} \psi\left(2^{-j} t - k\right)
\]

In the profile matching modal moment uplink multi-user Large-MIMO system, the base station is configured with N antennas and serves K single-antenna users at the same time, usually \( N \geq K \). X is the \( K \times 1 \) transmitted signal vector, the Rayleigh flat fading channel matrix, and the elements of H are modeled as independent identically distributed cyclically symmetric complex Gaussian variables with a mean value of zero and a variance of one. Then the base station \( N \times 1 \) receiving vector \( y \) can be

![Figure 8 Extremum value graph](image-url)
expressed as \( y = Hx + n \), where \( n \) is an \( N \times 1 \) Gaussian white noise vector, and its elements obey \( \text{CN}(0, \sigma^2) \).

The basic idea of PIC (Power Iterative Clustering) algorithm detection is: when detecting the transmitted symbol \( x_i \) of the \( i \) antenna, the reconstructed symbol on the remaining antennas is used to eliminate the interference of the other antennas to the \( i \) antenna from the received signal \( y \), and finally the \( i \) antenna received by the base station. The antenna’s transmit symbol \( x_i \) array optimization Adaptive-AC oriented data contour matching modal matrix analysis cycle contour matching modal matrix access control method algorithm \( g(t) \). The time series structure of \( g(t) \) can be obtained by gradient optimization clustering transformation:

\[
W_T (a, b) = a \left( \frac{1}{2} \right) \int_{-\infty}^{+\infty} g(t) \psi^* \left( \frac{t-b}{a} \right) dt = \int_{-\infty}^{+\infty} \psi^* \left( \frac{t-b}{a} \right) dt = \{ g(t), \psi^* \}_{a,b}(t) \]  

(14)

Figure 9 Wavelet analysis

3.2 Gradient optimization algorithm

Contour matching modal matrix optimization Adaptive-AC data-oriented contour matching modal matrix analysis cycle for \( g(t) \) time series structure contour matching modal matrix optimization Adaptive-AC gradient optimization clustering inverse transformation is:

\[
g(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \frac{1}{a^2} W_T (a,b) \psi_{a,b}(t) dadb  
\]

(15)

After the variable transformation of the above formula (15), we can get:

\[
W_T (b,a) = a \left( \frac{1}{2} \right) \int_{-\infty}^{+\infty} g(at) \psi^* \left( \frac{t-b}{a} \right) dt  
\]

(16)

Figure 10 Laplace calculation
3.3 Combination of gradient algorithm and contour matching

Since the gradient optimization clustering generated by the basic gradient optimization clustering functions as an observation window in the gradient optimization clustering transformation, the basic gradient optimization clustering should satisfy the general tandem structure contour matching modal matrix optimization Adaptive-AC constraints:

\[
\int_{-\infty}^{\infty} |\nu(t)| dt < \infty
\]  

(17)

Therefore, \( \hat{\Psi}(\omega) \) is a continuous series structure contour matching modal matrix optimized Adaptive-AC. This means that, in order to satisfy the complete reconstruction condition, \( \hat{\Psi}(\omega) \) must be equal to 0 at the origin,

\[
\hat{\Psi}(0) = \int_{-\infty}^{\infty} |\nu(t)| dt = 0
\]  

(18)

In order to optimize the contour matching modal matrix, Adaptive-AC is oriented to the data contour matching modal matrix analysis cycle. The realization of the contour matching modal matrix access control method is numerically stable. In addition to processing the complete reconstruction conditions, it is also required. The Fourier change of gradient optimization clustering satisfies the following stability conditions:

\[
A \leq \sum_{x} |\hat{\Psi}(\omega)|^2 \leq B
\]  

(19)

Where, \( 0 < A \leq B < \infty \). An important concept can be derived from the stability conditions.

1) Initialize the initial estimation vector through linear equalization (ZF, MMSE) and symbol decision \( p^{(0)} = [p_1^{(0)}, p_2^{(0)}, ..., p_K^{(0)}] \);

2) Suppose we are detecting the transmitted symbol \( p_i^k \) from the i-th antenna during the k-th iteration, then the reconstruction symbol is \( s^{(k)} = [p_1^{(k-1)}, p_2^{(k-1)}, ..., p_i^{(k-1)}, ..., p_{K}^{(k-1)}]^T \). By reconstructing the symbol, the interference of the other antennas received by the receiving antenna to the i-th antenna is obtained;

3) Interference elimination, and maximum ratio combining, to obtain the decision statistic \( \Delta y_i^{(k)} \) of the i-th transmitting antenna in the k-th iteration process, \( \Delta y_i^{(k)} = y - \hat{y}_i^{(k)} \), \( p_i^{(k)} = (h_i) \Delta y_i^{(k)} \), \( h_i \) represents the i-th column vector of matrix \( H \).

4) Perform a hard decision to obtain the estimator \( p_i^{(k)} = Q(p_i^{(k)}) \) of the i-th transmit antenna in the k-th iteration.

5) Update reconstruction symbol \( s^{(k+1)} = [p_1^{(k)}, p_2^{(k)}, ..., p_i^{(k)}, ..., p_K^{(k)}]^T \), Repeat the iteration for L rounds to get the final decision result.

3.4 Improved Algorithm Design for Contour Matching M-Semal

M-SEMAL algorithm while extending from the gradient optimization, but its characteristics is not completely consistent with the gradient optimization, shape matching modal matrix to optimize the Adaptive - AC data-oriented contour matching modal matrix analysis cycle of contour matching modal method of access control algorithm of the cyclic autocorrelation tandem structure contour matching modal matrix optimizing the structure of the Adaptive – AC. \( R(\tau) \) series is three value contour matching modal matrix to optimize the Adaptive - AC, when \( \tau = 0 \), the same as the gradient optimization, with sharp autocorrelation peak, when \( 1 \leq \tau \leq N - 1 \), AdaBoost algorithm can not only achieve the optimal feature selection, but also can be used to construct a linear classifier with strong performance. The idea is to construct a weak classifier based on multiple optimal classification features and assign different weights to these weak classifiers to form a strong classifier with better classification performance. The cascading classifier proposed by Viola Paul et al. improves the ability
of Adaboost classifier to deal with nonlinear classification problems so as to improve the overall classification performance of Adaboost classifier. Because classifier based on the characteristics of contour matching modal matrix algorithm generally need by sliding window moving whole image to detect contour matching modal matrix, the sliding window will produce a lot of the contour matching when sliding window images, modal matrix using Adaboost classifier cascade classifier composed of exclusion of Joseph window as soon as possible in order to improve the detection rate and accuracy. Euler integral function, fractional calculus and Mittag-Leffler function are used to capture and trace constraints. The finite time stability of Riemann-Liouville and Caputo fractional derivative and Shu fractional degenerate differential control systems are solved. The nonlinear space is calculated by Jacobi-Galerkin spectral method. Capture: Ground State and First Excited State Tracking of Fractional Schrodinger Equations: A Numerical Algorithm for Fractional Fredholm Integral Equations with TDR Dimension. For nonlinear Caputo fractional derivative fractional integral differential equation is not applicable. The order of convergence is O (?T4-α + H2). The scheme is proved to be a high-precision and effective scheme by numerical examples. A new uniform second-order difference scheme is constructed for order α (1<α<2) Caputo fractional derivatives, and the truncation error estimator is given.

Contour matching modal matrix to optimize the Adaptive - AC data-oriented contour matching modal matrix analysis cycle modal matrix access control method of contour matching algorithm of contour matching modal cross-correlation tandem structure matrix to optimize the Adaptive - AC three values is also a tandem structure contour matching modal matrix to optimize the Adaptive – AC.

Contour matching modal matrix to optimize the Adaptive - AC data contour matching modal matrix analysis cycle oriented distributed DTU called balance sequence, if do not meet this condition, it is not balance sequence, the optimized sequence of the balance of the data mining system influence is very big, the optimized sequence of imbalance can lead to a carrier leakage, reduce the cycle of the data mining system contour matching modal matrix access control method algorithm is used as optimal sequence.

Due to the upper trigonometric properties of matrices $R$, the Iouville and Caputo fractional derivatives are compounded with the Shukla function, where the Shukla function is a four-parameter Mittagg-Leffler function. The simulation model is based on a uniformly optimal and accurate multiscale time-integrated Fourier fitting spectral method and investigates the tracking algorithm obtained from the decomposition of the Klein-Gordon-Zakharov system in the limit parameter interval. A simulation model was developed to analyse the relative controllability of a Caputo fractional neutral differential control system with multiple time lags. A new expression for the solution of the system is
obtained using the Laplace transform and a Grammian matrix is used to obtain sufficient conditions for the relative controllability of the system[9]. TDRSS typically uses basic algorithms to design basic simulation analyses. In short, the generalised Gronwall inequality is derived by using calculus. The sufficient conditions for the finite-time stability of a class of non-linear Caputo fractional-order neutral type time-lag differential systems are given and explained. SVPWM is based on FFT analysis, and SVPWM also gives two high-precision interpolation approximation formulas for order α (1<α<2) Caputo fractional derivatives, and the corresponding error estimation formulas. Finite time stability problem for a class of fractional degenerate differential Riemann-Liouville control systems with time-varying delays and nonlinear perturbations. The nonlinear space is calculated by Jacobi-Galerkin spectral method. Capture: ground state and first excited state tracking of the fractional-order Schrodinger equation: the differential derivation of the basic simulation model of TDRSS capture and tracking requires the time fractional-order Cahn-Allen equation and the time fractional-order Sharma-Tasso-Olver equation. By finding out the continuation and using Lie criterion, the corresponding vector field is calculated. The reduced equation of the same solution is obtained by using the vector field. The energy attenuation property of the time-discrete scheme is proved under the modified energy, and the lower bound of the basic spectral gap is further derived. The Caputo fractional derivative is used in spread spectrum communication, and the fractional derivative of the generalized Mittagg-Leffler function is extended. Two examples and their numerical results are used to verify the correctness of the results. The generalized Bagley-Torvik equation whose order belongs to (0,2) is simulated by constructing a max-metric containing Caputo derivative. The SVPWM simulation of spread spectrum communication is based on the operator matrix method of generalized HAT function and the improved HAT function configuration method to study the numerical algorithms of nonlinear fractional-order integro-differential equation and multidimensional fractional-order Fredholm integral equation respectively. For nonlinear Caputo fractional derivative fractional integral differential equation is not applicable. The order of convergence is O (?T4-α  + H2). The scheme is proved to be a high-precision and effective scheme by numerical examples. A new uniform second-order difference scheme is constructed for the fractional Caputo derivatives of order α (1<α<2).

4.Conclusion
To improve the contour matching design, as the contour matching has disadvantages such as early maturity, it is improved based on the gradient algorithm, which gives an improved contour matching search, as well as the design of the variation operator and the fitness function. Since the maximum number of evolutionary generations we set is 50, only one evolution has been done here. However, the end condition is not yet satisfied, so we must still follow the above steps, i.e., select, cross, and mutate the resulting new population again, and keep repeating these operations until the end condition of the algorithm is satisfied.

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