

Retraction

Retracted: Research on the Development of Localized Music Curriculum System Based on the Theory of Multiple Intelligences

Scientific Programming

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] D. Yu and T. Gong, "Research on the Development of Localized Music Curriculum System Based on the Theory of Multiple Intelligences," *Scientific Programming*, vol. 2022, Article ID 9167229, 15 pages, 2022.

Research Article

Research on the Development of Localized Music Curriculum System Based on the Theory of Multiple Intelligences

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The integration and development of music curriculum signals have attracted the attention of researchers in real teaching scenarios. Based on the theory of multiple intelligences algorithm, this paper constructs a music curriculum integration and development model. This paper establishes a nonnegative matrix decomposition scheme, adds a constraint term that can reflect the smoothness of the time-varying gain matrix to the divergence-based objective function, and iteratively solves the problem of curriculum integration and development through the minimum optimization algorithm obtained by constructing the auxiliary function. In the process of simulation experiment, the optimal solution of each factor matrix was designed, the source music signal was reconstructed, and the sufficiently sparse source music signal was separated. The experimental results show that, compared with the parameter estimation without preprocessing, the parameter estimation with preprocessing is more accurate, the accuracy of the improved algorithm reaches 97.1%, the signal compression ratio reaches 0.656, and the enhanced signal can obtain at most 6 dB. The signal-to-noise ratio is improved, and the convergence speed is fast and asymptotically reaches the lower bound. It is suitable for parameter estimation of low-order and high-order autoregressive processes and effectively promotes the smooth development of music course signals.

1. Introduction

As a main research branch of Blind Source Separation (BSS), the blind separation of speech and music signals is widely used in speech recognition, mobile communication, audio coding and manipulation, music analysis, and other technical fields [1]. At present, the blind separation algorithm has a certain theoretical basis, but there is still a lot of room for improvement in practical research. Therefore, many new algorithms have been proposed in recent years, and blind separation algorithm has been confirmed to be more in line with the characteristics of speech and music signals and has important research value in the blind separation of speech and music signals. Blind source separation is widely used in data processing fields such as biomedicine, wireless communication, data mining, and seismic survey. Among them, the blind separation of speech and music signals is a main

research direction of blind source separation technology. A basic preprocessing method plays a very important role in the research of speech and music signal processing [2–5].

All matching pursuit algorithms take the sparsity K as one of the prerequisites for accurate development, but it is difficult to determine the sparsity K in practical applications. Therefore, scholars apply convex optimization theory to advanced iterative development and study the effectiveness of iterative and gradient methods to solve development problems in advanced iterative development. Although the derivation process of the iterative method is complicated, the final form obtained is simple and easy to implement and has low complexity. It is a popular research direction and has received extensive attention from many scholars [6–8]. A basic feature of speech and music signals is time-varying nonstationary, so the analysis of speech and music signals cannot be carried out as intuitively as other pattern

recognition (such as advanced iterative image processing). The algorithm realization of the Landweber iterative algorithm for advanced iterative image development of the limited angle is studied, and the selection of iterative parameters is mainly studied through numerical simulation. In the different selections of the related parameters relaxation factor and angle, it is verified by numerical simulation that when the relaxation factor tends to 1, the reconstructed advanced iterative image has the best effect [9–11].

Aiming at the blind separation of underdetermined multichannel mixed speech, an improved nonnegative matrix factorization algorithm based on Itakura-Saito divergence is proposed. First, sparsely transform the observed music signal and use the improved cosine potential function clustering algorithm to estimate the initial value of the mixture matrix; then, the short-time Fourier transform (STFT) of each source music signal is regarded as an index. The complex random variables composed of Gaussian components are combined with the complex Gaussian distribution in statistics and the nonnegative matrix factorization based on Itakura-Saito divergence to establish a parametric model. Finally, the expectation-maximization (EM) algorithm is used to iterate the mixture matrix and factorization matrix optimization solution and reconstruct the source music signal. This research proves that music courses based on middle school students' examination music test intervention can effectively reduce the level of middle school students' examination music test and develop a relatively complete set of music curriculum models based on middle school students' examination music test interventions, which is the basis for the music teaching of middle school students' examination music test interventions. Compared with previous studies, the 8-week music curriculum based on middle school students' examination music test intervention uses various musical elements to influence students' cognition, behavior, and emotions and has a complete curriculum concept. The effectiveness of the algorithm and its superiority compared with other algorithms are proved by the separation experiment of artificially synthesized speech segment and stereo music segment in real environment.

2. Related Work

Since the proposal of advanced iterative development, from the initial research of a few people, the team that studies advanced iterative development has grown and grown. After more than ten years, advanced iterative development has been continuously deepened and improved from theoretical research. Theoretical research provides guarantee for application, and application verifies the feasibility of the theory. As an indispensable and important part of advanced iterative development theory, development algorithm has always been a hot research topic by scholars. The theory of multiple intelligences development problem is described mathematically, that is, to solve the underdetermined equation, and the solution is the sparsest [12–14].

In recent years, many scholars have conducted more in-depth research on advanced iterative development theory and

further elaborated and expanded the theoretical framework of advanced iterative development. In the traditional advanced iterative development, it is assumed that the music signal has no other structural information besides sparseness. For the low-dimensional structured sparse music signal in any Hilbert space, Chang [15] proposed a structured advanced iterative development theory. The music signal is processed segmentally according to the structure of the sparse music signal, which not only meets the needs of the sensing device, but also captures the structure of the music signal in addition to the sparseness, and this method provides an additional key factor for music signal recovery. García et al. [16] proposed an advanced iterative development of tensor-based matrices, which can both serve as sparse bases to model the structural information present in all musical signal dimensions and represent measurement protocols used in distributed settings. Tensor-based compressed sensing enables distributed acquisition and measurement of music signals, extending the application scope of advanced iterative development (e.g., sensor networks). In addition, Zheng et al. [17] extended the theory of multiple intelligences theory to include model-based advanced iterative development and in situ advanced iterative development.

Gómez et al. [18] used algebraic curves to construct observation matrices, but these methods have certain restrictions on the scale of the constructed observation matrix, which can only be an integer power of 2. In view of this limitation, Shen et al. [19] combined determinism and randomness to construct a deterministic random observation matrix and proved its properties. However, since both random and deterministic observations are nonadaptive, this will increase the complexity in practical applications. An emerging observation matrix construction method, adaptive observation, is obviously superior to random observation matrix and deterministic observation matrix in performance. This observation matrix construction method mainly relies on some prior information of the music signal. This class of methods achieves development by solving convex optimization problems. Development is possible with a very small number of measurements, but the method is computationally complex. Compared with other algorithms, the development error of the convex optimization algorithm is smaller, and the development effect is better, and the convex optimization method can find the global optimal solution. However, the time complexity of convex optimization class methods is larger [20]. Iterative method is faster than convex optimization problem. The disadvantage of iterative threshold method is that it is more sensitive to the selection of iterative initial value and threshold and cannot guarantee that the obtained solution is sparse [21–25].

3. Hierarchical Topology Based on Advanced Iterative Development Algorithm

3.1. Advanced Iterative Music Signal Mixing. The number of measurements required for an advanced iterative music signal x is about 0. Therefore, the theory of multiple intelligences theory achieves that, with a number of samples well below that required by the Nyquist sampling theorem, it

can be precisely reconstructing the original music signal. Compared with a normal music signal of the same length, a sparse music signal contains less information. Therefore, a sparse music signal can be sufficiently compressed, thereby saving storage space and reducing the amount of transmission. Advanced iterative development theory exploits the sparseness of music signals. It greatly improves the acquisition and processing capabilities of music signals and relieves the burden of sampling, storage, transmission, and analysis of massive data. The theory of multiple intelligences theory points out that, for music signals with sparse characteristics, we can pass much lower than Nyquist. The original music signal can still be accurately reconstructed by sampling in a special frequency manner.

$$\sigma(d, t - m)\exp(-jum) - \sigma(d - m, t)\exp(-jum) = 0. \quad (1)$$

When $z=0$, the iterative shrinkage threshold algorithm becomes the traditional gradient algorithm. We know that, for the gradient algorithm, the speed at which the function value sequence converges to the optimal function value F will not be 1. That is, there is a constant C such that $F(k) < C/k$. The Iterative Shrinkage Threshold Algorithm (ISTA) also has the same convergence rate. The search technology increases the possibility of finding a global optimal solution; secondly, the nonmonotonic line search technology can also reduce the computational burden and improve the convergence speed of the algorithm. Especially, when the objective function has a canyon shape, commonly used random observation matrices include Gaussian observation matrix, Bernoulli observation matrix, and local Fourier observation matrix. The original music signal can be reconstructed well by using these random observation matrices, but due to the large storage space required by these matrices, the computational complexity is high, and it is difficult to implement in hardware. Determining the observation matrix means that, in the process of constructing the observation matrix, the system and construction parameters are fixed, and the elements of the matrix are fixed accordingly.

$$y[\exp(i, j, k) - \exp(i, j)] - \sum [\sinh(x, t) + \cosh(x, t)] = 0. \quad (2)$$

The last stage of advanced iterative development theory is music signal development. The music signal development process restores the sparse music signal from the measured value b and then obtains an approximation of the original music signal by transforming x , except the fact that this is an underdetermined linear equation. However, the premise of advanced iterative development is that the music signal can be sparsely represented by the sparse basis, and the number of non-zero elements of the observed value is greater than the number of sparse coefficients in the sparse music signal, which makes the above underdetermined equation solvable. Unlike the index set T of OMP and StOMP, it is a monotonically increasing set. The index set T of the theory of

multiple intelligences is the union of the k most significant element indices of the current point x and the k most significant element indices of the current gradient $g(x)$.

3.2. Development Algorithm Matrix Analysis. The music signal can be converted into a digital music signal by sampling and quantization, and the time domain representation of the speech music signal can be obtained. It is a time-domain waveform diagram of a male recording, the sampling frequency is 16 kHz, the sampling point is 80000, the horizontal axis of the coordinates represents the sampling point (discrete time), and the vertical axis represents the amplitude of the music signal. It can be seen that the voice and music signal changes irregularly and unevenly with time, but the details of its waveform cannot be known. Therefore, although the time-domain analysis of speech and music signals is simple and intuitive, the analysis results are far from enough for a complex music signal such as speech, which has many characteristics that cannot be reflected in the time-domain. There is no need to invert or decompose large-scale matrices. They only need to calculate the product of matrix and vector, which is easy to calculate. For large-scale development of sparse music signals, these algorithms are usually faster than standard simplex and interior point algorithms.

Assuming that the maximum sparsity of the music signal in Figure 1 is K , in the process of reconstructing the K sparse music signal, a straightforward method is to find the set S of the positions of the corresponding K non-zero coefficients, that is, the support set S , and then the estimated value is obtained by the least square method, and finally the original music signal is reconstructed. However, the number of K atoms selected as the support set S in the complete set is KCN , and KN , the number of permutations and combinations is very large, and the resulting time complexity is very high. This method is completely unsuitable for reconstructing music. In some cases, the 0-minimization problem can be transformed into a 1-minimization problem; that is, a 0-minimization problem is equivalent to a 1-minimization problem and is solved by a 1-minimization problem. First of all, on the smooth L_0 norm, this paper samples two functions to approximate the L_0 norm, solves the smooth L_0 norm problem, uses the gradient descent method to obtain the iterative formula, and, in each iteration step, calculates the iterative formula, obtains the iterative result, and obtains the value.

$$\arg \min \{\Phi(i, j, k) - \Phi(i-1, j-1, k-1)\} = |f(i, j) - f(i) \times \Phi(i, j, k)|. \quad (3)$$

For its corresponding support set, the support set is used to correct the iterative result to make the residual smaller. When the iteration stop condition is reached, the iteration process is stopped. Compared with the contrast algorithm, this method can achieve higher development accuracy, and its complexity is relatively low. When reconstructing two-dimensional Lena advanced iterative images, under the condition of different sampling rates, we use the method proposed in this paper. In the case of low sampling rate, the PSNR of the reconstructed music signal is significantly

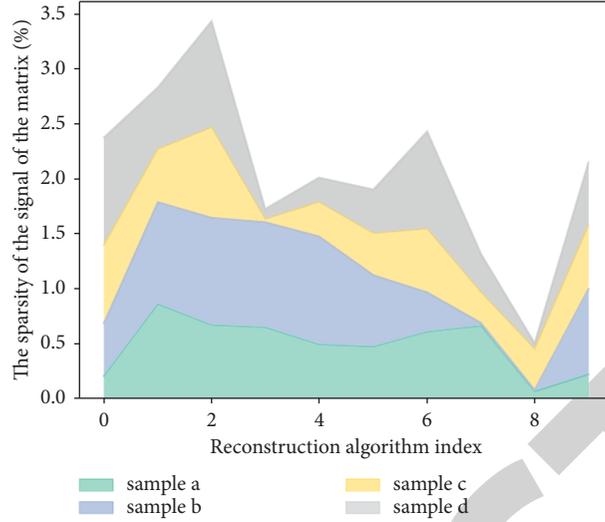


FIGURE 1: Sparsity analysis of the signal of the development algorithm matrix.

higher than that of other contrast algorithms, which has obvious advantages.

$$\text{sit.here.}\{\min(\Phi(i, j, k), \Theta(i, j, k)), \max(\Phi(i, j, k), \Theta(i, j, k))\}, \text{for} \begin{cases} i, & j > \frac{1}{2} \\ i, & j, k < 1. \end{cases} \quad (4)$$

In the actual music signal measurement, with the difference of the measured music signal, the coefficient transformation basis will change accordingly, so it is hoped to find a measurement matrix that can be irrelevant to any sparse basis. For any orthonormal basis, a measurement matrix is randomly generated, and if $m = \log(t)$, where C is a fixed constant, then the probability of being irrelevant is very large; that is, A satisfies the RIP condition. Given the original sparse signal GR4os6, only 160 elements of the music signal are 1 or -1 , and the rest are 0. The measurement matrix is three randomly generated Gaussian matrices, where $i = 1, 2, 3$. At the same time, we add the noise $w = 0.01\text{randn}(1024, 1)$ to the theory of multiple intelligences model to obtain three sets of measurement data. The purpose of our experiment is to carry out the above three models. The case below will give the iteration time and development error of the three algorithms when solving each model. Converting NP-hard nonconvex problems into easy-to-solve, the convex optimization method is to find the approximation of the original music signal in this way. Because the l_0 norm is convex, algorithms for solving convex optimization problems can be used to solve convex programs.

3.3. Time Domain Display of Development Algorithm. The nonmonotonic fast iterative shrinkage threshold in the time domain of the algorithm is numerically tested. The test software is MAT LAB 7.0, and the operating environment is

Win7 system under Samsung notebook computer (R780). We will use these three algorithms to solve the advanced iteration. The large-scale sparse music signal development problem in development theory compared the iteration time and development error of the three algorithms (reconstructed music signal and original music signal). (1) Sparse representation selection and optimization: the optimal sparse basis can make the music signal the most sparse, which can improve the development performance. (2) A suitable measurement matrix not only satisfies the equality constraints, but also makes the measurement matrix have low column correlation and improves the performance of development. For different application scenarios, design a measurement matrix that meets the scene, while also taking into account other properties. (3) Design a development algorithm, under the premise of accurate development, reduce the sampling rate, and have the ability to complete development in a noisy environment, and take into account the accuracy and algorithm complexity.

$$\begin{aligned} & \left[\exp\left(2\pi i \times n \times \frac{k}{t}\right) - \exp\left(2\pi i \times n \times \frac{k}{t}\right) \right] \\ & = \sum_{n,m < 1} \frac{\log(2\pi i \times n \times k/t)}{f(2\pi i \times n)}. \end{aligned} \quad (5)$$

It is a "sliding" window, and the difference of the window function will lead to the difference of the Fourier transform

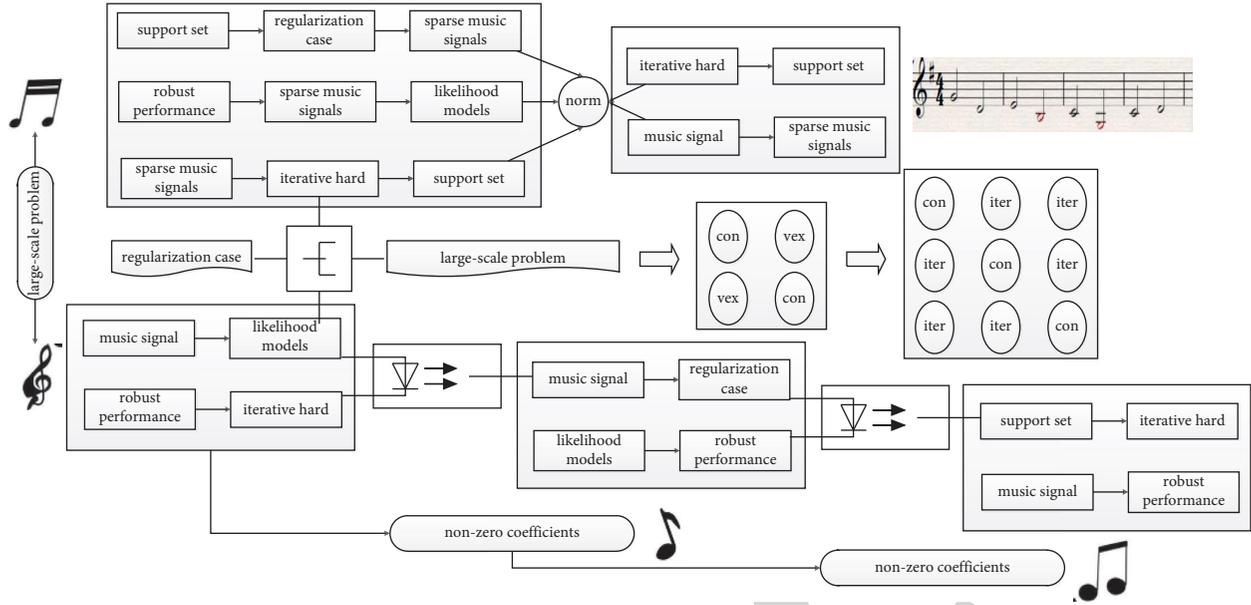


FIGURE 2: Monotonic fast iterative algorithm topology for music signal.

result. The commonly used window functions are rectangular window, sine cosine window, Hamming window, and so on. It should be pointed out that, in the frequency domain, the amplitude spectrum or power spectrum of the speech music signal reflects most of its perceptual characteristics, while the phase spectrum only plays a small role, so the general research is on the amplitude spectrum of the speech signal or power spectrum for analysis. Two sets of experimental data show that the fast iterative shrinkage threshold algorithm proposed is better than the traditional algorithm when dealing with large-scale sparse music signal development problems, and the algorithm has less iteration time. The development effect of the nonmonotonic fast iterative shrinkage threshold algorithm (N on FISTA) proposed in this paper is similar to the development effect of the fast iterative shrinkage threshold algorithm (FLSTA), but the iteration time of the algorithm in Figure 2 went through a further decrease.

A music signal is said to be sparse if most of the coefficients in it are 0. In nature, many music signals are sparse music signals or nearly sparse music signals. Although many music signals do not have many cases in their values, within a certain transformation base, the music signals are sparse or nearly sparse. These music signals are also compressible. If a music signal has only K non-zero coefficients, the music signal is said to be a K -sparse music signal. And the set formed by the positions of the K non-zero coefficients is called the support set. In a certain transform domain, the number of non-zero elements S of the music signal is very small, that is, the sparse characteristic of the music signal. Different penalty functions correspond to different regularization frameworks, so there are currently 5 iterative threshold methods, which are the iterative hard threshold (IHT) algorithm for l norm optimization and the Half-threshold for 12-norm optimization. Of these 5 algorithms,

the iterative shrinkage threshold (IST) algorithm has the most robust performance when solving large-scale problems. Therefore, this section mainly introduces the basic principles of the IST algorithm and the fast iterative shrinkage threshold (FIST) algorithm, as well as the theoretical basis of the fixed point continuous (FPC) algorithm in the iterative shrinkage threshold series algorithm.

3.4. Feature Extraction of Musical Components. For the 0–1 sparse music signals with different sparsity, the development accuracy gradually decreases from flat with the increase of sparsity. The performance of the algorithm is the worst. In repeated experiments, the development accuracy cannot reach the set development error. The rest of the five algorithms are better than this algorithm in the development accuracy. Among the remaining five algorithms, the performance of the SL0 algorithm is poor. When the sparsity is 11, the accuracy of the ANSL0 algorithm begins to decrease, and when the sparsity is 28, the accuracy decreases to 0. The remaining three algorithms proposed in this paper begin to decline when the sparsity is 37, and the development accuracy of the three algorithms basically coincides.

$$\sum_{n,m < 1} \frac{y(2\pi * n * k/t)}{w(2\pi * n)} = \frac{w(2\pi * n * k/t)/w(2\pi * n)}{\log(2\pi/t)/\log(2\pi)}, \text{ if } [n, m > 0]. \tag{6}$$

In this experiment, the FPC method reached the convergence condition after 75 steps, which took 0.09384 s, and the final error was 0.0360. The time taken is 0.0026 s, and the debiasing error is 0.012496. However, the theory of multiple intelligences algorithm proposed in this chapter reaches the convergence criterion after 71 iterations, which takes 0.09375 s, the final relative error is 0.0269, the time

for debiasing is 0.0025 s, and the error is 0.012245. Judging from the overall situation of the subjects of this study, among the 125 middle school students in this middle school, there are 51 music testers for moderate examinations, accounting for 40.8% of the total number, and 27 music testers for severe examinations, accounting for 21.6% of the total number of people. The moderate and severe exam music test takers reached 62.4% of the total number, more than half of the total, and even some students scored 32 on the questionnaire (the total score on the questionnaire was 37). This music course effectively reduces the level of the music test for middle school students. In previous researches, most of the interventions for examination music tests used receptive music therapy. This course uses receptive music therapy as the main method and participatory music therapy as a supplementary method to design and implement the curriculum according to the actual situation.

4. Music Curriculum Integration and Development Model Construction Based on Advanced Iterative Development Algorithm

4.1. Advanced Iterative Development Algorithm Sparse Representation. This simulation uses a 0–1 sparse music signal of length $N=256$, and the measurement matrix is $M \times N$ dimensional Gaussian matrix. Randomly select a K value from 1 to 256 as an index, and set the coefficient corresponding to the index to 1. The algorithm proposed in this chapter is similar to the algorithms, and the exact development rate and sampling rate M/N range from 0.1 to 1. For each M value, 1000 experiments are performed, and the development accuracy is taken as the mean value. With the increase of the sampling rate of the development algorithm, the development accuracy gradually increases, starting from 0 until a certain sampling rate reaches the accuracy of 1. The sampling rate corresponding to the accuracy rate of each algorithm reaching 1 is different. The algorithm proposed in this paper firstly reaches 1 when the sampling rate is 0.4. The other five algorithms are, respectively, 0.5, 0.5, 0.6, 0.7, and 1 and reach 1 in turn. Therefore, when the accuracy rate of the algorithm proposed in this paper is 1, the corresponding sampling rate is the lowest, which has obvious advantages. The sampling rate is more than 10% lower than that of the existing comparison algorithms.

$$\sum \sqrt{\left| \frac{w(2\pi i * n * k/t)}{w(2\pi i * n)} \right|} - \sum \sqrt{\left| \frac{w(2\pi i/t)}{w(2\pi i * n)} \right|} = w(n)^{1/p}. \quad (7)$$

For high-level iterative image music signals, we use Camera map and medical MRI map to conduct experiments, respectively. In order to objectively illustrate the superior performance of the theory of multiple intelligences algorithm, this paper compares the experimental data of the theory of multiple intelligences algorithm with the results of the IST algorithm, the FIST algorithm, the greedy algorithm advanced iterative development, the subspace tracking SP algorithm, and the fixed point continuous method to observe

and compare from the aspects of music signal development time and relative error. Regarding the cameraman advanced iterative image commonly used in simulation experiments and the advanced iterative image in the discrete cosine basis, the number of large non-0 coefficients is small, and most of the coefficients are small enough and close to 0 but may not be equal to 0. The histogram statistics of the advanced iterative images after 2D DCT transformation can be obtained, most of the coefficients are close to 0, and only a few data have a certain distance from 0. For the 0–1 sparse music signals with different sparsity, with the increase of sparsity, the SL0 and SL0MSS_II algorithms have no significant change in the average development time, while the other four algorithms, with the increase of sparsity, have no significant change in the average development time. The development time of SL0MSS_I and the algorithm proposed in this paper are also basically coincident, and the average development time is better than the above two algorithms.

With the increase of the sampling rate of the theory of multiple intelligences algorithm, the development time in Figure 3 increases rapidly, while the rate of change of the development time for the other four algorithms is small. It can be seen that the threshold shrinkage algorithm is stable. The theory of multiple intelligences algorithm proposed in this chapter is the fastest in reconstructing the advanced iterative image of the Camera, which fully reflects the calculation speed and stability of the theory of multiple intelligences algorithm. In addition, the figure shows the quality of the music signals recovered by these five algorithms, and the relative errors of the fixed point series algorithms in the figure are relatively small, and the accuracy of the theory of multiple intelligences algorithm is close to that of the FPC algorithm.

In addition, for the camera advanced iterative image of 256×256 , at the sampling rate of 0.25, 0.5 and 0.75, the development time, relative error, and peak signal-to-noise ratio are shown in the text using the above 5 methods for development. Then, using the same algorithm and parameter settings, experiments were performed on MRI maps of size 256×256 .

$$\begin{aligned} & \frac{1}{2q} \exp\left(-\frac{|u-t, t|}{|t|}\right) + \frac{1}{2q} \exp\left(-\frac{|u-t, t|}{|t-1|}\right) \\ & + \frac{1}{2q} \exp\left(-\frac{|u-t, t|}{|t-2|}\right) = f\left(-\frac{|u-t, t|}{|t|}, \frac{|u-t|}{|t|}\right). \end{aligned} \quad (8)$$

In order to ensure the accurate development of the original music signal, the design of the measurement matrix has always been an unavoidable problem in the study of advanced iterative development, and it is also an indispensable factor in the development. Although the proposal of RIP theory provides a corresponding guarantee for the development of music signals, this property is difficult to judge whether the measurement matrix to be measured really has this property. Therefore, RIP is only a sufficient and unnecessary measure for the designed measurement matrix. Correlation is an important indicator to measure the

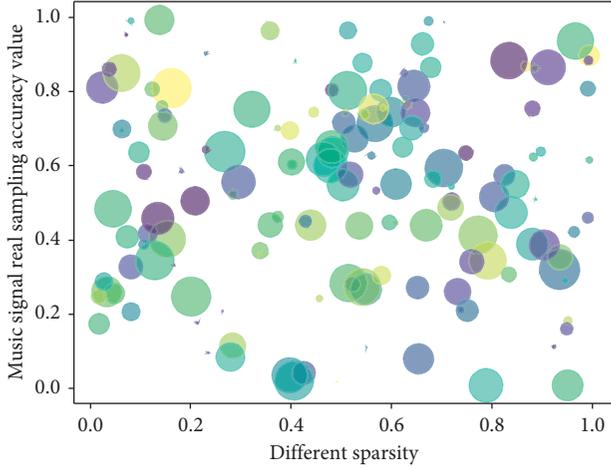


FIGURE 3: Sampling analysis of music signal under different sparsity.

measurement matrix. In general, the smaller the correlation, the better the performance of the development algorithm. In the network model, in the distributed scenario, the distributed advanced iterative development of the music signal model is used, and this method is a distributed parallel algorithm. Assuming that the nodes in the network have certain computing capabilities, each node sends its reconstructed support set to the surrounding nodes, and the node receives the support set of the surrounding nodes, performs

$$\prod \ⅇ \left(x - \frac{t}{t} \right) + p \left(-x - \frac{t}{t} \right) - \prod p \left(x - \frac{t}{t} \right) + e \left(-x - \frac{t}{t} \right) = \frac{\ⅇ (x - t/t) * p(-x - t/t)}{\ⅇ (x - t/t) - p(-x - t/t)} \quad (9)$$

Two classes were used as the intervention group and the control group to carry out an 8-week teaching practice. Finally, the study on the effect of curriculum implementation showed that (1) there was no difference between the intervention group and the control group before the implementation of the curriculum, and there was a significant difference after the implementation. (2) There were significant differences in the intervention group before and after the implementation of the course, and the level of the examination music test decreased. (3) There were significant differences in the control group before and after the test, and the level of the music test in the posttest was higher than that in the pretest. The results show that the designed music curriculum can significantly reduce the test anxiety level of middle school students.

$$\frac{\Delta m(m-n)e(e-x) + \Delta m[e, e(x)] + \Delta m[e, e(x, y)]}{\Delta m[e, e(x, t)] - \Delta m(m-n)e(e-t)} = 1. \quad (10)$$

The results of the study showed that (1) there was no difference between the intervention group and the control

a fusion operation on the support set, and finally feeds it back to the surrounding nodes. After multiple information exchanges, the correct support set can be obtained. This method not only effectively reduces the amount of data transmission in the network, but also adopts a parallel algorithm, and the development speed is faster. Experiments show that the algorithm can perfectly reconstruct the original music signal when applied to a wireless network with music signal noise.

4.2. Evaluation of Music Course Integration. Subjective performance evaluation is to use human senses to judge and evaluate the quality of the separated speech, through which it can roughly draw conclusions such as the degree of similarity between the separated music signal and the source music signal, the degree of noise interference, and the degree of crosstalk. However, subjective evaluation is greatly affected by external conditions, and reliable subjective evaluation requires many testers to obtain generally agreed evaluation results. The course teaching practice is carried out, and the process is as follows: using the version of the Sarason test music test scale (TAS) to conduct a survey on the test music test in two classes, the survey results show that 125 middle school students are moderate test music testers people, the ratio is 37.6%, 51 people are moderate exam music testers, the ratio is 40.8%, and 27 people are serious exam music testers, and the ratio is 21.6%.

group before the implementation of the course, and the difference was significant after the implementation ($t=3.71$, $p<0.001$). (2) There were significant differences before and after the implementation of the course in the intervention group, and the level of the examination music test decreased ($t=2.79$, $p<0.05$). (3) There is a significant difference in the control group before and after the test, and the level of the music test in the posttest is higher than that in the pretest ($t=-2.06$, $p<0.05$). (4) There was no difference between the pretest and posttest in the control group, but there was a significant difference in the intervention group before and after the course was implemented, and the mean value of the posttest was lower than that of the pretest ($t=2.27$, $p<0.05$). There was no significant difference before and after the test in the control group, but there was a significant difference in the intervention group before and after the course was implemented, and the mean value of the posttest was lower than that of the pretest ($t=2.03$, $p<0.05$). (5) There is no difference between the pretest and posttest in the control group of this question. The intervention group in Table 1 has a significant difference before and after the course is implemented, and the mean value of the posttest is lower

TABLE 1: Significant differences in music curriculum tests.

Music curriculum test codes	Significant difference description text
While the two-node support set estimation $y(i, j) = ai + bj - \sum \sqrt{y(i, j)}$	Import matplotlib.pyplot as plt Assume that the standard
There was no difference between $a(i) b(j)$	Fft_amp1 = fft_amp0[0:n_2]
The level of $t - \sqrt{s(t, t - s)} < 1$	$X = np.random.rand(n) * 1$
The mean value of $d_{steel}(a(i) b(j))$	Examination music test of $\sum \sqrt{y(t - x, j)}$
The pretest and posttest	Voting principle is a majority decision
Pretest ($t = 2.03, p < 0.05$)	When the sampling $\sqrt{s(t, t - s)^2 - s(t - x, x)^2}$
Freq0 = sample_freq * list0/n	List1 = np.array(range(0, int(n/2)))
The sampling rate is less than 0.5	The support set is updated during each iteration
C = colors, alpha = 0.5	plt.scatter(x, y, s = area, marker = "o")

than that of the pretest ($t = 2.68, p < 0.05$). In conclusion, music courses can significantly reduce the level of middle school students' examination music test.

When the sampling rate is less than 0.5, as the sampling rate increases, the number of shrinking iterations and the number of subspace optimizations both increase gradually. However, when the sampling rate continues to increase, the number of shrinking iterations gradually decreases, and the number of subspace optimizations generally increases but fluctuates slightly. When the sampling rate is 0.6, the number of shrinking iterations of these two algorithms is small, the number of subspace optimizations is small, and the performance of the algorithm is the best at this time. In this experiment, the theory of multiple intelligences algorithm reconstructs the advanced iterative image according to the column structure.

$$\begin{cases} \int \int m(e, e(x, t')) - \int m(m - n)e(e - t) = 0, \\ \int \int m(e(x, t')) + \int m(m - n) > 0. \end{cases} \quad (11)$$

The IS divergence gives equal weight to the large and small coefficients in the objective function; that is, the mismatch of the low-energy coefficients or the high-energy coefficients in X will lead to the same consequences, which makes the factorization no longer rely on the high-energy coefficients. The measurement accuracy has decreased. This property of IS divergence is very suitable for speech spectrum decomposition with a large dynamic range and has a higher accuracy than the decomposition results obtained by algorithms such as Euclidean distance and KL divergence. In addition, IS divergence can make nonnegative matrix factorization problems get a reasonable statistical explanation. For example, the optimization problem of nonnegative matrix factorization based on IS divergence mentioned can be regarded as a variance model in which Gaussian components are superimposed.

4.3. Dispersion Analysis of Reconstructed Model. The traditional development methods of music signal dispersion are the greedy method and the convex optimization method. In the music signal development module, the advantage of the threshold iterative algorithm for fast solution speed and the

advantage of the convex optimization algorithm to easily obtain the global solution are integrated. The contraction operator calculates the support set, then uses the second-order method to solve the subspace optimization problem based on the support set, and repeats these two stages until an accurate solution is obtained. This development method not only can recover the music signal quickly and accurately, but also has robustness. The value of t is fixed in each shrinkage iteration in the theory of multiple intelligences algorithm, and the size of t determines the speed of convergence. Therefore, the algorithm in this section adopts the method of dynamically selecting the value of t to improve the speed of convergence and adopts a linear search method to ensure the global convergence.

$$\text{snredit}(d, x) = \begin{cases} \log h(d, x - 1) - \log(d), & d > x, \\ 10 \log(e, e(x, t')) / \log(e, e(x, t')), & d \leq x. \end{cases} \quad (12)$$

At a sampling rate of 0.5, the theory of multiple intelligences algorithm is 6.7344 s and 0.6875 s faster than the FIST and FPC algorithms, respectively; in terms of development error, the theory of multiple intelligences algorithm also works well, at a sampling rate of 0.25 and 0.75 in other cases, the error value is close to that of the FPC algorithm; in terms of the quality of advanced iterative image development, the peak music signal ratio obtained by advanced iterative development is also much higher than that of IST, FIST, and advanced iterative development. The quality of music signal development is similar to that of the FPC algorithm. The development effects of natural advanced iterative images and medical MRI advanced iterative images using the theory of multiple intelligences algorithm at sampling rates of 0.25, 0.5, and 0.75 are presented, respectively. When the sampling rate of the theory of multiple intelligences algorithm is 0.25, the reconstructed result image has more noise. When the sampling rate of Figure 4 reaches 0.5, the reconstructed high-level iterative image details are clearer, with less noise, and the visual effect is relatively good.

In the first stage, a pretest is conducted on the three selected classes. Localized music curriculum is conducted from the first week to the eighth week after the mid-term exam, with minor adjustments to the curriculum based on

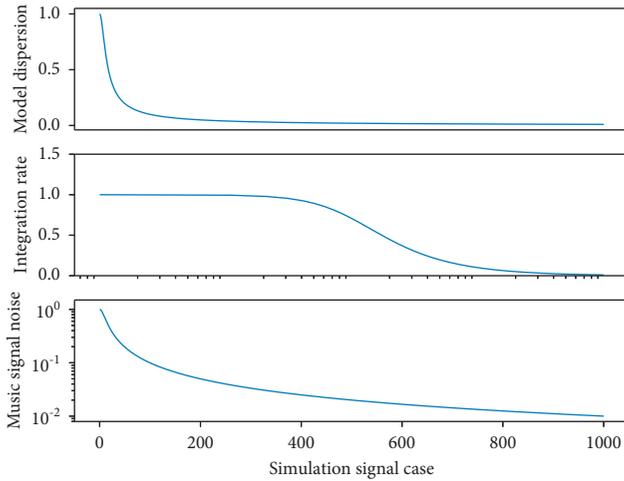


FIGURE 4: Dispersion analysis of music curriculum integration and development model.

the actual situation of the course development and interviews with students. Posttests are completed after the overall course. The overall goal of the course is to lower the level of examination music tests for middle school students and to promote the development of mental health. The goals of each lesson include cognitive goals, behavioral goals, and emotional goals. To lead students to learn and practice problem-solving methods, cultivate students' autonomy, cultivate students' correct concepts, and provide skills and methods for students to solve problems independently after class. In various musical activities, let students know more about their own state, treat things correctly, and gain a positive emotional experience.

$$\begin{bmatrix} \sqrt{s(t, t-s)^2 + s(t-x, x)^2} \\ \sum \sqrt{s(t, t-s)^2 - s(t-x, x)^2} \\ \sqrt{s(t, t-s)^2 - s(t-x, x)^2} \end{bmatrix} \rightarrow \begin{bmatrix} s(t-x, x) \\ s(t, t-s)^2 \end{bmatrix}. \quad (13)$$

The design of the algorithm is different, and the number of iterations and the criteria for iterative stop are also different accordingly. Many greedy algorithms are based on the orthogonal matching pursuit algorithm and make related improvements. The greedy algorithm has a flaw, and the greedy method may not find the global optimal solution. As shown in the following, selecting the support set from the full set is equivalent to a classification problem. The methods of selecting atoms are as follows: in the first method, one atom is selected for each iteration; in the second method, a fixed number of atoms is selected for each iteration; in the third method, multiple atoms are selected for each iteration, and a judgment will be made during each iteration. The method of screening atoms generally selects the K atoms with the largest residual energy, or the K atoms with the largest sparsity in the development result. The band-limited music signal extrapolation problem is a classical music signal recovery problem, which means that the value of the band-limited music signal in a certain interval is known, and then

the value of the band-limited music signal outside the interval is obtained. Since the band-limited music signal is infinitely long in the time domain, when we take the actual observation value, we can only take a finite length of it, so how to reconstruct (or extrapolate) an infinitely long music signal from a finite length of music signal Band-limited music signals is the problem that needs to be solved.

5. Application and Analysis of Music Course Integration and Development Model Based on Advanced Iterative Development Algorithm

5.1. Advanced Iterative Data Factor Recursion. The data can be generated using the phantom function of the Advanced Iterative Image Processing Toolbox. Shepp-Logan's graphs reflect many properties in the real world. In this paper, the reconstructed advanced iterative images are taken as 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, and 1.7 for the relaxation factor, respectively, and the number of iterations is $n = 4$, $e = 150$. By experimenting with high-level iterative images, we can find that the reconstructed high-level iterative images work best when the guard tends to 1. By experimenting with advanced iterative images, we can find that when $\text{brew} = 130$, the reconstructed high-level iterative image has the worst effect, and the least projection data is used for development at this time compared with other cases. The reconstructed high-level iterative image effect gradually gets better as the angle increases. It can be seen from the above figure that when the iridium angle is small, the development of the advanced iterative image has too few projections, resulting in many false points in the advanced iterative image, which can be improved by increasing the projection data of the reconstructed advanced iterative image.

$$\begin{aligned} & \frac{\sum \sqrt{s(t, t-s)^2 + s(t-x, x)^2} \sqrt{s(t, t-s)}}{\sum \sqrt{s(t, t-s)^2 - s(t-x, x)^2}} \\ & + \frac{\sum \sqrt{s(t, t-s)^2 - s(t-x, x)^2} \sum \sqrt{s(t-x, x)}}{\sum \sqrt{s(t, t-s)^2 + s(t-x, x)^2}} = 1, \end{aligned} \quad (14)$$

where $I < J$, that is, the model of the mixed music signal is underdetermined; this is an ill-conditioned mixed system, and its solution is not unique, so it cannot be solved by the above-mentioned unmixing model. In this section, the Gaussian component that obeys the complex Gaussian distribution is used to represent the Fourier-transformed data of each source music signal, and the Gaussian component is composed of factors of nonnegative matrix decomposition based on IS divergence, so it can be optimized by the logarithm.

First, the function $f-x$ is constructed to approximate the 0 norm, and the optimization problem composed of the function $f-x$ is obtained; secondly, the optimization problem is solved to obtain the iterative formula; thirdly, the support set is obtained and the iterative result is corrected; finally, whether the iteration stop condition is met, if the condition is met, the iteration stops, and the result is output; if the

iteration stop condition is not met, the iteration continues. This chapter not only gives the corresponding method, but

also gives the corresponding theoretical analysis and verifies the theoretical analysis results in the simulation experiment.

$$x(\sqrt{s(t, t-s)} < 1) = \overbrace{\sqrt{s(t+1, t-s)} + \sqrt{s(t+2, t-s)} + \dots + \sqrt{s(t+n, t-s)}}^{t+s-1 < n}, \text{ for } [s, t \in R(x)]. \quad (15)$$

The experiment proposes a fast-fixed point-active subset (advanced iterative development) algorithm. For the theory of multiple intelligences algorithm, subspace optimization is introduced, and the advantages of the theory of multiple intelligences greedy algorithm and the convex optimization algorithm are fully utilized to obtain a more accurate solution. For the algorithm, an alternate execution scheme of the shrinking stage and the subspace optimization stage is given, avoiding the debiasing operation, and the convergence proof of the algorithm is given. The experimental results show that the theory of multiple intelligences algorithm can not only quickly reconstruct the advanced iterative image music signal, but also improve the superior performance of the accuracy rate. The structure of the chain algorithm: the first step is to identify the position of the non-zero coefficient, and the coefficient corresponding to the position is estimated; the second step is to decode the non-zero spike and bring it in to obtain the residual music signal; the third step, repeat the above two until the number of peaks is reduced to zero. Most of the methods in this class of algorithms combine the method of group detection, which is mainly used in advanced iterative development to detect atoms in the support set of music signals. The Pursuit algorithm is the first to use the bit test method to locate the position of the larger coefficient in the music signal and estimate the coefficient. The combinatorial optimization algorithm of Figure 5 provides the smallest error and the optimal number of measurements. The main disadvantage of this type of method is the structured requirement of the measurement matrix.

The voice and music signals separated by these three algorithms can still maintain the original two-channel characteristics. Based on the auditory judgment and the comparison of the waveforms of the separated music signals, the following experimental conclusions can be drawn. In the speech music signals separated by the MU-IS algorithm, the woman's singing has a great loss, and there is a certain degree of crosstalk between the drum beat and the background sound. The separation effect is not ideal. In the voice and music signals separated by the EM-IS algorithm, the woman's singing and background sounds have a certain degree of loss, and there is crosstalk in the drum sound, so the separation effect is still not ideal. The separation results of the algorithm in this paper show that the three sounds are accurately and clearly separated, and the interference is small, and the separation effect is very ideal. The representative formula of the system is given, and its convergence condition is given. On this basis, this paper researches the algorithm realization of the Landweber iterative algorithm for advanced iterative image development with limited angle

and mainly studies the selection of iterative parameters through numerical simulation. In the different selections of the relaxation factor and the angle α of the relevant parameters, it is verified by numerical simulation in Table 2 that when the relaxation factor tends to 1, the reconstructed advanced iterative image has the best effect.

The development algorithm is designed by using the smooth 0-norm method. The basic steps of the algorithm are divided into three steps: in the first step is to solve the optimization problem constructed by the approximation function, and the iterative formula of the algorithm is obtained; in the second step, the adaptive update step size is to update the search direction. When the iteration stop condition is met, the algorithm stops working. By selecting as few bases as possible, the observed music signal can be represented by characterizing the music signal on this set of bases. It uses the sparse characteristic of the music signal to replace the independent characteristic to realize the blind separation of the mixed music signal. The sparse quantity analysis has a good effect in the study of the blind separation of the mixed signal under the underdetermined condition. The sparse component analysis algorithm requires that the observed music signal be a sparse music signal. The so-called sparse music signal means that the value of the music signal is zero or close to zero at most of the time, and the value of only a few moments is obviously not zero.

5.2. Implementation of Music Course Integration Simulation.

In this experiment, three channels of speech and music signals are used, which are the speaking sounds recorded by three different people in the laboratory. The duration is 11 seconds, the sampling frequency is 16 KHz, and the sampling point is 190218. The time domain waveform is shown in the text. The abscissa represents the number of sampling points, and the ordinate represents the amplitude of the music signal. Perform STFT on the observed speech and music signal, take $a = 1024$, $b = 0.5$, and obtain the polar coordinate scatter in the frequency domain as shown in the text. The abscissa in the figure represents the angle of the polar coordinate, and the ordinate represents the length of the polar coordinate. Blind source separation refers to separating the source music signal by only using the observed information of the mixed music signal under the condition of unknown information (unknown source music signal, unknown mixing method, unknown channel information, etc.). In the absence of any prior conditions, it is difficult to accurately separate the source music signal, so blind source separation studies the algorithm of estimating the music signal under the premise of some basic assumptions.

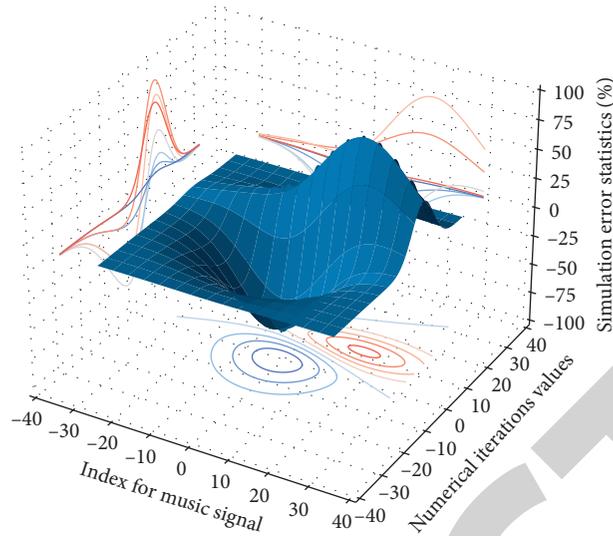


FIGURE 5: Advanced iterative image music signal error statistics.

TABLE 2: Advanced iterative numerical simulation of development.

Iterative number	Effect r	Parameter factor p	Relaxation factor	Simulation matrix
100	1.773	0.633	179	[0.367 0.16949 0.22258]
200	1.737	0.613	99	[0.324 0.31756 0.14123]
300	1.701	0.635	25	[0.998 0.96972 0.72094]
400	1.665	0.606	110	[0.191 0.88447 0.52587]
500	1.629	0.684	150	[0.952 0.20307 0.69078]
600	1.593	0.672	5	[0.802 0.57197 0.52361]

$$\begin{cases} y(i, j) = ai + bj - \sum \sqrt{y(i, j)}, \\ y(i, j, k) = ai + bj + ck - \sum \sqrt{y(t - x, j)}. \end{cases} \quad (16)$$

This paper uses two sets of experiments under the Matlab 7.8.0 software platform to prove the effectiveness of the algorithm in this chapter. The first set of experiments uses artificially synthesized mixed speech segments, and the source music signal and mixing matrix are known; the second set of experiments uses popular songs from high-quality CDs. Among the 125 students, there were 47 music testers for mild exams, accounting for 37.6% of the total, 51 music testers for moderate exams, accounting for 40.8% of the total, and 27 music testers for severe exams, accounting for 21.6% of the total. The problem of the music test in the middle school students' examination is very serious, and it needs the attention of the school and the society.

$$\begin{aligned} & \begin{bmatrix} x(t-1, t-s) \\ \dots \\ x(t-n, t-s+n) \end{bmatrix} \begin{bmatrix} \sin(t-1, t) \\ \dots \\ \sin(t-n, t) \end{bmatrix} \\ & = \text{foulier}(f(x, t)) \log \begin{bmatrix} f(t-1, t-s) \\ \dots \\ f(t-n, t-s+n) \end{bmatrix}. \end{aligned} \quad (17)$$

The improved cosine potential function method is used to estimate the initial value of the mixture matrix. Experiments show that the algorithm has a great improvement in accuracy. The statistical model of the source signal is established, and the EM algorithm is used to iteratively solve the optimal solution based on each parameter in IS-NMF. The experiment proves the effectiveness of the algorithm in this chapter and also shows that the separation of the EM algorithm is accurate when the initial value of the mixing matrix is accurate. Performance has been greatly improved. After the implementation of the course, there was a significant difference between the intervention group and the control group in the examination music test, and the examination music test score in the intervention group was significantly lower than that in the control group, indicating that the music course can effectively alleviate the anxiety of middle school students in examinations. Before and after the implementation of the course, there was no significant difference between the control group and the intervention group. Moreover, the mean value of the posttest in the intervention group in Figure 6 is significantly smaller than that of the pretest, which proves that, after the implementation of the course, the students' sense of rejection of the test is reduced, and they can face the test calmly, thereby reducing the test music test.

Since both the signal algorithm and the theory of multiple intelligences algorithm use the first-order shrinkage

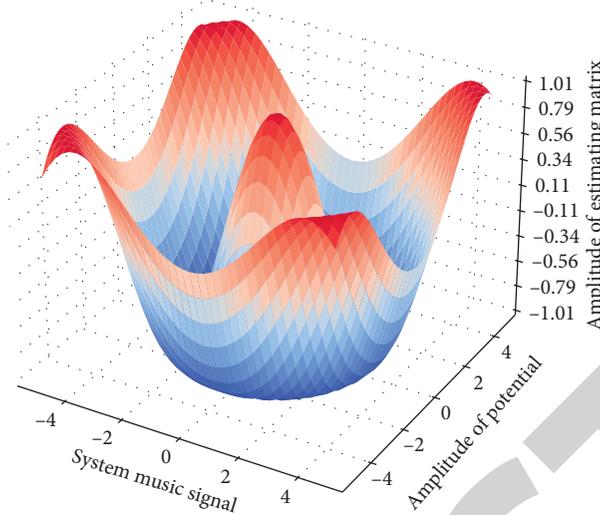


FIGURE 6: The distribution of the estimation matrix of the cosine potential function of the music signal.

method (FPC and FFPC) and the second-order conjugate gradient (CG) method to approach the optimal solution alternately, while the FPC and the theory of multiple intelligences are both first-order, therefore, the convergence speed of the signal algorithm and the theory of multiple intelligences algorithm is faster than that of the FPC and the theory of multiple intelligences algorithm. The paper shows the development speed of the signal and the theory of multiple intelligences more vividly. When the sampling rate exceeds 0.6, the second-order subspace optimization times are more, and the algorithm converges to the exact solution faster. The computational error of the theory of multiple intelligences algorithm decreases rapidly with the increase of the sampling rate. When the sampling rate is below 0.6, the development error of the theory of multiple intelligences algorithm is the smallest. When the sampling rate continues to increase, the development error of the theory of multiple intelligences is also relatively small, close to the signal.

5.3. Example Application and Analysis. The theory of multiple intelligences algorithm is executed on each node and consists of two main parts: first, there is the CS development algorithm DIAT; second, the estimated support set is fused. Among them, the fusion operation includes two sub-methods, namely, the consistency strategy and the expansion strategy. With the theoretical convergence established, when IAT is a part of DIAT, the convergence of IAT helps prove the convergence of DIAT. Furthermore, the subalgorithms used by the two strategies of consistency and expansion in the fusion operation help find relevant side information, which makes DIAT have a theoretical basis. In the following subsections, we will introduce the parts of the algorithm one by one, and the fourth part will provide a theoretical analysis of these methods. As the sampling rate increases, the PSNR of the six algorithms increases.

$$\left\langle \frac{k(n, m) | t a(i, \sqrt{i+1}) + b(j, \sqrt{j+1}) }{\langle k(i) | t a(i-1, \sqrt{i+1}) + b(j-1, \sqrt{j+1}) \rangle} \right\rangle = \langle k(n, m) | t f(a, b)(i, \sqrt{i+1}) \rangle. \quad (18)$$

In the sampling rate range of 0.2 to 0.6, the PSNR of the proposed method is significantly better than other comparison algorithms. The algorithm has the lowest performance and the worst development of advanced iterative images. When the sampling rate is 0.8, the method proposed in this paper basically coincides with the algorithms SL0 and ANSL0 and is better than the algorithms SL0. Therefore, in the case of low sampling rate, the advantages of the algorithm are more obvious. Among them, the input and output connectivity are, respectively, consistent with the nodes in the communication link receiving or sending information, and the given network is the interconnected and static network. In order to verify the practical performance of the

DIAT algorithm, the simulation experiment adopts a type of network: structured network. Structured network, two sets in-Lp, and out-Lp consider the topology of the network in Figure 7 with nodes on the same circle.

In addition, nonnegative matrix factorization has the characteristics of fast and accurate calculation and is an effective algorithm for processing large-scale data, so the theory of nonnegative matrix factorization has contained great potential since it was proposed. In terms of blind source separation, the nonnegative matrix factorization algorithm is a new way to solve the blind separation of mixed speech and music signals. It does not have the limitations of prior conditions such as source music signal independence

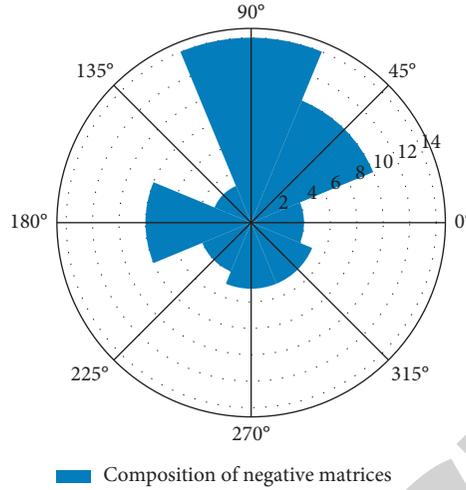


FIGURE 7: Nonnegative matrix factorization output of iterative algorithm.

and non-Gaussian distribution in general BSS and is also consistent with practical applications (e.g., advanced iterative image data, document statistics) requirements to disallow negative elements are consistent. The observed data points are clustered in these directions. If all the time points of the observed music signal t are clustered, the mixture matrix A can be estimated. After estimating the mixing matrix, solving the estimated music signal is transformed into the problem of solving the underdetermined equation. Since the solution is not unique, it is generally necessary to introduce constraints to solve it.

$$\begin{cases} d_{\text{steel}}(a(i)|b(j)) = \frac{a(i)}{b(j)}, \\ d_{\text{steel}}(a(i, \sqrt{i+1})|b(j, \sqrt{j+1})) = \frac{a(i, \sqrt{i+1})}{b(j, \sqrt{j+1})}. \end{cases} \quad (19)$$

Among the voice and music signals separated by the algorithm, one channel has a large loss of voice, and the other two channels have certain loss and crosstalk. The algorithm can basically accurately separate the complete three channels of voice and music signals, but there is still a certain loss. In this case, the music signal waveform separated by the algorithm in this chapter is closest to the source music signal waveform, and there is almost no loss and crosstalk in terms of auditory discrimination. Before and after the implementation of the course, the intervention group constituted a significant difference, and there was no difference in the control group. The mean value of the posttest in Table 3 is significantly lower than that of the pretest, which proves that, through the implementation of the course, the students can better adapt to the environment during the test than before and can correctly handle the test, thereby reducing the level of the test music test.

In order to reduce the amount of communication data in the network, and the sensor node itself has a certain computing power, considering the importance of accurate support set estimation in the algorithm, this section proposes an adaptive threshold iterative development method in distributed advanced iterative development. This method

TABLE 3: Description of the music signal waveform separated by the algorithm.

Description unit	Signal size	Noise value	Communication data rate
Post-test 1	0.681	0.009	0.805
Post-test 2	0.708	0.557	0.976
Post-test 3	0.921	0.097	0.790
Post-test 4	0.468	0.413	0.950
Post-test 5	0.421	0.249	0.511
Post-test 6	0.463	0.473	0.195

is different from the iterative threshold algorithm in the theory of multiple intelligences. This method obtains the support set through the iterative method, realizes the interaction of the support set information in the network, and fuses the support set information and uses the result as the edge information to the IAT algorithm. The current node receives data from surrounding nodes and fuses it. If the conditions are not met, it is fed back to the surrounding nodes; otherwise, it is sent to the upstream node. The node adopts advanced iterative development technology to realize data collection, performs preliminary development through its own inherent computing power, sends the reconstructed support set to other nodes in the network, receives the support set information sent from other nodes, and the node fusion processing, local statistical data, use of local statistical data, combined with its own results, and continues to reconstruct until the conditions are met, and the development is completed.

6. Conclusion

This paper mainly considers the iterative shrinkage threshold class algorithm to solve the music signal development problem in advanced iterative development theory. This kind of algorithm can be used to solve large-scale signal development problem due to the simplicity of calculation. This algorithm improves the global convergence speed of the algorithm on the premise of ensuring the simplicity of the

traditional iterative shrinkage threshold algorithm calculation. This paper proposes a block-based fast fixed point-active subset (advanced iterative development) algorithm. The simulation results show that the music signal error of the advanced iterative image reconstructed by the theory of multiple intelligences algorithm is smaller, and the peak signal-to-noise ratio is relatively high, and the visual effect of the advanced iterative image is the best. When solving large-scale optimization problems, not only the storage and transmission space of the measurement matrix is saved, but also the music signal can be reconstructed quickly and accurately. Numerical experimental results show that when the nonmonotonic fast iterative shrinkage threshold algorithm solves the problem of music signal development, the iteration time of the algorithm is shorter.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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