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Research Article

The Improvement Effect of Online Teaching Based on Intelligent Speech Recognition Technology on the Teaching Management Mode in Colleges and Universities

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In order to improve the advanced nature of teaching management mode in colleges and universities, this paper analyzes the teaching management process in colleges and universities combined with intelligent speech recognition technology. For the dataset of linear teaching speech information distribution, in the case of overlapping of various datasets, this paper finds the overlapping points of various datasets through an algorithm. Moreover, this paper makes full use of the known information to find a vector that can equivalently represent the linear teaching speech information where each data point is located. After that, this paper takes it as the feature vector of each data point and then performs clustering through spectral clustering to obtain the clustering result. The experimental research results show that the model in this paper has a good effect on speech recognition in college teaching, and the model in this paper has a good role in promoting teaching management in colleges and universities.

1. Introduction

As a first-level administrative management organization in a university, a college is a collection of multiple or single disciplines and majors, and it is a very important part of the internal management system of colleges and universities. At present, the college-level management system of most colleges and universities in China is still very imperfect, and each college has not yet formulated an effective management system according to the school's system and the actual situation of the college. In addition, the management relationship between universities and colleges has not been completely straightened out, which also affects the release of energy from college-level units and makes the teaching management work of colleges lack vitality. Therefore, the implementation of two-level management of the school and the school needs to be based on the school, and the focus should be placed on the management system of the school. At the same time, it is necessary to establish a college-level teaching management mode that is fast and efficient, and is conducive to the full play of the functions of each college. First of all, it is necessary to solve the problems existing in the current process of college-level teaching management in Chinese universities.

In the traditional college management process, colleges and universities will emphasize the function of the organizational structure and its standard procedures. The "external control" management mainly achieves unified goals through standard, procedural, and general standard methods and procedures [1]. It is required that the goals of each college are consistent, while ignoring the unyielding characteristics and methods of each college, adopting a centralized management principle, and emphasizing the control of the process, in order to avoid problems in each college, so, no matter big or small, the school is responsible for details. With careful control, the college has little autonomy, and everything has to be reported to the school for instructions, which often results in the phenomenon of "external control" management, which makes it impossible for the college to solve problems in time [2]. From the perspective of the college as a whole, the college is often regarded as a tool or way to achieve the school's goals. It is a passive system that must be tightly controlled and has no clear autonomy, responsibility, and obligation at all; “external control” management emphasizes the management of the organization, as long as the organization. The goal is clear. People can work effectively, so they will be more inclined to supervise the college and constantly introduce new regulations to control the school. This has resulted in the expansion of institutions at the school level, the college’s dependence on the school has become stronger, and the college has become ineffective. In the process of college-based teaching management, colleges and universities emphasize that there are many different ways for each college to achieve its goals, highlighting flexibility, and each college should be based on its own different conditions [3]. Take a variety of approaches. Rather than adopting a standard method for college management, this allows each college to have a larger space for activities to develop and formulate teaching management methods suitable for the college; the power and responsibility are moved down to the college, which is a prominent feature of modern college management phenomenon, because the daily goal of college teaching management is efficiency and problem solving rather than escaping or avoiding the problem [4]. The college-based management should effectively discover the problems of the college itself, solve them in time, and make due efforts to improve the teaching efficiency: the college-based management does not deny that the college is a tool or way to achieve goals, but believes that to achieve the school. There are many ways to achieve the goals of the school. Therefore, on the premise of realizing the school goals, the college has greater autonomy, assumes certain responsibilities and obligations, conducts effective management by itself, develops teaching, allocates teachers and materials, solves problems according to the characteristics of the school problems, and achieve goals [5]; the college-based teaching management emphasizes the establishment of a suitable environment, allowing members of the college to participate in the realization of the goal, fully excavating and developing the human resources in the college, and giving full play to their enthusiasm, so as to improve the teaching quality more effectively [6].

In the external control management model, college managers often think that the goals are clear, simple, and static, the college is only a tool and means to achieve these goals, and the value of teachers is the value of the tool; the college-based teaching management model believes that the college is not only a student. The place of learning and growth is also the place where the faculty and staff learn and grow. If the potential of students and faculty cannot be continuously developed, the potential of the college or even the entire school will not be developed [7]. Decision-making is a participatory process. All members of an organization have an equal opportunity to influence decisions and actions. Under the strict control of external control management, the decision-making of the college is mostly made by the administrative staff of the school and then handed over to each college for implementation. The faculty and staff of the college rarely have the opportunity to participate in the decision-making and are regarded as unimportant; in a complex educational environment, teaching tasks are diverse and require the wisdom, imagination, and efforts of many people to complete. Therefore, the decision-making method at the school level is gradually transformed into “decentralized” or “participatory,” so that more people, including the faculty, staff, students, and even the parents of the various colleges, involved, and they will be more actively involved in the teaching and management of the college [8]. In terms of leadership style, the leadership style of external control management focuses on the lower level, thinking that technology and interpersonal relationships are very important to achieve goals, while ignoring cultural leadership [9]; when the background and ideas are more and more divergent, the dean should lead by example, help and guide the members of the college to understand the meaning of various activities of the college, eliminate differences and misunderstandings between individuals, and clarify unstable and uncertain factors [10].

The primary task of the project management implementation of the teaching management information system is to clarify the goals of the project. Only correct and clear goals can ensure the success of the project. The goal of the implementation of the teaching management information system project of the School of Mechanical and Electrical Engineering is to deliver a complete set of information systems that can meet the teaching management of the college, and each functional module can realize sub-functions to meet the functions of the entire system. The realization of system functions can save manpower, standardize teaching management, realize auxiliary analysis, and provide basis for high-level decision-making. This goal is consistent with the long-term development strategy of the college [11]. Quantitative benefits include building a school management platform, reducing labor costs, improving work efficiency, and improving service levels for teachers and students [12]. Qualitative benefits include giving full play to the role of people, improving service quality, realizing the informatization of the educational process, establishing a more effective teaching management mechanism, scientifically and uniformly allocating teaching resources, and ensuring the healthy and sustainable development of the school [13].

When the actual situation in the project implementation process deviates from the project management plan, contingency measures must be taken to reduce the project risk caused by not considering the impact of the change on the overall project goal or plan. Change control runs through the project, and the project manager is ultimately responsible for it [14]. Changes need to be managed carefully and continuously to maintain the project management plan. During the implementation of the teaching management information system project, each stakeholder can make a change request orally, but all change requests must strictly implement the change management process to prevent scope creep caused by randomness [15]. The focus should be to assess the time and cost impact of the change and provide the results of the assessment. Change requests are issued during the execution of an instructional management information system project including corrective actions, preventive actions, and defect remediation [16]. During the implementation of the project, the output of the teaching management information system often does not conform to the management system of our school, and the result is not what we need. At this time, it needs to be corrected. Therefore, before implementing certain modules, some preventive measures will be taken to exclude the factors that will affect the output to ensure the desired output result [17].

This paper combines the intelligent speech recognition technology to analyze the teaching management process in colleges and universities, improve the teaching management mode in colleges and universities, and improve the efficiency of teaching management in colleges and universities.

2. Speech Recognition Technology

2.1. A New Linear Speech Information Clustering Algorithm. Generalized principal component analysis (GPCA) algorithm clusters linear speech information data by partitioning the dataset into corresponding subspaces by using algebraic geometric methods. Marc Pollefeys et al. proposed a spectral clustering algorithm based on local subspace affinity (LSA).

GPCA is a method of partitioning subspaces, which uses algebraic geometric methods to partition a dataset into corresponding subspaces. The joint distribution of k linear subspaces can be fitted by a set of polynomials of degree k, and the derivative of these polynomials at a point is a normal vector of the subspace at that point. We assume that any point in the dataset is $x \in R^k$, the dataset is in n different linear subspaces Ω_c, and any point $x \in R^k$ in the dataset satisfies $b_i^T x = 0$. Among them, b_i is the vertical vector of the subspace to which x belongs. The original dataset is $X \in R^K$, and the data in the dataset are in n different linear subspaces X_c, $\cup X_c = X, c = 1 \ldots n$. We set the vertical vector of these n linear subspaces to be $b_c, c = 1 \ldots n$, and for $x_i \in X_c$, there is $b_c \cdot x_i = 0$. Then, for any $x \in X$, there is $\prod_{c=1}^{n} b_c \cdot x = 0$, which is $\prod_{c=1}^{n} (b_{c1} \cdot x_1 + \ldots + b_{cK} x_K) = 0$. Among them, K is the dimension of the subspace, and this polynomial is expanded to get

$$c_1 x_1^n + c_2 x_1^{n-1} x_2 + \ldots + c_{M_n} x_K^n = V_n(x)^T C. \tag{1}$$

Among them, $V_n(x)$ is the Veronese map of x. C can be composed of left singular vectors corresponding to several minimum singular values of $V_n(x)$, and then b_c is obtained by factoring, and the vertical vector of each subspace is obtained. Then, by clustering, each data point is divided into its nearest linear subspace.

The LSA method mainly includes the following steps:

(1) The arc cosine angle between each sample point is calculated and sorted to obtain each K sample point closest to the sample data$_i$.

(2) For each sample point, itself and the K nearest sample points are formed into a matrix, and a local affine subspace Ωi is fitted to the matrix by singular value decomposition (SVD).

(3) The similarity matrix is computed: the distance between the local affine subspaces can be measured by the principal angle between them. The principal angle μ_{ij} between the local affine subspace Ω_i of data$_i$ and the local affine subspace Ω_j of data$_j$ is calculated as

$$\mu_{ij} = e^{\left(-\Sigma_{m=1,\ldots,M} \sin^2\left(\theta_{ij}^m\right)\right)}. \tag{2}$$

Among them, θ_{ij}^m is the m-th principal angle between the local affine subspaces Ω_i and data$_j$ of the local affine subspace Ω_j.

(4) Spectral clustering: Through the spectral clustering method, the obtained similarity matrix is used as input, and the clustering result is obtained.

Spectral curvature clustering linear speech information clustering algorithm is based on multi-channel clustering technology. Usually, at least $d+1$ data points are required to define a d-dimensional affine subspace. Spectral curvature clustering uses a multi-channel similarity measure to describe the possibility that $d+2$ data points come from the same latent linear speech information, so as to construct the similarity measure matrix W between data points. We set $m\Omega_{d+2} = \{x_{il}\}_{l=1}^{d+2}$ to be $d+2$ randomly selected data points, and spectral curvature clustering is based on the probability of polar curvature to define a multi-way similarity $S_{i_1,i_2,\ldots,i_{d+2}}$:

$$S_{i_1,i_2,\ldots,i_{d+2}} = \exp\left(-\frac{1}{2\sigma^2} diam^2(\Omega_{d+2}) \sum_{l=1}^{d+2} \frac{(d+1)!^2 vol^2(\Omega_{d+2})}{\prod_{1\le m\le d+2, m\ne l} \left\| x_{im} - x_{il} \right\|^2}\right). \tag{3}$$

If and only if $i_1, i_2, \ldots, i_{d+2}$ is different, there is $S_{i_1,i_2,\ldots,i_{d+2}} = 0$. Among them, $\operatorname{diam}(\Omega)$ represents the radius of the set Ω, and $\operatorname{vol}(\Omega)$ represents the volume of the $d+1$-dimensional simplex formed by the points in the set Ω. The similarity matrix W is defined as

$$w_{ij} = \sum_{k_2,\ldots,k_{d+2}} S_{i,\mathbf{k}_2,\ldots,\mathbf{k}_{d+2}} S_{j,k_2,\ldots,k_{d+2}}. \tag{4}$$

In spectral curvature clustering, the initial sampling in the iterative sampling will significantly affect the final clustering result, it is easy to fall into the local optimal solution, and the algorithm is unstable.

2.2. A New Linear Speech Information Clustering Algorithm. For two straight lines in the same plane, in general, there is an intersection (there is overlap). For three straight lines on the same plane, in general, there are three intersections, as shown in Figure 1. Among them, $p1$, $p2$, and $p3$ are 3 overlapping points. For n straight lines, there are $n(n-1/2)$ intersections.

We assume that there are n types of datasets, each type of data conforms to the linear speech information distribution, and there is overlap between various types of data. First, the method of finding density peaks is used to obtain the overlapping points of various data, and the overlapping point set $P = \{p1, p2, \ldots, pk\}$ between various types of data is obtained. The algorithm to find the set of overlapping points in the sample is as follows:

Input: set of data points X

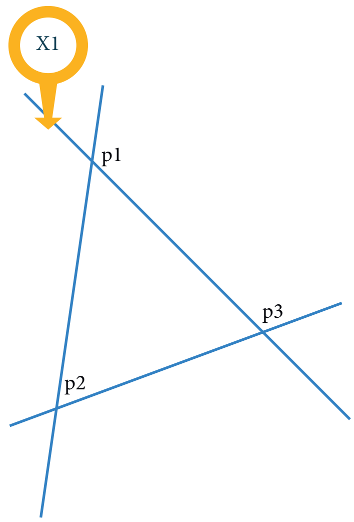


Figure 1: Linear speech information data with overlapping points.

Output: set of overlapping points $P = \{p1, p2, \ldots, pk\}$

step: 1: The algorithm is based on the assumption that the sample points at the overlap of each linear subspace are denser. For each sample point x_i, feature attribute ρ_i is calculated. Among them, ρ_i represents the local density of sample point x_i, and δ_i represents the minimum distance between sample point x_i and all points with higher local density than x_i. The calculation method of ρ_i is$\rho_i = \sum_j \exp[-(d_{ij}/d_c)^2]$.

Among them, d_{ij} represents the Euclidean distance between the sample point x_i and the sample point x_j, and d_c represents the truncation distance.

2: The calculation method of the feature attribute δ_i, δ_i is $\delta_i = \min_{j:\rho_j > \rho_i}(d_{ij})$.

δ_i is the minimum distance between sample point x_i and all points with higher local density than x_i. For the point with the highest density, there is $\delta_i = \max_j(d_{ij})$.

3: Only ρ_i and δ_i of the overlapping point are relatively large. For the point concentration with high density, the point near the overlapping point is only ρ_i which is larger, δ_i is equal to the distance between it and the overlapping point, the distance between the two points is very close, and δ_i is smaller. From this, we can draw a two-dimensional decision diagram by finding the ρ_i and δ_i of each sample point and obtain the overlapping point.

As shown in Figure 2(a), there are two types of linear data with overlapping points. According to the above method, the decision diagram is drawn, as shown in Figure 2(b), and the point in the upper right corner of the diagram is the overlap point.

We set P_i, P_j to represent two vectors and define the degree of parallelism s_{ij} between the two vectors as

$$s_{ij} = abs\left(\frac{P_i \cdot P_j}{\|P_i\|\|P_j\|}\right). \quad (5)$$

The closer the degree of parallelism is to 1, the more parallel the two vectors are.

The new linear speech information clustering algorithm consists of the following steps:

(1) The overlapping point is found: according to Algorithm 1, the overlapping point set $P = \{p1, p2, \ldots, pk\}$ is found.

(2) The feature vector is calculated: for the sample point, $x_i \in R^d$, d is the sample space dimension. For the overlapping point set $P = \{p1, p2, \ldots, pk\}$, we find $x_i p_k = (x_i - p_k)/\|x_i - p_k\|$ separately, and then there must be m vectors that are nearly parallel (the angle is small or close to 180°). According to formula (7), the degree of parallelism of each vector is calculated, the two vectors $x_i p_1^*$ and $x_i p_2^*$ with the highest degree of parallelism are taken, and the calculation method to obtain its average value as a eigenvector V_i, V_i of the sample point x_i is

$$V_i = \frac{x_i p_1^* + x_i p_2^*}{\|x_i p_1^* + x_i p_2^*\|}. \quad (6)$$

Among them, if the subtraction operation between vectors just results in a zero vector, the negative vector of the subtraction vector can be subtracted. The eigenvectors of a set of points belonging to a linear subspace are parallel to each other.

(3) The similarity matrix W is calculated: the calculation formula of the similarity w_{ij} between the two sample points is

$$w_{ij} = abs\left(\cos\left(\theta_{ij}\right)\right). \quad (7)$$

Among them, θ_{ij} represents the angle between the two corresponding eigenvectors of sample point x_i and sample point x_j:

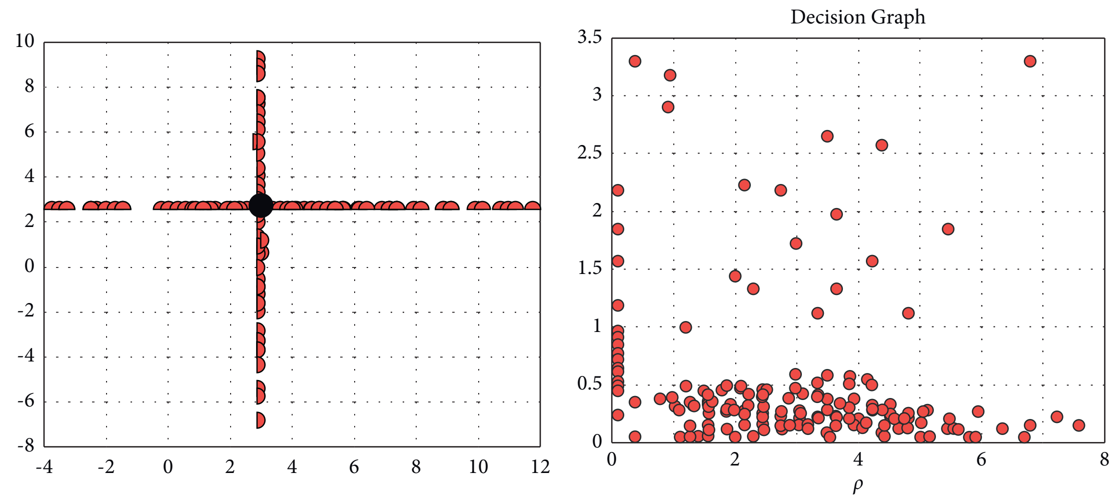
$$\cos\left(\theta_{ij}\right) = \frac{V_i \cdot V_j}{\|V_i\| \cdot \|V_j\|}. \quad (8)$$

For two sample points in a linear subspace, their eigenvectors are nearly parallel, that is, the sample point similarity $abs(\cos(\theta_{ij})) \approx 1$. The two sample points that are not in a linear subspace have a larger angle between their eigenvectors. When the eigenvectors are vertical, there is $abs(\cos(\theta_{ij})) \approx 0$. As shown in Figure 3, it is the angle between the characteristic vectors and the corresponding cosine value.

(4) Spectral clustering: The clustering result of the data is obtained by applying the spectral clustering method to the constructed similarity matrix W.

3. Experimental Results and Analysis

In all the experiments in this paper, the clustering accuracy is used as the criterion to judge the clustering performance. At the same time, the performance of the algorithm is verified



(a) (b)

FIGURE 2: Overlapping points are found. (a) Two types of linear data with overlapping points. (b) Decision diagram.

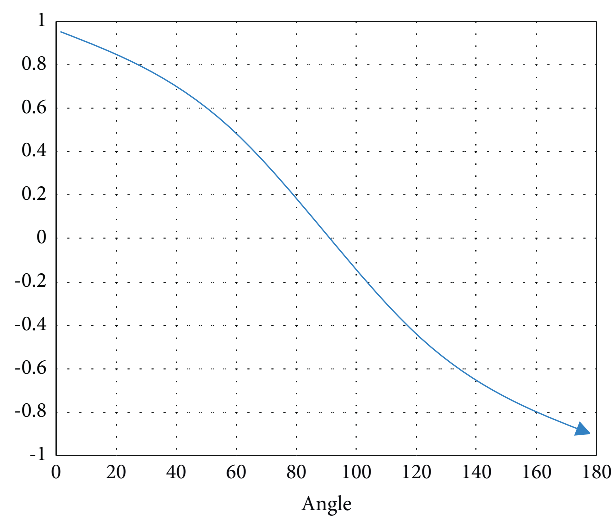


FIGURE 3: The cosine value corresponding to the angle.

and evaluated in the absence of speech noise and in the presence of speech noise. Among all possible labels, the classification accuracy with the largest alignment with the true label category is the final clustering accuracy, and the formula is

$$\text{clustering accuracy} = \max \sum_{i=1}^{N} \frac{\delta\left(\text{labels}_i = \text{truelabels}_i\right)}{N}. \quad (9)$$

Among them, labels represent the clustering label of the sample point x_i in the algorithm, true labels represent the true label of the sample point x_i, and $\delta(\cdot)$ represents the delta function. The higher the clustering accuracy, the better the clustering performance of the algorithm.

First, experiments are carried out on simulated data to verify the clustering performance of the new linear speech information clustering algorithm. The simulation generates 4 types of data that conform to the distribution of linear speech information, and each type of data has 150 sample points and a total of 600 sample points. At the same time, the 4 sets of data overlap each other, and there are 6 intersections.

The original dataset is shown in Figure 4. As can be seen from the figure, there are four types of data in the original dataset, and each type of data conforms to the linear distribution of speech information. Moreover, there are overlaps between various types of data, and the data to be clustered at the overlaps are generally difficult to process.

In the absence of noise and speech noise, the clustering results of GPCA, LSA, K-flats, and the algorithm in this chapter are shown in Figure 5. It can be seen from Figures 5(a)–5(c) that in the absence of speech noise, the clustering effects of the GPCA algorithm, the K-flats algorithm, and the algorithm in this chapter are all ideal. In Figure 5(d), the overlapping points are clustered into one category, and there are two types of data that are mistakenly clustered into one category. The clustering effect of the LSA algorithm is poor.

On the basis of the original dataset, some speech noises are randomly generated, as shown by the star-shaped points in Figure 6. In the presence of speech noise, the clustering performance of some linear speech information clustering algorithms will be affected because the premise of many linear speech information clustering algorithms is based on the premise that there is no influence of speech noise, such as the least squares method. If there is speech noise, the 2 paradigms of the error will increase significantly, which will increase the error and cause the result to be too biased.

The clustering results of GPCA, LSA, K-flats, and the algorithm in this chapter are shown in Figure 7. It can be seen from the comparison that although there are speech noise and outliers, the algorithm in this paper still has a good clustering effect. First of all, speech noise will not affect the search for overlapping point sets in Algorithm 1. The characteristic attribute δi of speech noise is large, while the characteristic attribute ρi is small. Because the speech noise is relatively scattered, there are no other sample points around, and the local density is small.

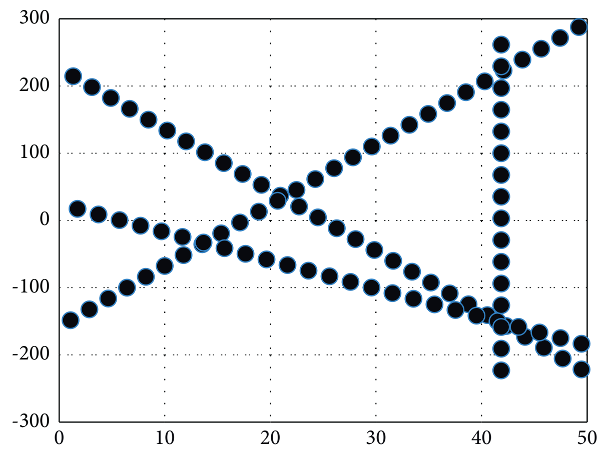


FIGURE 4: Original dataset.

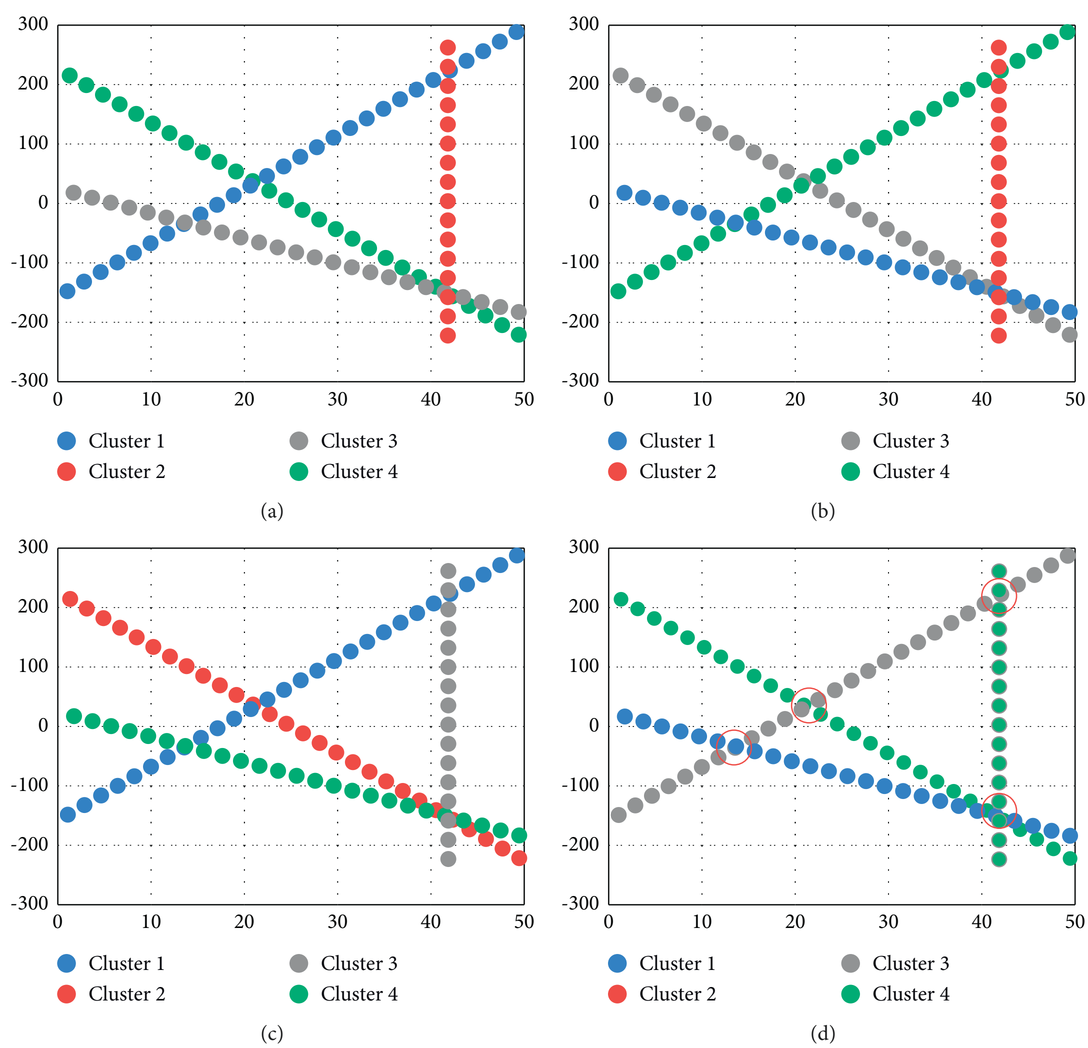


FIGURE 5: Clustering results of each algorithm without speech noise. (a) Clustering results of the algorithm in this paper. (b) GPCA clustering results. (c) K-flats clustering results. (d) LSA clustering results.

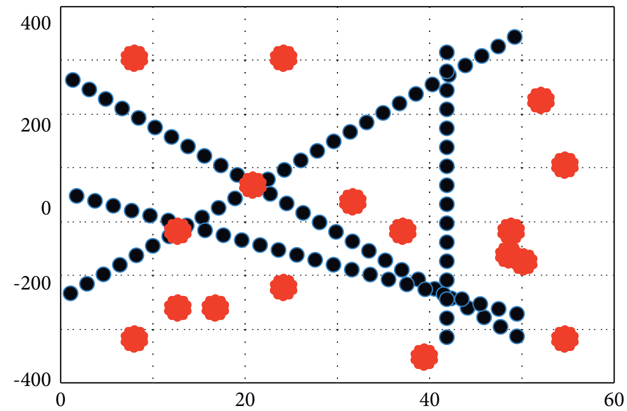


Figure 6: Original dataset with speech noise.

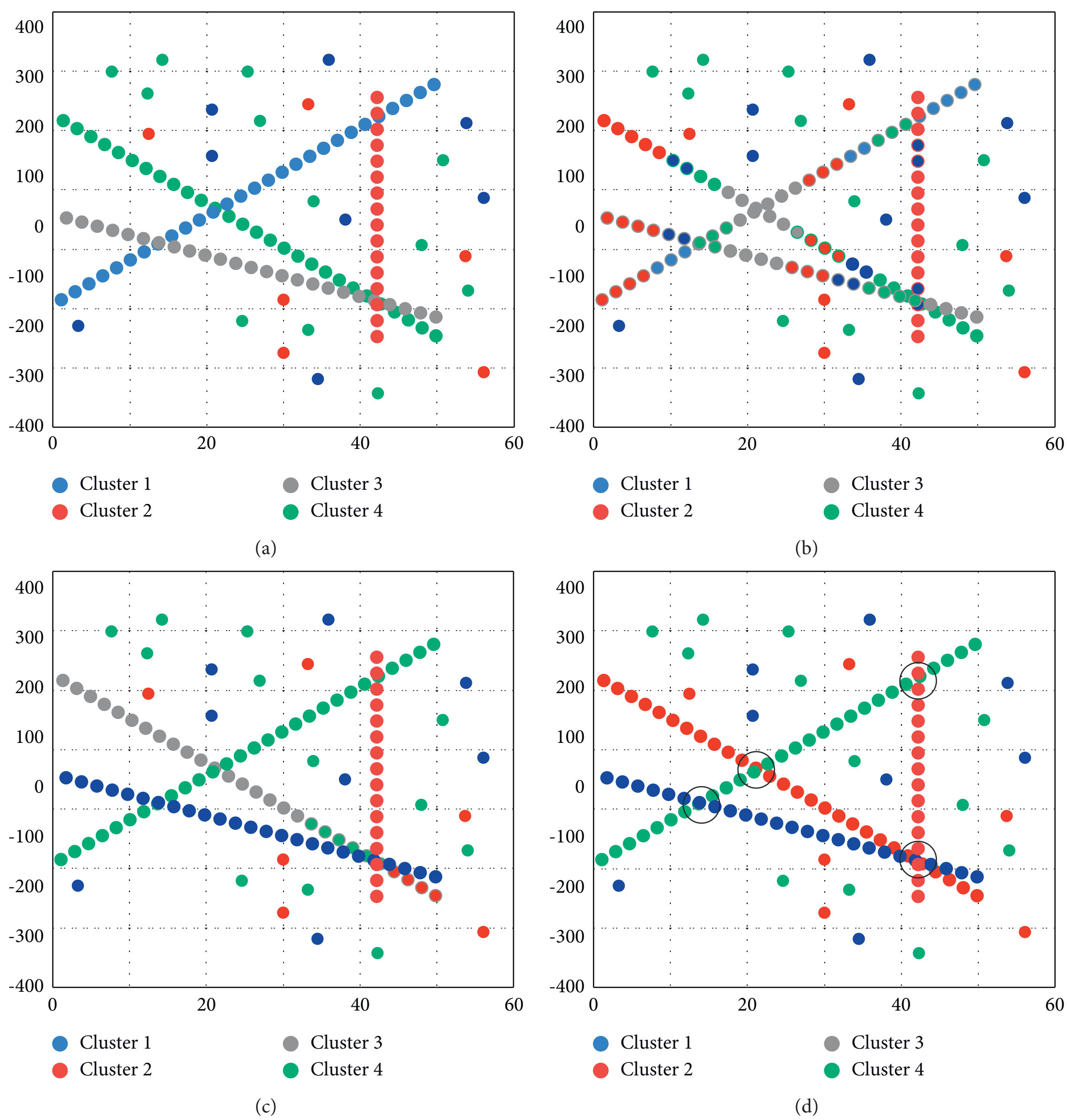


Figure 7: Clustering results of each algorithm in the presence of speech noise. (a) Clustering results of the algorithm in this paper. (b) GPCA clustering results. (c) K-flats clustering results. (d) LSA clustering results.

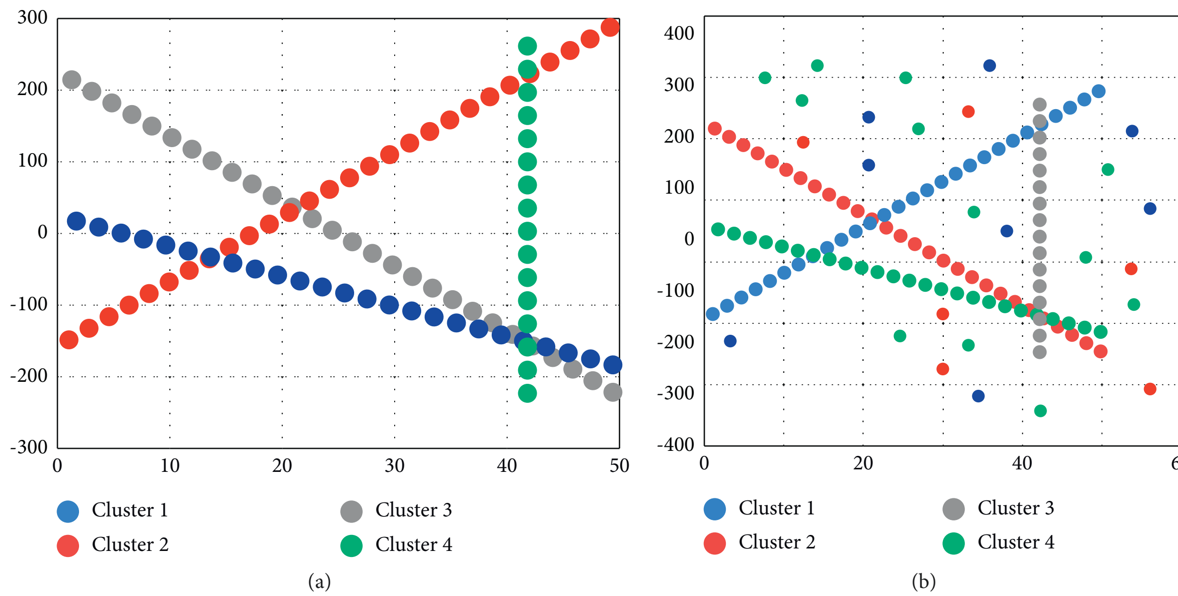


FIGURE 8: Clustering results of spectral curvature clustering algorithm. (a) In the case of no interference point. (b) In the presence of interference points.

The spectral curvature clustering algorithm generally has an ideal clustering effect in the absence of speech noise and in the presence of speech noise, as shown in Figure 8.

However, the spectral curvature clustering algorithm suffers from a disadvantage. That is, the algorithm adopts a random sampling strategy in the initial sampling in the iterative sampling. In some cases, the randomly sampled sample points are all in different linear speech information distributions. As a result, the calculation of multi-channel clustering similarity is biased, which significantly affects the final clustering result, the algorithm often falls into the local optimal solution, and the algorithm is unstable. For the same dataset, 200 experiments are performed, and the accuracy rate will occasionally be very low. As shown in Figure 9, the clustering accuracy rate of multiple experiments will be lower than 70%, all of which are trapped in the local optimal solution. However, after the data points of the algorithm proposed in this paper are determined, the search for overlapping points is fixed, and there is no randomness problem in the subsequent process, so there is no stability problem in the algorithm in this chapter.

In the dataset experiments with and without speech noise, the clustering accuracy of the four methods is shown in Table 1. It can be seen from Table 1 that in the absence of speech noise and outliers, the clustering effect of the GPCA algorithm is the best and better than other algorithms. The clustering effect of the algorithm proposed in this paper is relatively ideal, but for the LSA algorithm, the clustering effect is poor. In the presence of speech noise and outliers, the GPCA and K-flats algorithms have very unsatisfactory clustering effects due to the limitations of their own algorithms, while LSA does not properly handle the data points where the speech information overlaps. Its clustering effect is not ideal whether there is speech noise or not. The algorithm in this paper is not affected by speech noise and outliers, and can also process data points where speech information overlaps. In both cases, the clustering effect is ideal.

In this paper, the time-frequency distribution of the rearranged spectrum is obtained from the multi-component signal, and the method of clustering is used to sort the multi-component signal.

For example, for the multi-component signal composed of 3 signals in Table 2, its expression is

$$\begin{aligned} s(t) &= \exp\left[j2\pi\left(0.05t + 0.4t^2\right)\right] \\ &\quad + \exp\left[j2\pi\left(0.45t - 0.4t^2\right)\right] + \exp\left[j2\pi(0.32t)\right]. \end{aligned} \tag{10}$$

The time-frequency distribution diagram of the obtained rearrangement spectrum is shown in Figure 10. It can be seen from the figure that the time-frequency distribution sample points of each single-component signal are in line with the linear speech information distribution. However, there is overlap between each single-component signal, so it is suitable to use the algorithm of this chapter for clustering and obtain the time-frequency distribution point set of each single-component signal.

When the sampling frequency is too large, there are too many sample points in the time-frequency distribution, which will cause the calculation of the clustering algorithm to be too slow. Therefore, for each time point, it only extracts n points with the highest energy peaks as sample points, where n is the number of signal components. Then, it clusters the extracted main sample points and then sorts the signals. The sample points obtained are shown in Figure 11. Among them, in order to make the sample point components meet the requirements of the algorithm in this paper, the energy value is the same value.

This algorithm is used to cluster the sample points, and the clustering results are shown in Figure 12. The

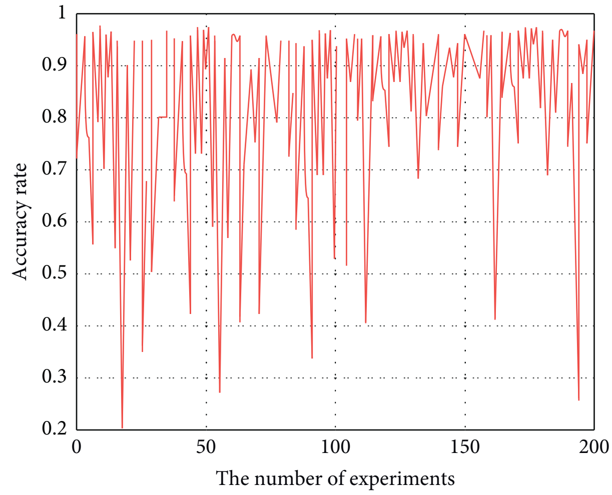


FIGURE 9: Accuracy rate of 200 experiments of SCC algorithm.

TABLE 1: Comparison of accuracy rates of various algorithms.

Method	GPCA	LSA	K-flats	The algorithm proposed in this paper
Accuracy (no speech noise)	98.51	68.55	96.23	96.34
Accuracy (presence of speech noise)	46.02	68.16	69.14	95.83

TABLE 2: Parameters of multi-component signal.

	Modulation	Initial frequency	Frequency modulation
Signal component 1	Linear FM	0.05	0.40
Signal component 2	Linear FM	0.45	−0.40
Signal component 3	Constant frequency	0.32	0.0

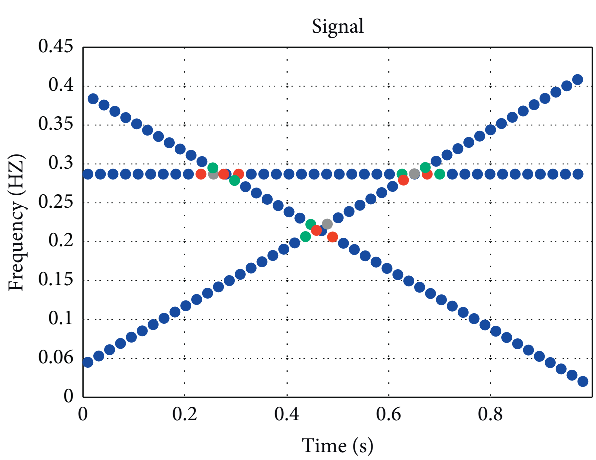


FIGURE 10: Time-frequency distribution diagram of the rearranged spectrum of the multi-component signal (10).

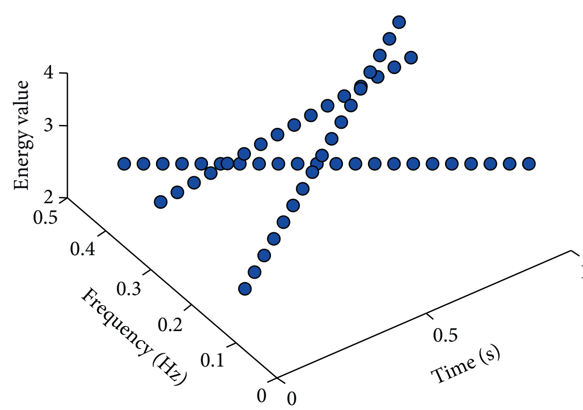


FIGURE 11: Original sample point set.

parameter estimation is shown in Table 3. It can be seen from the table that the parameter estimation error of the multi-component signal is small. Since the processing of the time-frequency distribution of multi-component signals at the overlapping point has not been well resolved, the time-frequency distribution at the overlapping point has some deviations, and the clustering results will be affected to some extent. However, the overall clustering effect is ideal.

In this paper, a new clustering method of linear speech information is presented by exploiting the geometric properties between data points. In this paper, the overlapping points between each linear subspace are obtained by finding the peak density of data points. Then, using the geometric properties between data points and

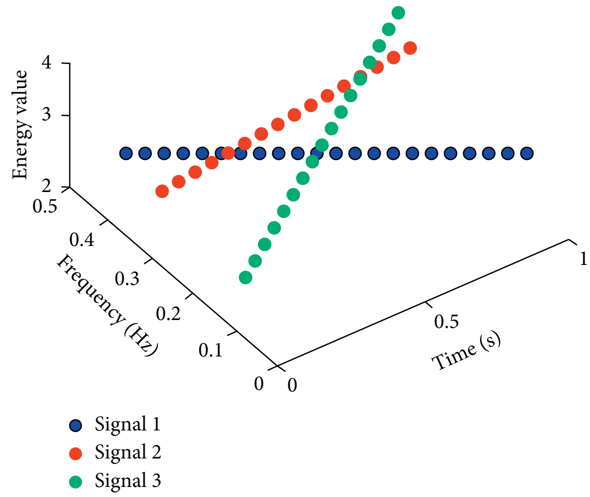


Figure 12: Clustering results.

Table 3: Parameter estimation of multi-component signals (10).

	Actual value	Estimated value
Carrier frequency of component signal 1	0.050	0.053
Frequency modulation of component signal 1	0.400	0.393
Carrier frequency of component signal 2	0.450	0.443
Frequency modulation of component signal 2	−0.400	−0.405
Carrier frequency of component signal 3	0.320	0.318
Frequency modulation of component signal 3	0.0	0.002

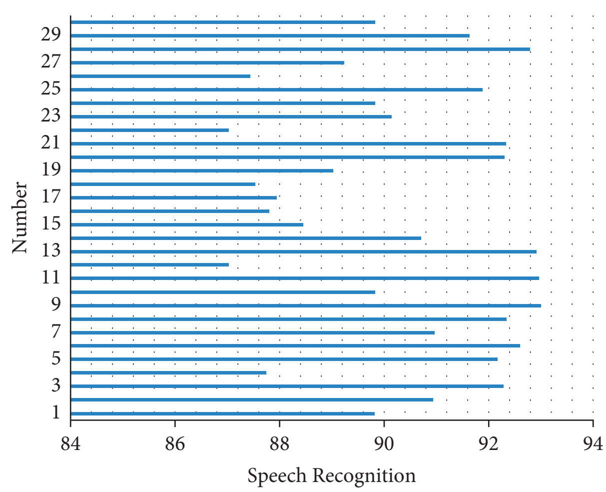


Figure 13: The effect of the model proposed in this paper on speech recognition in college teaching.

overlapping points, the constructed data points can be equivalently represented as eigenvectors of the linear subspace in which they reside. After that, the absolute value of the cosine value of the angle of the eigenvectors between the data points is obtained as the similarity between the data points, the similarity matrix is constructed, and finally the clustering result is obtained by spectral clustering. The experimental results show that the clustering effect of this method is ideal in both simulated data and real data. However, the algorithm has certain limitations; that is, the distribution of data points needs to be uniform, and there are overlapping points between various types of data.

On this basis, this paper explores the effect of this model in speech recognition in college teaching and obtains the results shown in Figure 13.

Through the above research, it is verified that the model in this paper has a good effect in college teaching speech recognition. On this basis, the promotion effect of the model proposed in this paper on the teaching management of colleges and universities is explored, and the results shown in Figure 14 are obtained.

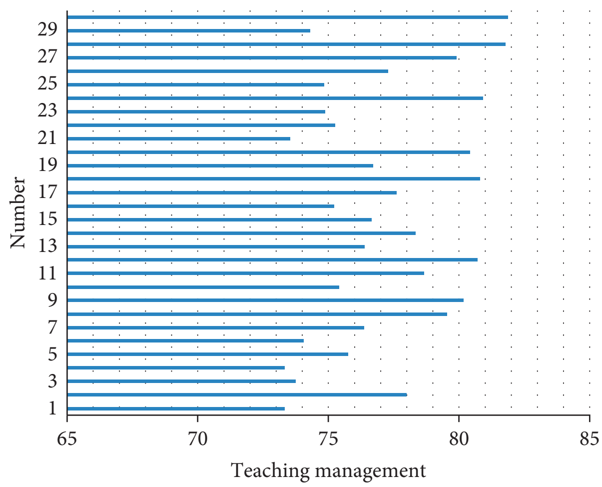


Figure 14: The promotion effect of the model proposed in this paper on teaching management in colleges and universities.

The above research verifies that the model proposed in this paper has a good role in promoting teaching management in colleges and universities.

4. Conclusion

The goal of teaching management information system project implementation is the smooth use of the system. In order to deliver the teaching management information system, the various scopes of work in the implementation process must be completed, and aspects such as technical support and human resources must be evaluated. At the same time, for the smooth implementation of the project, the school should also clarify the measures taken and the resources to be invested to ensure that the project is completed on time. At the same time, the teaching management information system can bring quantitative and qualitative benefits to schools. This paper combines the intelligent speech recognition technology to analyze the teaching management process in colleges and universities, and improve the teaching management mode of colleges and universities. The experimental research results show that the model proposed in this paper has a good effect on speech recognition in college teaching, and the model proposed in this paper has a good role in promoting teaching management in colleges and universities.

Data Availability

The labeled dataset used to support the findings of this study is available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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