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Comprehensive exploration of the independent component based on the study of music signal collection

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ABSTRACT

The data analysis needed in collecting music signal can be divided into two kinds: one is the Principal Component Analysis ; the other one is Independent component analysis. In the collecting process both methods all have their own superiority, but the later one has less errors than the former one. So in the exploration, this paper firstly introduce the principal component analysis, whose key part and also one of preconditions of its practice is the pretreatment. After the pretreatment's efficient projection and integration to original data and multidimensional data, bleaching process will effectively analysis the linear variation of other vector data, so that intensity projection can keep in highly accurate. Finally this paper systematically presents the theory of Independent Component Arithmetic, and in this process the paper largely explores maximization, no gauss and kurtosis, making Independent Component Analysis and Principal Component Analysis harmoniously develop in this study. By this way two methods can have a positive effect on the increasing rationality of this study and lay a solid method and data foundation for the music signal collection, making the analysis more reasonable and the analysis steps more targeted.

KEYWORDS

Music signal collection; Independent component analysis; Principal component analysis; Exploration and study.

INTRODUCTION

Collecting and disposing music signal is a relatively complex process, needing to do a detail and comprehensive analysis of data, so that the representation of independent component can be further explored. This paper mainly analysis the pretreatment, whitening, independent component arithmetic and kurtosis, making the pertinence of music signal collection to be clearly reflected and original data's characteristics and analysis aspects more explicit. Through the introduction above, the analysis though of this paper has showed us that they share a close connection with each other. And in this paper the perspective of comprehensively analyzing independent component always keeps certain accuracy.

SIGNAL PRETREATMENT

Principal component analysis is a method to count, process, analysis, and compress and finally extract data, making new variety has an ideal derivation process in this process. However, new variety has some relations that do not exist in the original ones, and the linear combinations share no relationship with each other. In the building of original variety the efficient using of the new variety can make inequality and change minimum. From the geometric angle, in the data processing of the principal component, there will be an orthogonal coordinate system, in which the axis will rank the data according to the variance of original data. The original data that have higher variance can efficiently describe the original data, further limited dimension also can be used to present. The principal aim of principal component analysis share many similarities with the independent analysis. However, in principal component analysis redundancy is presented by relative quantitative between data; and in independent component analysis there is no emphasis on dimension reduction. In the process of analyzing data, the advance of principal component analysis is that the result can be got only through analyzing second order statistic, so the complicity and complex can be reduced.

In the collection aspect, the main direction of principal component analysis in data analysis is to find a more ideal subspace. If multidimensional data have projection in this space, the component between data can produce the highest variance.

Suppose in $X = [x_1; x_2; \dots; a_n]^T$, x is a random variable in a space with n dimension, and the vector average value is $m_{ix} = E\{\ X\ \} = 0$, so the co variation can be $C_{ox} = E\left\{X^{2T}\right\}$ **[2]**.

In principal component analysis, its main target is through the scientific searching of orthogonal transformation matrix to get $W^T = [w_1; w_2; \dots w_{in}]$, and in this process x in the vector with n dimension has experienced an efficient orthogonal transformation and give us a vector component. After the efficient calculation we get that y_1 represents vector component whose value range is that $i = 1; 2; \dots; m$, but there is not and detail relation between vector component and random component.

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{bmatrix} \qquad \textbf{(1)}$$

The covariance of y is its diagonal matrix, the detail is shown below:

$$C_y = E\left\{yy^T\right\} = diag\left(\lambda_1 \lambda_2 \cdots \lambda_n\right) \qquad \textbf{(2)}$$

Through the above matrix we can efficiently get

$$y_1 = w^T x \qquad \textbf{(3)}$$

However, in all data when the projection direction is equal to 1w the vector component $y_1$of principal component analysis is the largest. And the variance $E\{y_1^2\}$also is the largest, which is also treated as the main principal. By using the same method to make all vector component and all vector quantity to do orthogonal transformation, so that we can get the second new vector w_2. But this needs a precondition that is $w_1^T w_2$must keep be 0, and if it is kept $y_2$can be ensured to be the second main component. Only meeting the bellow limits, such process can continue.

(1)However in the process of calculating new direction, all new directions must can do orthogonal transformation with all original directions.

$$W_i^T W_j = 0, \forall j < i, \left\|W_i\right\| = 1. \qquad \textbf{(4)}$$

(2)After doing projection, all data should have their relative largest variance.

And all vectors referred above can form an orthogonal with the projection of $w_{i,}$ so between new components.

$$y_i = W_i^T X\,(i = 1, 2, \cdots m) \quad \textbf{(5)}$$

There is no relation in main component analysis. The new component is

$$E\left\{y_i, y_j\right\} = E\left\{(W_i^T X)(W_j^T X)\right\} = 0, i \neq j\,. \quad \textbf{(6)}$$

A simple example bellow can directly reflect the physical meaning of main component analysis.

First, choosing a group of two-dimensional data from Figure 1 (a). And the data x is mainly as [2.5, 0.5, 2.2,1.9, 3.1, 2.3, 2, 1, 1.5, 1.1] and the data y is [2.4, 0.7, 2.9, 2.2, 3.0, 2.7, 1.6, 1.1, 1.6, 0.9]. Then do the principal component analysis of this group data and the result is a two-dimensional data with feature vector as axis. Through projecting the vector direction with a high feature value among all two-dimensional data, the data can be shown clearly, which is the principal component often referred.

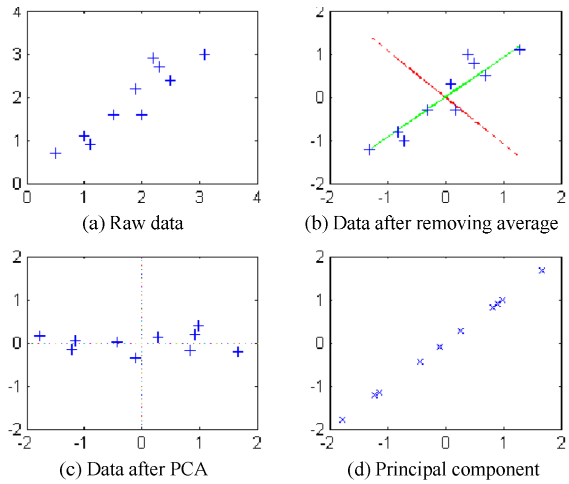

Figure 1 : PCA's simple example

In principal component analysis, Figure1(a)is as the original data and Figure1(b)is as the data without average value. The two lines represent the feature vector in the covariance matrix of two-dimensional data, in which full line represents the feature vector with the largest value,while the dash line refers to the vector with lower value. Figure 1(c) has clearly shown that principal component analysis is a process of efficiently transforming the data. In original data coordinate x and y are two axis, but after the transformation they become feature vector axis, diminishing the connection between two data. However, in Figure 1 (d) the original data are completely contrary to Figure1 (a), so that date can be efficiently compressed and further the one-dimension data can be transformed to the two-dimensional data. In principal component analysis, random variables linear relation has been efficiently cut,so that every random variable can fully present its own features, making the exploration of the hidden information in signal more easy. But because in principal component analysis the actual calculation needs to input the probability data, which enables the second order statistic features to be fully reflected. And in this process every principal component can do orthogonal process with each other, so they cannot remain their independence. However, in statistics precept, the signal feature in size is included in the advanced features of probability density function, so only when they are the multi-variance data in the building process of signal source the principal component analysis is efficient enough. Following, this paper will introduce the difference existing in processing non-Gauss signal between principal component analysis and independent component analysis (shown in Figure 2 bellow).

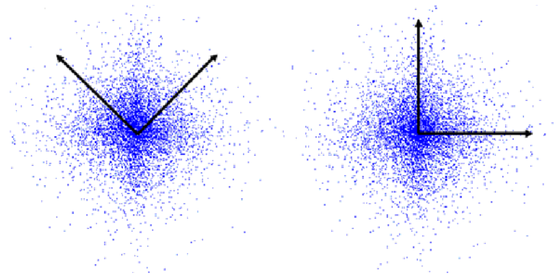

Figure 2 : The difference between PCA and ICA

Figure 2 shows that the distribution of index's two-dimension data is relatively clear. However, in PCA the big variance's feature value has some difference compared with its axis's pointing direction, reflecting some certain defects in PCA. The main reason is that in PCA the data distribution reflected is belong to Gaussian data,but the data referred here is not. ICA can make the feature vector be reflected on the axis more clearly.

WHITENING

Whitening is a simple definition of a processing method usually used in independent analysis, which is a necessary part in ICA.

Usually the random vector refers to the basic process of transforming x to y through whitening process, the detail is show bellow:

$$y = VX \tag{7}$$

In the process of whitening the vector matrix y can meet the condition $R_y = E\left\{yy^T\right\} = I$,so that the relation between vector component can meet the condition $E\left\{y_i y_j\right\} = \delta_{i_j}$. If y is 0, it means the vector's covariance matrix is equivalent to identity matrix. The whitening of mixed signals is the process to move the connection between all vectors, so among all vector components there is no detail relation. In this process V presents the whitening matrix.

In this process $E = (e_1, e_2, \cdots e_n)$ should be efficiently defined, making covariance matrix $C_x = E\left\{XX^T\right\}$ be the specific feature vector matrix as the basic condition. And $D = diag(d_1, d_2, \cdots d_n)$ is the diagonal matrix based on the condition that C is the essential condition. The whitening matrix is calculated through the following formulation.

$$V = D^{-\frac{1}{2}} E^T \tag{8}$$

When d is a positive number this matrix can be got. However, in the data analysis all natural numbers are positive, so their feature values also remain consistent. The follow example clearly reflect the essence of whitening. And Figure 3 has fully presented the distribution of two opposite cods. All average values between principal components should be 0 and the covariance keeps 1. So that the probability's density function is:

$$p(s_i) = \begin{cases} \frac{1}{2\sqrt{3}}, |s_i| \leq \sqrt{3} \\ 0 \quad ,\text{others} \end{cases} \tag{9}$$

The distribution of two independent codes reflected in Figure 3(a) is uniform and also in positive direction.. However, in the following matrix the two codes ($s_1$and s_2) are efficiently mixed.

$$A = \begin{bmatrix} \frac{5}{10} & \frac{10}{2} \end{bmatrix} \tag{10}$$

Figure 3 is the joint distribution Figure of x1 and x2 achieved through being mixed. In it the two codes are whitened efficiently to diminish their connection, so that the joint distribution can be clear reflected, the detail is shown in Figure 3 bellow.

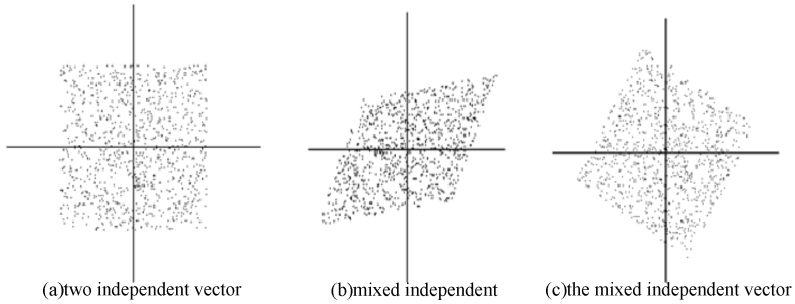

Figure 3 : The essence of whitening

The introduction above has clearly reflected that whitening is the data pretreatment needed in ICP, whose essence is to wipe off the connection between vectors and at the same time to integrate their scaling. This process shows that PCA usually adopts whitening.

THE METHOD OF ICA ALGORITHM

In ICA the relative calculating process is to confirm the algorithm's index, so that every index can have a relative target functions and all these functions will be optimized, making ICA can do the efficient calculation of the target function. However, in the process of calculating these optimized information and cumulate, the formulation mainly is equal to notable function plus optimization algorithm through efficient tender.

The maximization of non-gauss

In the analysis process the random proportion x is calculated through the formulation:

$$X = As \quad \textbf{(11)}$$

This vector is the linear combination of an independent component. The supposed independent components share the same distribution.. In order to calculate the independent component we suppose y_i is an estimated independent component, the formulation is below:

$$y_i = b^T X = \sum_i b_i x_i \quad \textbf{(12)}$$

Tb is the disjunctive matrix. so x, As is calculated through the formulation below.

$$y_i = b^T As = Zs \quad \textbf{(13)}$$

Kurtosis

Kurtosis is the forth-order cumulate of random variable. It can calculate the non-gauss of a random variable. If random variable's kurtosis is 0, the random variable is Gaussian, but if kurtosis is bellow 0, the random variable is linear quadratic Gaussian; above 0, super Gaussian.

For the random variable x with the average value of 0, the definition of kurtosis is :

$$kurt(x) = E\left\{x^4\right\} - 3(E\left\{x^2\right\})^2 \quad \textbf{(14)}$$

If the random variable x has unit variance, (3-31) can be simplified as:

$$kurt(x) = E\left\{x^4\right\} - 3 \quad \textbf{(15)}$$

Kurtosis or its absolute value is used as non-gauss measurement in ICA and other fields, because no matter in calculation or in theory it is very simple. Kurtosis can be calculated through data's forth-order matrix and kurtosis also has the linear feature: if 1x and 2x are tow random variance, the following two formulations are permanent establishment：

$$kurt(x_1 + x_2) = kurt(x_1) + kurt(x_2) \quad \textbf{(16)}$$

$$kurt(ax_1) = a^4 kurt(x_1) \quad \textbf{(17)}$$

In the formulations, a is the constant. Although as a kind of non-gauss kurtosis is simple and practical, in the practical application because its value can only be calculated through test components, there are some defects existing in kurtosis. The main problem is that kurtosis is very sensitive to outliers. The following example can reflect this problem. In a Gauss random variable with 1000 samples, its kurtosis is 0.0086, close to 0. Then when the sample turns to 10, the kurtosis is 7.2163. So a sample value can become higher. The value of kurtosis is decided by some observation values distributed at the edge, but these values may be worry or unrelated, or in other words, if kurtosis is not stable, it is not a non-gauss robust measurement.

CONCLUSION

The introduction above is this paper’ s analysis and exploration of independent components based on the study of music signal collection, and has made a detail discussion of some important parts, making the collecting of music signal data more scientific and efficient and providing a guaranteed condition to music signal collection, which can provide a strong method and data support for the further study on relative fields.

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