Identification of Ancient Glass Components Based on Grey Correlation Analysis

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Abstract. The article is based on mathematical modelling of the significant data of the two categorize glass specimen to examine the factors influencing the climate of the covering of the glass artefacts, to derive statistical patterns and correlations of the chemical composition content, on this basis, the subclasses are classified, and the accurate categorization manner applied to the analysis and discovery of glass composition is given. On the basis of data processing, the association between weathering of glass surface and glass kind, adornment and color is analyzed by using visual histogram. And it was found that the weathering of lead-barium glass was more serious than that of high-potassium glass, that B-grain decoration was easily weathered, and that black and light blue glass were the most severely weathered. The most significant effect on weathering is due to the content of silica in the lead-barium group, and the most significant effect on weathering is due to the content of sodium oxide in the high-potassium group. The correlations between the 14 chemical components in the two categories of high potassium glass and lead-barium glass were analysed by establishing a grey correlation analysis model, and the correlations between the different chemical components in the different categories were calculated and ranked. Similarly, the correlation between lead oxide and magnesium oxide was the highest in the high potassium group, while strontium oxide, tin oxide and sulphur dioxide were all less correlated, i.e. the correlation between this component and other chemical components was characterised by the ANOVA.

Keywords: Analysis of Variance, Component Identification, Grey Correlation Analy.

1. Introduction

Ancient glass products in China were made locally from locally sourced materials after absorbing foreign technology passed through the Silk Road, and thus were similar in appearance to foreign glass products, but not in chemical composition. The main raw material for glass is quartz sand, the main chemical composition of which is silica. Fluxes are added to make glass, and the type of flux can lead to differences in its main chemical composition [1]. The type of flux can lead to differences in the main chemical composition of the glass, and as ancient glass is highly susceptible to environmental influences during burial, it is subject to varying degrees of weathering, leading to significant changes in the surface and internal structure and chemical composition of the glass, which in turn affects the judgement of its type [2].

The article uses data from a group of ancient glass artefacts in China, which archaeologists have classified into two types, high potassium glass and lead-barium glass, based on the chemical composition of the artefact samples and other testing methods. In addition, the surface weathering of different types of glass samples was analyzed. In addition, the correlation between the chemical compositions of different types of glass samples was analyzed and the differences of correlation were compared.

This allows us to build multiple data analysis models for different problems, consider from multiple perspectives during analysis, and find the optimal solution within a certain range, providing a better method for composition analysis and type identification of ancient glass articles.

2. Materials and methods

2.1. Analysis of the weathering of the glass surface

The analysis of glass composition requires an analysis of the weathering of the glass surface in relation to the type, decoration and colour of the glass, followed by an analysis of the pattern of change in chemical composition content in relation to the type of glass and a prediction of the chemical composition content before weathering [3].

Therefore, it has the ability to first pre-process the data provided, including outliers and de-compartmentalisation of multiple indicators, and then to analyse the statistical patterns of the fourteen chemical constituents by combining the glass types into two groups, high potassium and lead-barium, making an analysis with the help of the most basic statistic, variance, to determine whether the sub-typed independent variables have a significant effect on the numerical dependent variable by testing whether the means of each overall are equal. The variance of the content of each of the fourteen chemical components was calculated separately, and these were compared in order of magnitude, with larger variances having a greater effect on the dependent variable weathering.

2.2. Grey correlation analysis model

Grey relational analysis is a manner to quantitatively describe and contrast the energetic development of the system. The fundamental idea is to determine the tightness of the association by determining the geometric resemblance between the allusion data column and some comparison data columns, which reflects the correspondence between the curves [4]. The measurement of the correspondence between solutions in the target space is called the amount of correlation.

A dull correspondence analysis model was used to analyse the correspondence between the various chemical components for different categories of glass samples, i.e. a model was needed to measure the degree of correlation between the different factors [5]. Once the model has been constructed, the grey correlations of the different chemical components are calculated and compared. The grey correlation coefficients calculated for the different categories of glass were then subjected to an ANOVA, which was used to determine the differences in the correlations between high potassium glass and lead-barium glass [6].

3. Model construction and testing

3.1. Relationship between the different indicators of glass and the degree of weathering

Based on the information given in the question, the data in the form with a sum of components between 85% and 105% were considered as valid data. The analysis revealed that the sum of components of the two groups of samples with serial numbers 15 and 17 were not within the valid range and should be excluded. After data exclusion, each sampling point was normalised again to facilitate subsequent calculations.

The data in Table 1 was first analysed for the relationship between decoration, type and colour and weathering, and the data in Table 1 was sorted using Excel to filter the data for glass decoration A, B and C and surface weathering, for glass types high potassium glass and lead barium glass and surface weathering, and for glass colour and surface weathering.

Table 1. Surface weathering corresponding to different ornamentation

Cultural Heritage Codification No.	Ornamentation	Surface weathering	Cultural Heritage Codification No.	Ornamentation	Surface weathering	Cultural Heritage Codification No.	Ornamentation	Surface weathering
02	A	Weathering	50	A	Weathering	32	C	No weathering
03	A	No weathering	53	A	Weathering	33	C	No weathering
04	A	No weathering	07	B	Weathering	34	C	Weathering
05	A	No weathering	09	B	Weathering	35	C	No weathering
06	A	No weathering	10	B	Weathering	36	C	Weathering
18	A	No weathering	12	B	Weathering	37	C	No weathering
19	A	Weathering	22	B	Weathering	38	C	Weathering
20	A	No weathering	27	B	Weathering	39	C	Weathering
21	A	No weathering	01	C	No weathering	40	C	Weathering
23	A	Weathering	08	C	Weathering	41	C	Weathering
28	A	Weathering	11	C	Weathering	43	C	Weathering
29	A	Weathering	13	C	No weathering	51	C	Weathering
30	A	No weathering	14	C	No weathering	52	C	Weathering
42	A	Weathering	15	C	No weathering	54	C	Weathering
44	A	Weathering	16	C	No weathering	55	C	No weathering
45	A	No weathering	17	C	No weathering	56	C	Weathering
46	A	No weathering	24	C	No weathering	57	C	Weathering
47	A	No weathering	25	C	Weathering	58	C	Weathering
48	A	Weathering	26	C	Weathering			
49	A	Weathering	31	C	No weathering			

3.2. Construction of the grey correlation analysis model

By to do the correlation analysis, we need to specify the reference data series (parent series), there is no data series that can obviously reflect the behavioural characteristics of the system in this question, so we choose the silica, which has a relatively large content of chemical components, as the parent series, and record it as X_0, the value of the first moment is $X_0(1)$, the value of the second moment is $X_0(2)$, the value of the kth moment is $X_0(k)$, so the reference series can be expressed as $X_0=(X_0(1), X_0(2), \ldots, X_0(n))$.

The remaining chemical components are treated as comparative series (subsequences), denoted as $X_1, X_2, \ldots, X_k$, and are represented in a similar way to the reference series with $X_1=(X_1(1), X_1(2), \ldots, X_1(n)), \ldots, X_k=(X_k(1), X_k(2), \ldots, X_k(n))$.

The model developed in this question, for a reference data series X_0, has several comparison series $X_1, X_2, \ldots, Xn$ and requires the following association to act for the dissimilarity between each comparison curve and the allusion curve at each instant.

$$\mathrm{New}_i(k)=\frac{\min(\Delta_i(\min))+0.5\max(\Delta_i\max)}{\left|X_0(k)-X_i(k)\right|+0.5\max(\Delta_i(\max))} \tag{1}$$

Where $\mathrm{New}_i(k)$ is the relative difference between the comparison curve X_i and the reference curve X_0 at the kth moment, called the correlation coefficient of X_i to X_0 at moment k. 0.5 is the resolution coefficient, denoted as new.

The selected reference series and the comparison series are both chemical components with the same magnitude and do not need to be made dimensionless, and the series are primed before calculating the correlation coefficients. After processing the data, the correspondence coefficients and grey correspondence are calculated and the chemical components are ranked according to the magnitude of the grey correlation, the higher the correlation, the closer the chemical components are to each other [7].

4. Results and analysis

4.1. Analysis of the results of the different indicators of glass and the degree of weathering

Figure 1 shows that the proportion of weathering is greater for B-grain, A-grain has little effect on weathering, and C-grain is more susceptible to weathering than A-grain; Figure 2 shows that both types of glass have some effect on weathering, and lead-barium glass is more severely weathered than high-potassium glass; It can be seen from Figure 3 that black glass is most seriously weathered, followed by light blue, followed by blue-green and dark green. Black glass is most seriously weathered, followed by light blue, followed by blue-green, dark green and purple. Green and dark blue have little influence on weathering [8].

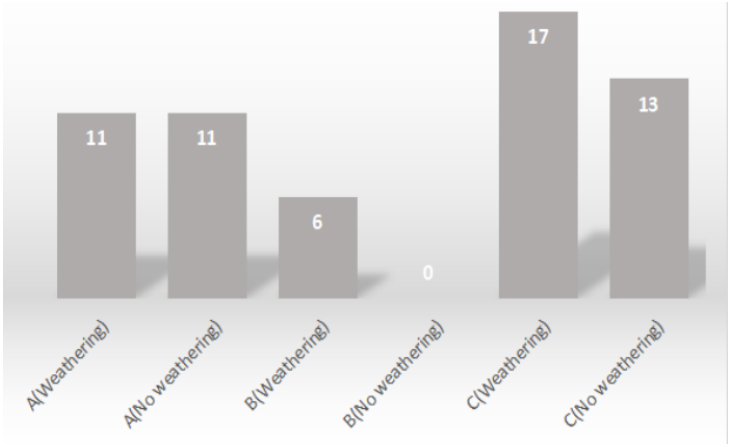


Figure 1. Relationship between decoration and weather

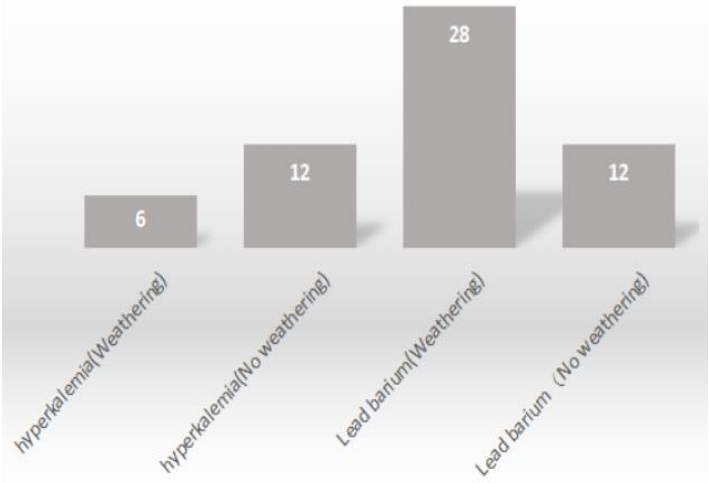


Figure 2. Relationship between type and weather

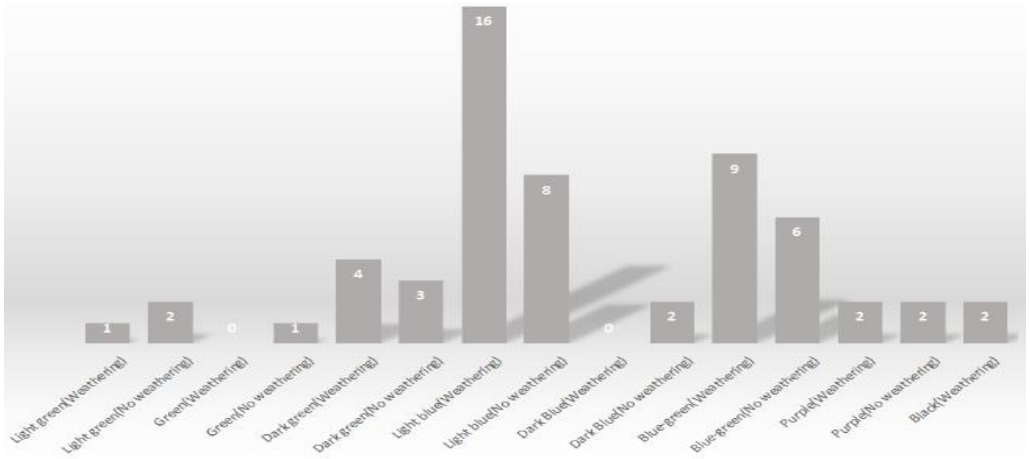


Figure 3. Colour in relation to weathering

4.2. Analysis of the results of the grey correlation analysis model

Substituting the data into the model to solve for it gives the following results as shown in Table 2 and Table 3.

Table 2. Correlation and variance of the chemical components of the lead-barium group

Chemical formation	Silicon dioxide	Sodium oxide	Potassium oxide	Calcium oxide	Magnesium oxide	Aluminium oxide	Iron oxide	
Score	(SiO2)	(Na2O)	(K2O)	(CaO)	(MgO)	(Al2O3)	(Fe2O3)	Variance
Relevance	4.4545	4.4367	4.4528	4.3888	4.4417	4.3464	4.4417	
Chemical formation	Copper oxide	Lead oxide	Barium oxide	Pentoxide	Strontium oxide	Tin oxide	Dioxide	
Score	(CuO)	(PbO)	(BaO)	Phosphorus (P2O5)	(SrO)	(SnO2)	Sulphur (SO2)	0.57980926
Relevance	4.3887	3.7367	4.1362	4.3216	4.3408	3.765	1.5776	

Table 3. Correlation and variance of chemical components in the high potassium group

Chemical formation	Silicon dioxide	Sodium oxide	Potassium oxide	Calcium oxide	Magnesium oxide	Aluminium oxide	Iron oxide	
Score	(SiO2)	(Na2O)	(K2O)	(CaO)	(MgO)	(Al2O3)	(Fe2O3)	Variance
Relevance	6	4.8165	3.1959	3.9633	5.5971	4.3359	5.3277	
Chemical formation	Copper oxide	Lead oxide	Barium oxide	Pentoxide	Strontium oxide	Tin oxide	Dioxide	
Score	(CuO)	(PbO)	(BaO)	Phosphorus (P2O5)	(SrO)	(SnO2)	Sulphur (SO2)	2.03973858
Relevance	5.2374	5.8245	4.4954	2.4362	2.2222	2.2222	2.2222	

Silica was chosen as the parent series for both groups. When the data was initialised, it was found that some of the chemical components contained mostly "0" values, which would affect the validity of the algorithm analysis and therefore required special treatment [8]. The difference was deliberated from the correspondence data to determine the difference in the correlation between high potassium glass and lead-barium glass.

5. Conclusions and Discussion

5.1. Conclusion

Potassium oxide has the highest correlation in the lead-barium group, followed by magnesium oxide, iron oxide and sodium oxide, representing a strong association and high correlation between them. Of these, sulphur dioxide has the least association, i.e. less association with other chemical

components. Similarly the high potassium group has the highest correlation for lead oxide, followed by magnesium oxide, iron oxide, copper oxide, etc., representing a powerful association and a high correspondence between them [9]. Strontium oxide, tin oxide and sulphur dioxide are all less well correlated, with less strong associations between them and other chemical components.

The small variance of the correlation for the lead-barium group indicates that the variability between the individual chemical components is small and the correlations are all within a certain range, with strong correlations between the chemical components. The higher variance of correlation for the high potassium group indicates that there is a high variability between the correlations of the individual chemical components.

5.2. Discussion

Grey correlation model: The grey correlation analysis method makes up for the regrets caused by the use of mathematical and statistical methods for systematic analysis. It is equally applicable to the size of the sample and the presence or absence of a pattern in the sample, and is computationally small and convenient, not to mention that the quantitative results do not match the qualitative analysis [10].

Grey correlation models: require a current determination of the optimal value of each indicator, which is too subjective and difficult to determine for some indicators. There may be disagreement between the quantitative consequence and the qualitative analysis, leading to distortion and reversal of the relationships and laws of the system.

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