Study on Composition Analysis and Identification of Ancient Glass Products

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Abstract. The Silk Road, as a channel of cultural exchange between China and the West in ancient times, promoted the development and dissemination of glass technology and culture in ancient China. The analysis of the chemical factors of ancient glass is of great help to the study of the economy. The main research content of this paper is to analyze the chemical content of ancient glass products. To analyze the correlation of different types of chemical components, first of all, this paper uses SPSS to carry out grey correlation analysis. According to the grey correlation degree, we can screen out the elements with the greatest degree of correlation between each chemical component and it. Then, the paired samples t-test was used to analyze the differences in chemical composition association between different categories. At the significance level a = 0.05, it was found that except for SO2, there were significant differences in the chemical composition of other elements among different categories.

Keywords: Grey relational analysis, Paired sample t-test, Ancient glass.

1. Introduction

The chemical composition of ancient Chinese glass is different from that of foreign glass. However, ancient glass is vulnerable to weathering due to the influence of burial environment. The effect of weathering is the change of the internal composition of glass, which will lead to the deviation of the judgment of its category. The study of the internal composition of ancient glass plays an important role in promoting social and economic development. At present, a small amount of qualitative and quantitative chemical composition analysis, density determination and other scientific and technological tests have been carried out in the inspection [1].

Therefore, it is necessary to propose a comprehensive model [2] to analyze the internal composition of glass. Firstly, the data were preprocessed, and the evaluation objects of high-potassium glass were constructed, and the grey correlation analysis was constructed to screen out the elements with the greatest correlation degree corresponding to each chemical composition, which could provide a basis for further distinguishing glass types.

2. Grey correlation within-group analysis

To analyze the relationship between the chemical components of different types of glass relics (silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide, sulfur dioxide, magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide). We construct an evaluation object n (where n is the chemical composition that plays a major role in high-potassium glass) and m indicators (where m is the chemical composition that plays a major role except n) for high-potassium glass, and the corresponding observed values of the main chemical compositions are a_{ij}, i=1, 2…14, j=1,2…14, Construct gray correlation analysis, the specific steps are as follows [3]:

Step1: Pretreatment of evaluation index

The m indexes are preprocessed. To eliminate the influence of dimension, we normalize them and construct the evaluation matrix: $B=(b_{ij})_{n\times m}$

Step2: Determine the series to be compared with the reference standard

The comparison column is

$$b_i = \{b_{ij} \mid j = 1, 2, \cdots, m\}, i = 1, 2, \cdots, 14 \tag{1}$$

That is, b_i is the standardized index vector value of the i chemical component to be evaluated.

The reference standard number column is $b_0 = \{b_{0j} \mid j = 1, 2, \cdots, m\}$.

where $b_{0j} = \max\limits_{1\le i\le n} b_{ij}, j = 1, 2, \cdots, m$. That is to say, the reference standard number is the index value of the best evaluation object.

Step3: Calculate grey correlation coefficient

$$\varepsilon_{ij} = \frac{\min\limits_{1\le s\le n}\min\limits_{1\le k\le m}\left|b_{0k} - b_{sk}\right| + \rho \max\limits_{1\le n\le s}\max\limits_{1\le k\le m}\left|b_{0k} - b_{sk}\right|}{\left|b_{0j} - b_{ij}\right| + \rho \max\limits_{1\le s\le n}\max\limits_{1\le k\le m}\left|b_{0k} - b_{sk}\right|} \tag{2}$$

Where $i = 1, 2, \cdots, n,\ j = 1, 2, \cdots, m$, ε_{ij} is the correlation coefficient of the comparison sequence b_i with respect to the reference sequence b_0 on the fourth index, and ρ is the resolution coefficient ranging between $0 \sim 1$. $\min\limits_{1\le s\le n}\min\limits_{1\le k\le m}\left|b_{0k} - b_{sk}\right|$ and $\max\limits_{1\le n\le s}\max\limits_{1\le k\le m}\left|b_{0k} - b_{sk}\right|$ in the formula are the minimum difference of two stages and the maximum difference of two stages.

Step4: Calculate the grey correlation degree

According to the calculation formula of grey correlation degree:

$$r_i = \sum_{j=1}^{m} \omega_j \xi_{ij},\quad i = 1, 2, \cdots, n \tag{3}$$

Wherein ω_j is the weight of the j chemical composition index variable x_j, and r_i is the grey correlation degree of the i object to be evaluated to the virtual ideal object.

3. Grey correlation analysis

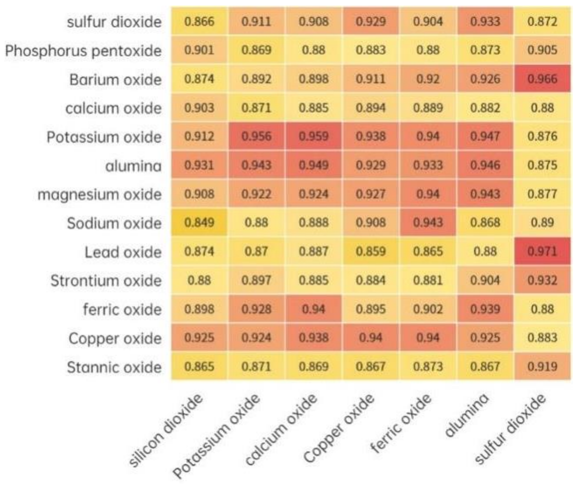

Figure 1. Thermodynamic diagram of grey correlation analysis of high-potassium glass

Take the resolution coefficient $\rho = 0.5$ in this question, calculate the correlation coefficient between the chemical components [4] in pairs, and further calculate the correlation degree of each chemical component [5],which is shown in Figure 1.

Figure.1 is the grey correlation degree of silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide and sulfur dioxide in high-potassium glass with silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide, sulfur dioxide, magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide.

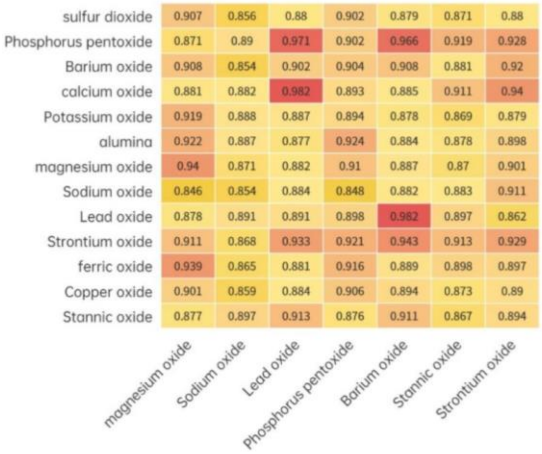

Figure 2. Thermodynamic diagram of grey correlation analysis of high-potassium glass

Figure 2 is the grey correlation degree of magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide with silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide, sulfur dioxide, magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide in the high-potassium glass.

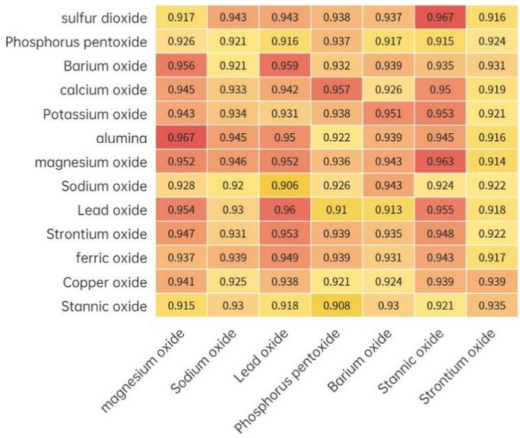

Figure 3. Thermodynamic diagram of grey correlation analysis of Pb-Ba glass

Figure 3 is the grey correlation degree of silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide and sulfur dioxide in lead-barium glass with silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide, sulfur dioxide, magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide.

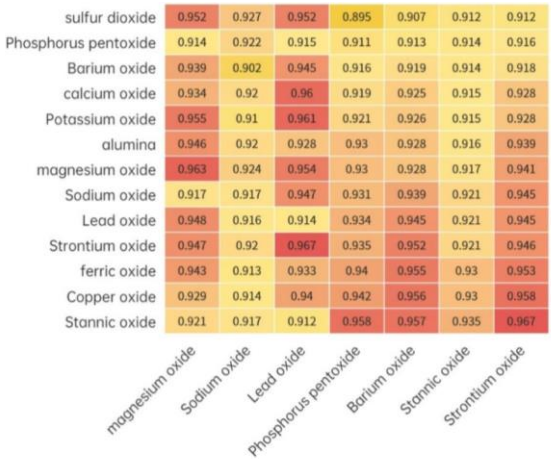

Figure 4. Thermodynamic diagram of grey correlation analysis of Pb-Ba glass

Figure 4 is a grey correlation degree of magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide with silicon dioxide, potassium oxide, calcium oxide, copper oxide, iron oxide, aluminium oxide, sulfur dioxide, magnesium oxide, sodium oxide, lead oxide, phosphorus pentoxide, barium oxide, tin oxide and strontium oxide in the lead-barium glass.

4. Analysis of results

To analyze the difference of chemical composition correlation among different categories [6], we take silicon dioxide as an example, combine the results of grey correlation analysis [7] in Table 1, and draw the difference data chart of high potassium glass silicon dioxide correlation [8] and lead-barium glass silicon dioxide correlation, which shows that the difference data chart shows a trend of high in the middle and low at both ends. It shows [9] that although the data is not normal, it can be considered to obey the normal distribution [10]. Due to the small sample size ($n \le 30$), We can use distribution theory to infer the differences between different types of glass. And the magnitude of the difference in the chemical composition content of the two glasses is reflected by the value of the effect amount $Cohen's\ d$.

Table 1. Difference of association of chemical components in different categories

Pairing variable	T Value	P Value	$Cohen's\ d$
SiO_2	-8.236	0.000	2.284
SO_2	-2.234	0.045	0.62
P_2O_5	-6.5	0.000	1.803
BaO	-2.904	0.013	0.805
K_2O	-4.101	0.001	1.137
Al_2O_3	-4.567	0.001	1.267
MgO	-7.561	0.000	2.097
Na_2O	-9.665	0.000	2.681
PbO	-3.208	0.008	0.89
SrO	-5.833	0.000	1.618
Fe_2O_3	-3.899	0.002	1.081
CuO	-3.507	0.004	0.973
SnO_2	-6.136	0.000	1.702

In the case of significance level $\alpha = 0.05$, the original hypothesis H_0 is that there is no significant difference between different categories of elements[11], and the following table is obtained by using $SPSS$ for analysis:

From the perspective of the value of statistic P , we can see that only SO_2 is not significant. Accepting the original hypothesis, it shows that there is no significant difference between the two different categories of SO_2 . From the perspective of effect size, only SO_2 has an effect size less than 0.8, and the difference between the other elements is particularly large. This can further explain that there are significant differences in the correlation of chemical composition among different categories of elements except SO_2 . However, the effect size of SO_2 is greater than that of 0.6. From the meaning of effect size, SO_2 also has significant differences between the two different categories, that is, for high-potassium glass and lead-barium glass, the correlation of their internal chemical composition is very different.

5. Conclusion

In this paper, a comprehensive analysis model is established for ancient glass products. First of all, this paper preprocesses the index, determines the reference standard and the grey correlation coefficient, and then carries on the grey correlation analysis. The model can provide a basis for the classification of ancient glass by screening out the elements with the greatest degree of correlation between each chemical composition and the corresponding elements. The model has good robustness and can accurately and quickly screen out related factors.

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