# A Visual Coding Method for Geographic Statistics Based on the Pattern Recognition Feature of Optic Nerve in Cerebral Cortex

**Zuofei Tan, Zhaoxia Wang*, Shenglin Li, Qinghui Ren, Bo Song**

**ABSTRACT**

The human visual system can easily identify a variety of objects, all thanks to its powerful pattern recognition capability. One theory holds that the brain's visual recognition mechanism is mainly achieved by single neurons and complex neurons located in area V1 of the cerebral cortex. Both types of cells decompose and synthesize the visual signals from sensory organs to extract their pattern features (Riesnhuber *et al*., 1991). However, in the information visualization field where logic is quite complicated, the visual recognition system of human beings has great limitations and can only effectively recognize complex visual patterns after the complex information is pretreated by a set of scientific visual coding methods. In the context of geographic statistics, based on the single neurons and complex neurons model and Gestalt psychology, this paper proposes a visual coding method based on aggregation and subdivision (AS method) to visualize geographic statistics. The simulation test results show that the AS method can deliver a good mapping relationship between geographic locations and a good rectangular aspect ratio and thus can achieve high visual perception efficiency.



**Key Words:** Visual Cortex, Pattern Recognition, Single Neurons and Complex Neurons Model, Gestalt Psychology, Visual Coding, Cartogram, Tree Graph

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## Introduction

The cerebral cortex is a high-bandwidth parallel processor that processes massive number of visual signals, with the maximum bandwidth being up to 100MB per second. With a strong pattern recognition capability, it can perceive visual symbols faster than numbers or text by several orders of magnitude, and large amount of visual information is processed at the subconscious stage. According to the features of the brain neurons in processing visual signals, there are two types of neurons - single neurons and complex neurons. The former is only interested in signals of a particular direction and scale, such feature of which is called the selectivity of single neurons (Hubel *et al*., 1959). When neurons with direction selectivity process signals, they decompose the signals into multiple channels according to their scales and directions. The signals in each channel have a specific dimension and direction. Opposite to that of single neurons, the signal processing mechanism of complex neurons synthesizes and compresses signals from different single neurons or channels (Serre *et al*., 2005). Throughout the process of visual perception, humans acquire visual information through the retinal M and P ganglion cells, transmit information through the neurons connected to the brain to the visual cortex of the brain, including the striate cortex (V1) and extrastriata cortex (V2, V3, V4 and V5). The visual cortex processes and encodes the signals

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in such sequence: single neurons, complex neurons, ultra-complex neurons and higher level of ultra-complex neurons, to form visual perception. Through visual perception, humans can respond to the information in the real world and make decisions, which influence their behaviors in the world and ultimately influence the real world. Therefore, visual perception is not just a process of passive reception, but also a process of active exploration. Through visual coding of various kinds of information in the real world in a way that human vision can perceive, humans are able to actively explore the outside world and gain new knowledge (Ward *et al.*, 2010). There are many methods for visual information coding. For example, numbers or text can be used to express the characteristics of an object, and people read the numbers or text through their visual organs and dismantle, analyses and extract the information contained in it. However, this kind of visual coding is not visual enough, so a certain amount of brain storage will be occupied during the reading process, and moreover, the brain will have to perform semantic analysis and extraction of the connotations to finally gain the knowledge, which greatly reduces the efficiency of knowledge acquisition. But if visual symbols are used for coding, they can directly express the structural characteristics of things (Keim *et al.*, 2010), so this method, which makes people digest and extract information on the subconscious level, can effectively improve the efficiency of knowledge acquisition.

This paper proposes a visual coding method based on the pattern recognition feature of the optic nerve in the cerebral cortex. By combining the tree graph theory with geographic information, this paper integrates geographic statistics fragments into visual coding symbols that conform to the principles of Gestalt psychology and proposes a visual symbol layout method based on the idea of aggregation and subdivision to improve people's knowledge acquisition and reasoning abilities of geographic statistics.

## Overview of the Visual Coding Method for Geographic Statistics

The brain can store and process much less information than the retina receives, so it will selectively process external information, which is called selective attention in the visual perception field (Kanwisher *et al.*, 2000). In addition, the visual information decomposition and synthesis process of the cerebral cortex is very much in line with the Gestalt laws (Evans *et al.*, 2017), which point out that human's visual perception tends to extract characteristic and pattern information implicated in complex visual objects. The laws are mainly composed by a set of principles - proximity, similarity, continuity, closure, good figure and past experience, etc.:

(1) Proximity: elements tend to be perceived as aggregated into groups if they are near each other;

(2) Similarity: elements tend to be perceived as aggregated into groups if they are similar to each other in shape, colour or other features;

(3) Continuity: oriented units or groups tend to be integrated into perceptual wholes if they are aligned with each other;

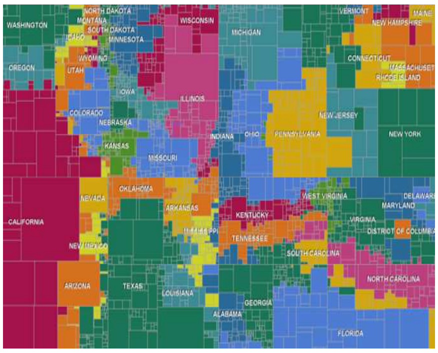
(4) Closure: elements tend to be grouped together if they are parts of a closed figure;

(5) Good figure: elements tend to be grouped together if they are parts of a pattern which is a good figure, meaning as simple, regular and orderly as possible;

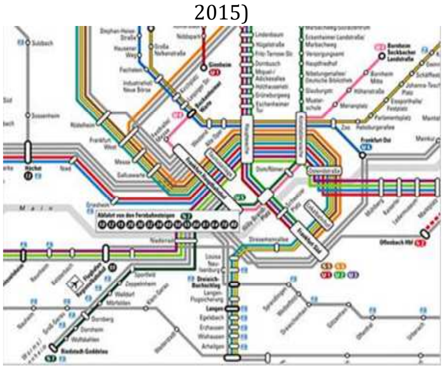
(6) Past experience: elements tend to be grouped together if they were together often in the past experience of the observer, which improves the recognition degree of visual elements.

The Gestalt laws are widely applied in the information visualization field, as shown in Figure 1. Researchers are seeking for visual coding methods that can convert all kinds of information in the world into the most suitable visual symbols based on Gestalt Psychology. Humans are living in a three-dimensional space, so the knowledge they obtain from the real world often contains location information. With the increasing popularity of geographic information applications, the visual coding method for geographic statistics has also become a research hotspot in the visualization and visual cognition field. Recent studies have found that the working principle of the human visual perception system depends on the relative judgment of the perceived object. Therefore, the visual coding method for geographic statistics is also a process of feature difference visualization based on basic markers like points, lines, and planes. This process is also called visual channel (Munzner e*t al.*, 2015).

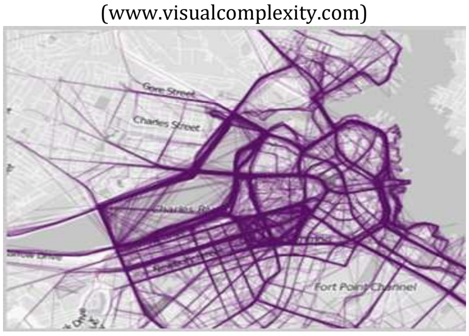
In the process of geographic statistics visualization, observers are more concerned with statistics related to regional extent, such as demographics (Forster e*t al.*, 1966), polls (Gastner e*t al.*, 2005), impact scope of hurricanes (Curtis e*t al.*, 2006), vegetation cover (Graser, 2012), and degree of traffic congestion (Ward *et al*., 2010), etc. One representative method is the coding method based on point symbols (Liu *et al*., 2013), as shown in Figure 2.



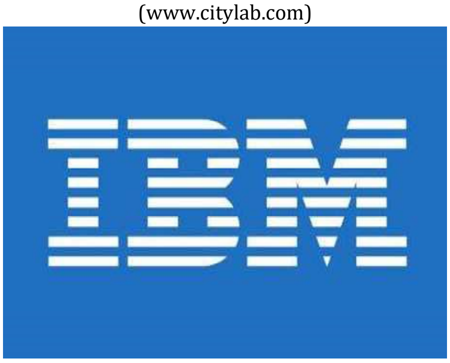
(a) Similarity and past experience, Tree graph (Ghoniem *et al*., 2015)



(b) Good figure and similarity Schematic traffic map (www.visualcomplexity.com)

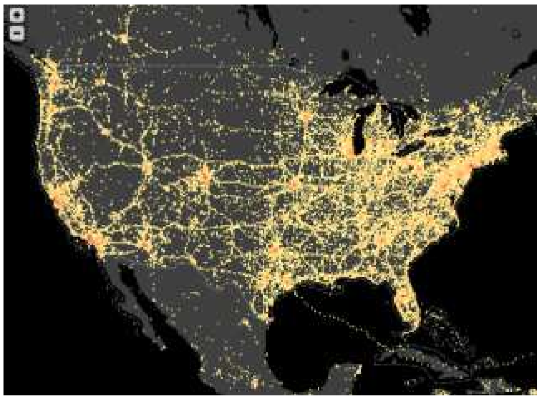


(c) Proximity and closure Daily running chart (www.citylab.com)




(d) Continuity and closure IBM trademark (image.baidu.com)

**Figure 1.** Visually coded information based on Gestalt psychology



(a) Heat map

(b) Symbol map

**Figure 2.** Point-graph-based visual coding method

The experimental results show that, for information with huge differences in density distribution, the point map, on one hand, suffers from large loss of information, and on the other hand, can result in huge waste of limited display space. There are some other examples. The line graphs drawn based on the edge binding algorithm (Yang *et al*., 2016) (Koblin, 2006) are widely used to code the interesting correspondences between geographical locations, but the excessively dense connecting lines lead to high visual complexity. In terms of the plane-graph-based coding method for geographic statistics, the representative ones are histograms and bubble graphs (Bremer, 2015), which are used to encode the classes, values, levels and intervals of statistics, as shown in Figure 3. However, this coding method cannot prevent observers from having some misunderstandings due to overlap of graphics.

Coding of geographic statistics by means of tree graph can solve the problem of understanding deviations caused by classification level and geographic distribution density (Ghoniem *et al*., 2015), as shown in Figure 4.

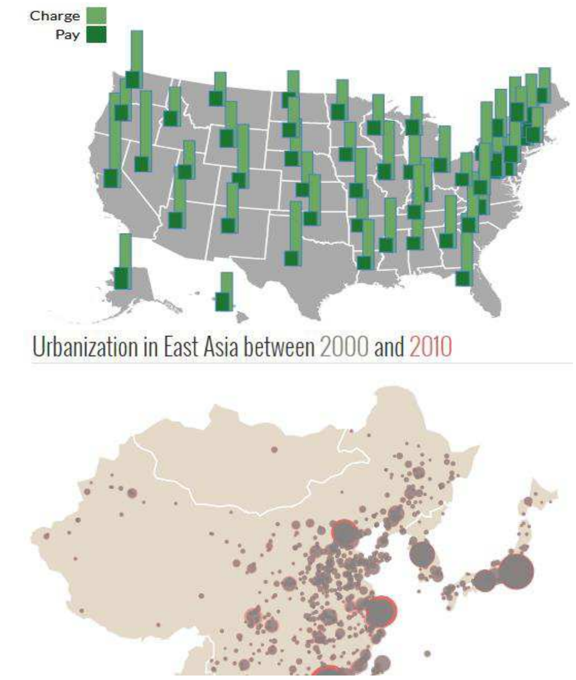



**Figure 3.** Plane-graph-based visual coding method

However, it is very difficult to apply the mainstream tree graph layouts in the location-based visual coding because these layout methods all depend on the strict sequential relations of sample data, that is, the changes of statistical information over time will not affect the observers' visual exploration in the spiral, S-shaped, vertical or horizontal direction. Moreover, currently there are few location-based tree graph coding methods, and there are problems in the rectangular readability of data.

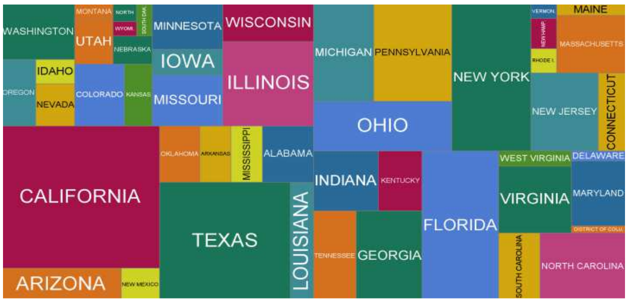
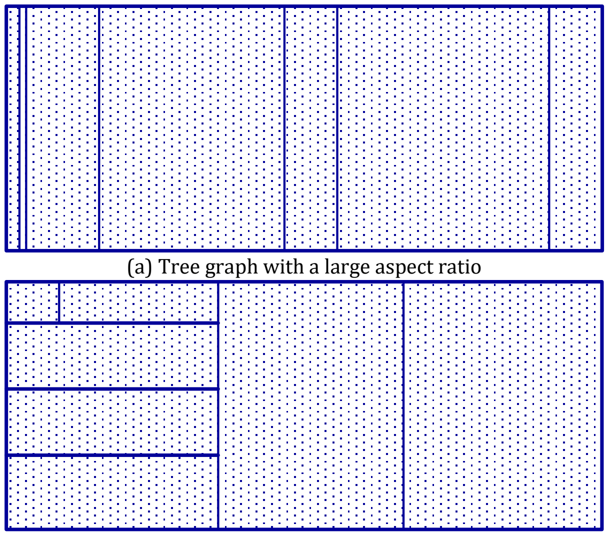



**Figure 4.** Tree-graph-based visual coding method

## Visual Information Coding Method Based on Rectangular Aggregation and Subdivision

This section presents a tree-graph visual coding method based on aggregation and subdivision, which is used to address the poor readability of geographic statistics. The analysis in this section focuses on two parts – statistics rectangular aggregation mechanism and subdivision mechanism.

In the tree graph layout process, geographical location is one of the factors that must be considered. In addition, the rectangular aspect ratio of the tree graph has a significant impact on the visual readability of the statistics. As shown in Figure 5, the display interface needs to enable the observer not only to "perceive" the differences between geographic statistics, but also to quickly "perceive" and "manipulate" the corresponding rectangular blocks, that is, to make the visually coded objects easier to recognize. Rectangles with a large aspect ratio is not easy to observe or manipulate, and the closer the aspect ratio is to 1, the better interaction feature the statistical information rectangle will have.



(a) Tree graph with a large aspect ratio

(b) Tree graph with a small aspect ratio

**Figure 5.** Comparison of tree graph rectangle distributions

The whole process of the aggregation and subdivision mechanism consists of the following steps: (1) determine the geographic coordinates corresponding to the data and the circumscribed rectangle of the entire visual area; (2) Call the aggregation operation process for data aggregation according to the sequence in the longitude or latitude direction; (3) Call the subdivision operation to subdivide the aggregated data to generate the subdivided rectangles for the next round, which contain the aggregated data sets subdivided; (4) release the aggregated data in the subdivided rectangles and perform data aggregation and subdivision again according to the aspect ratios of the rectangles; (5) terminate the algorithm when the number of rectangular blocks is equal to the number of data points.

*Statistics rectangle aggregation mechanism*

Aggregation is to integrate a bunch of individuals into a group. Aggregation helps data analysts visually discover the category and similarity information contained in the data.

The aggregation mechanism proposed in this section is mainly built on this pre-condition - bar-like rectangles caused by large data differences in the adjacent rectangles should be avoided as much as possible in the tree graph. As shown in Figure 6, sporadic data close to each other are aggregated into large data blocks so that small and large data blocks will not be subdivided into one rectangle, thereby avoiding bar-like rectangles.

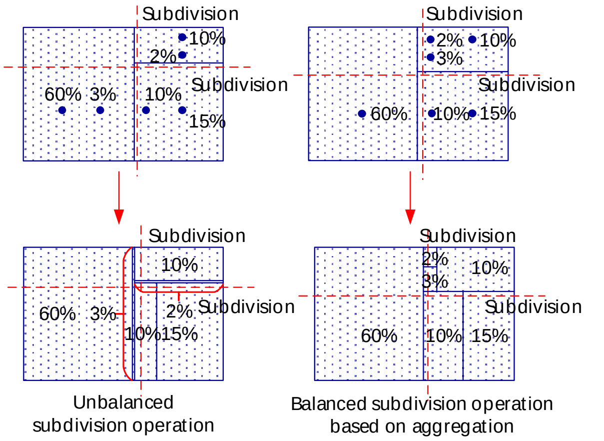



**Figure 6.** Subdivision operation diagram

Under the initial conditions, the aspect ratio of the target map should be calculated first. The main purposes are: (1) to select the sorting criteria: if the horizontal distance is greater than the vertical one, the administrative areas are sorted from west to east with the centroid longitude as the reference; if the vertical distance is greater than the horizontal one, the administrative areas are sorted from south to north with the centroid latitude as the reference; (2) to determine the size of the rectangle to be subdivided, that is, to generate a circumscribed rectangle containing the target map according to the aspect ratio or generate the initial rectangle at the aspect ratio of the observation interface. This rectangle is used to subdivide the statistics or data distributed on the target map. After the initial sequence of data is determined, the continuous data are aggregated according to the distances between the data. This aggregation method has the following advantages: (1) it does not affect the horizontal and longitudinal distribution of data points; (2) it helps reduce the aspect ratios of the rectangular sub-blocks generated so as to improve their readability and operability.

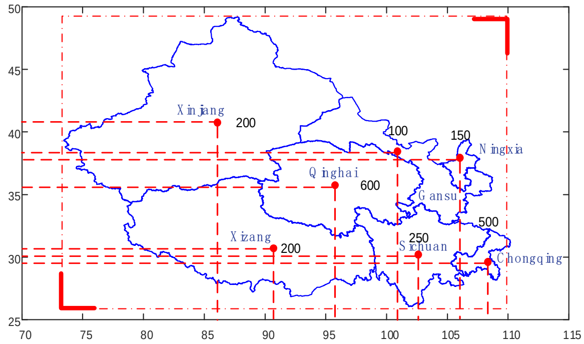



**Figure 7.** Administrative map of 7 provinces in China

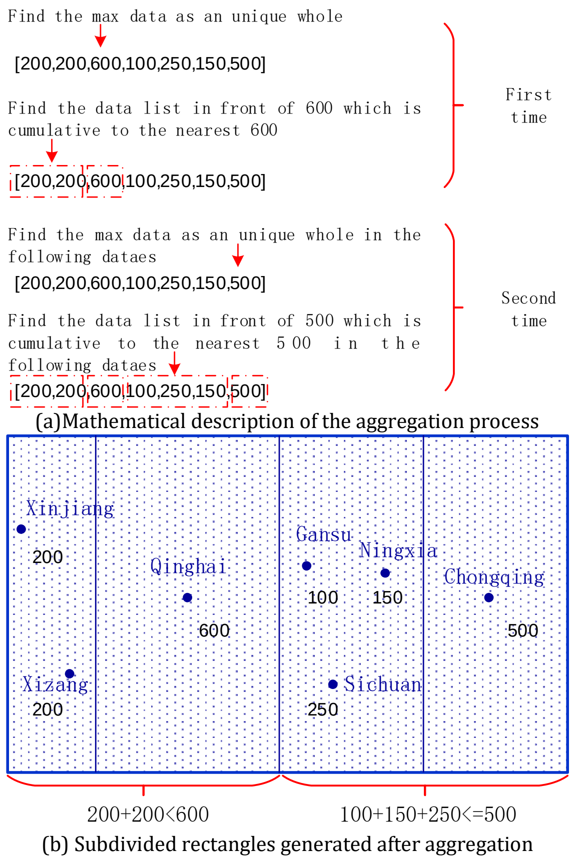



**Figure 8.** Aggregation operation demonstration

The basic principle of aggregation is to find a data point that contains the maximum value from the data point sequence, calculate the accumulated statistics of the data points arrayed before the abovementioned one and select a cumulative continuous sequence closest to the maximum data value for aggregation. This paper takes the administrative map of the 7 provinces in West China in Figure 7 as an example, and the corresponding aggregation operations are demonstrated in Figure 8 (a) and (b). Suppose that there are a set of demographic data describing the populations of 7 provinces in the east-west direction and that the total quantity is 2000. As the transverse distance of the circumscribed rectangle is greater than its longitudinal one, the 7 provinces are sorted from west to east according to their geographic centre-of-mass coordinates. First, by referring to the mathematical description in Figure 8(a), we find the maximum data, which is the data of Qinghai Province. Then we sum up the data of the two provincial-level administrative regions - Xinjiang and Tibet - west of Qinghai Province and find that the sum is the closest to 600 but less than 600. Therefore, we aggregate the data of Xinjiang and Tibet and regard the data of Qinghai and the sum of the Xinjiang and Tibet data as two independent data wholes; after integrating the data of the first three provinces, we perform the same operations on the subsequent 4 provinces – selecting the maximum value and aggregate the data added up. Before subdivision, the data of the 7 provinces are integrated into four groups with small differences in values, as shown in Figure 8(b).

*Statistics rectangle subdivision mechanism*

The subdivision operation is similar to the WM algorithm, but it uses the aggregated data sets as the basis for subdivision. For example, if we are to subdivide the data in Figure 8, we will take the 4 aggregated data sets as the basis, and determine the number of subdivisions and the subdivision positions according to the aspect ratio of the circumscribed rectangle and additional conditions.

First, the algorithm determines an integer closest to the aspect ratio of the circumscribed rectangle, but an integer is not enough to satisfy the subdivision conditions, because the integer value depends not only on the aspect ratio, but also on the number of data points in the corresponding rectangle. After aggregation, the integer will be relevant to the number of aggregated data sets. As shown in Figure 8(b), the first rectangle from the left contains two data points, but its aspect ratio is up to 5:1. Therefore, there should be restrictions on the subdivision times:

(1) When the number of data points is greater than the aspect ratio of the rectangle and the aspect ratio is close to or greater than 2, the integer closest to the aspect ratio should be the reference number of subdivisions;

(2) When the number of data points is greater than the aspect ratio and the aspect ratio is close to 1, the number of subdivisions should be 2;

(3) When the number of data points is less than the aspect ratio but greater than 1, the number of data points should be the number of subdivisions;

(4) When there is only one data point, the rectangle should not be subdivided.

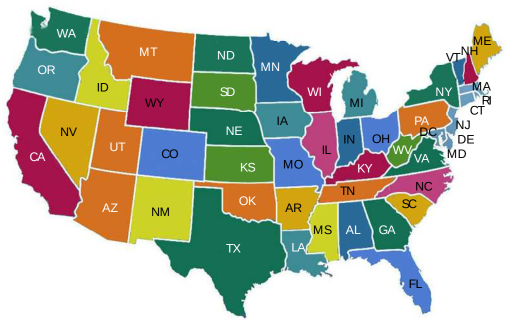
The number of subdivisions mentioned above refers to the number of rectangles generated after subdivision. Through the above mechanism, the subdivision operation can divide the target rectangle more efficiently and minimize the aspect ratio while ensuring the subdivision process proceeds normally.

In addition, in the rectangle subdivision process, we first need to calculate the average value of each subdivided rectangle according to the number of subdivision times and the sum of the data values in the rectangle to be subdivided; however, this value can only serve as a reference for the subdivision rather than the final result of subdivision. The purpose of subdivision is to differentiate the distribution of different values at each data point, so the position of subdivision depends on both the average value and the distribution of data points or data sets. Take the values in Figure 8 for example. The specific subdivision process is as follows: first, set the number of the initial rectangle to be subdivided as 1 and determine whether the rectangle to be subdivided is the last one; if not, sum up the values based on the distribution of the aggregated data sets until the sum exceeds the average value of the subdivided rectangles, which, in this figure, is 1000; determine whether the sum after the value of the critical data set is added (the difference between the sum and the average value is 0) or before it is added (the difference is 600) is closer to the average value. In this figure, subdivision is performed in the former case (the difference is 0).

## Simulation Analysis

Now we firstly take the demographic data of the provincial administrative regions in the U.S. and China and then the urban population in China as the minimum subdivided rectangles for visual comparison using the WM coding method (Ghoniem *et al.*, 2015) and the aggregation and subdivision (AS) coding method, respectively and compare the advantages and disadvantages of the two methods. Figure 9 shows the Administrative maps of the U.S. and China which free of islands and enclaves.

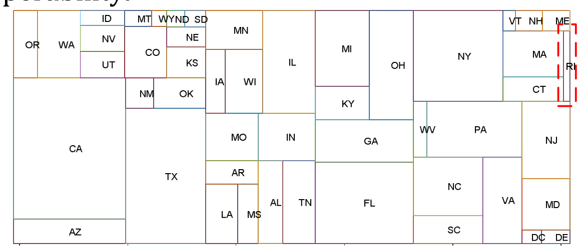

(a) Provincial administrative division in China



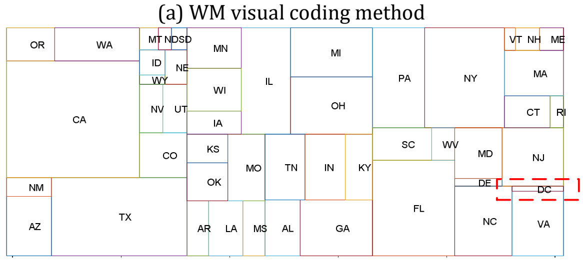

(b) State administrative division in the U.S.

**Figure 9.** Administrative divisions in the two countries

Figure 10 shows the visualized maps of the U.S. population generated by the WM visual coding method and the AS visual coding method, respectively. Relatively speaking, the aspect ratio of rectangle b is closer to 1, while the rectangles longitudinally distributed on the map generated by the WM method in Figure 10(a) have larger aspect ratios. The specific aspect ratios and standard deviations are shown in Table 1. It can be seen that the average aspect ratio under the WM method is slightly greater than that under the AS method, but that the standard deviation is slightly smaller than that under the AS method. The reason is that the AS method combines adjacent data points with similar values into one data set so that the adjacent data points can achieve better aspect ratios. However, due to the large differences in the values of the selected maximum points in the data aggregation process, there are often large differences between data sets. As a result, the standard deviation is greater. In the case of provincial populations in China, as shown in Figure 11, the WM method not only delivers a greater mean aspect ratio than the AS method, but also results in a higher standard deviation. Finally, in the case of urban populations in 355 prefecture-level cities in China in 2015, Figure 12 shows the visualized population maps generated by the two coding methods. The data in the third row of Table 1 show that at the city-level statistical yardstick, the AS coding method has better visual readability. Therefore, in general, with the refinement of granularity, the AS method can generate rectangular blocks that are much closer to the square shape, indicating that it is superior to the WM method in terms of readability and operability.

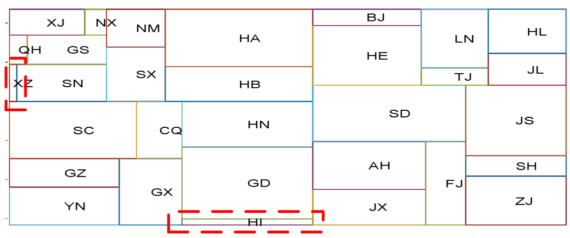



(a) WM visual coding method

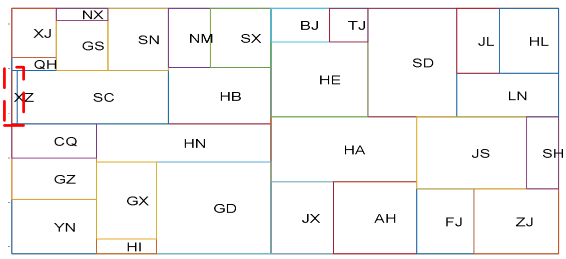



(b) AS visual coding method

**Figure 10.** Visual effects of different visual coding methods in the analysis of state population in the U.S.




(a) WM visual coding method




(b) AS visual coding method

**Figure 11.** Visual effects of different visual coding methods in the analysis of state population in China

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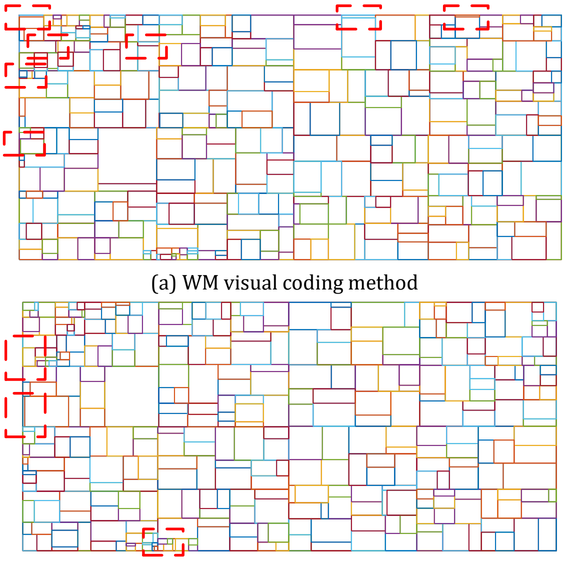

(a) WM visual coding method

(b) AS visual coding method

**Figure 12.** Visual effects of different visual coding methods in the analysis of urban population in China

**Table 1.** Performance comparison of the two coding methods

| Administrative division | WM visual coding method | | AS visual coding method | |
|---|---|---|---|---|
| | Mean aspect ratio | Standard deviation of aspect ratio | Mean aspect ratio | Standard deviation of aspect ratio |
| Provinces in China | 2.4186 | 2.3809 | 2.1245 | 2.2139 |
| States in the U.S. | 2.0783 | 1.3779 | 1.9234 | 1.6372 |
| Cities in China | 2.1048 | 2.3134 | 1.8751 | 1.5768 |

## Conclusion

This paper studies the visual coding method based on visual perception. It analyses the visual pattern recognition mechanism of the single neurons and complex neurons model and the visual coding method based on Gestalt principles and studies the visual coding mechanism of geographic statistics. Through the above analysis, this paper proposes a visual coding method for geographic statistics based on aggregation and subdivision (AS algorithm). Through the aggregation mechanism, the method can minimize the rectangular aspect ratio to ensure the good visual readability; through the subdivision mechanism, it realizes the mapping of geographic locations in the tree graph to ensure the similarity of the geographic location relations of the statistics. The simulation results show that the AS method delivers better readability than the WM method.

## Acknowledgement

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