

Spherical Binary Images Matching

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Abstract. In this paper a novel algorithm is presented to match the spherical binary images by measuring the maximal superposition degree between them. Experiments show that our method can match spherical binary images in a more accurate way.

Keywords: spherical binary image, matching, icosahedron, subdivide.

1 Introduction

Spherical image plays an important role in optics, spatial remote sensing, computer science, etc. Also, in the community of computer graphics, spherical image frequently finds applications in photorealistic rendering^[1], 3D model retrieval^[2], virtual reality^[3] or digital geometry processing^[4-5].

Compared with various algorithms for planar images matching and retrieval, there is nearly no analogy for spherical ones up to now. But in some occasions, one can't avoid facing the task of matching spherical images. Since spherical binary images (SBIs) are used in a majority of cases, we emphasize our attentions on them. In this paper we propose an effective method to match SBIs by measuring the maximal superposition degree between them.

2 Our Method

In our research, we assume that the similarity between SBIs can be measured by the maximal superposition degree between them, which also accords with the visual apperception of human beings. While we know that spherical surface is a finite-unbounded region, it hasn't any information of border and also we can't find its start and end, which baffles the matching. The key of this problem is trying to obtain the result in a finite search space and the error is certain to decrease along with the increase of search space. That is to say, we need to be capable of explicitly controlling the error according to practical requests. In this paper, we divide the SBIs into umpty equivalent regions and compare the difference between the corresponding regions of two SBIs, the sum of which is the superposition in an orientation. Then we rotate one SBI around its center with given rule and make another analogical calculation. And after finite comparisons, their similarity can be obtained by choosing the case with the most superposition.

As we know that regular polyhedra are uniform and have facets which are all of one kind of regular polygon and thus better tessellations may be found by projecting regular polyhedra onto the unit sphere after bringing their center to the center of the sphere. A division obtained by projecting a regular polyhedron has the desirable property that the resulting cells all have the same shapes and areas. Also, all cells have the same geometric relationship to their neighbors. So if we adopt a regular polyhedron as the basis to divide the SBIs, their distribution will also satisfy the requirements of uniformity and isotropy. Since the icosahedron has the most facets of all five types of regular polyhedra, we adopt it as a basis in our realization.

The division for a SBI has random orientation, which makes it difficult to compare. For simplification, we firstly investigate the method to compare two SBIs in the same orientation. As the SBIs have been divided into 20 equivalent spherical triangles, our method is to subdivide each into four small ones according to the well known geodesic dome constructions for several times (Fig.1) to form more compact trigonal grids. If the gray of the SBI in the position of a grid's center is 1, we tag this grid with 1, or otherwise 0. Then we totalize the superposed grids with the same tags and calculate its proportion as the metric for similarity.

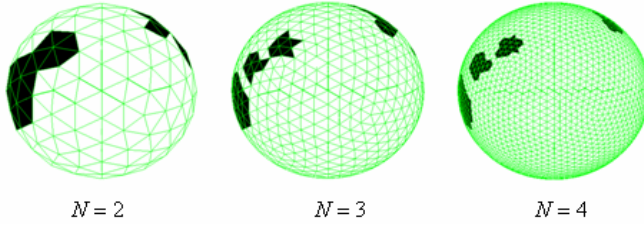


Fig. 1. The grids for a SBI in three resolutions

Suppose that the spherical icosahedron basis has been subdivided for N times and m be the number of superposed grids with the same tags, then the similarity S between

the SBIs in this orientation can be defined as $\frac{m}{20 * 4^N}$.

Comparison of SBIs in the same orientation only reflects the superposition degree in one situation, and therefore to obtain an all-around matching, we have to search for more orientations to get the actual similarity. The varieties of orientation are achieved through two steps in our realization:

Firstly, we rotate the icosahedron basis of one SBI around its center to obtain another posture which is superposed with the prior one. Because the icosahedron has a "Symmetrical Group(SG)" with its rank being 60, we need only rotate it 60 times to get the most superposition in the group, that is, the max superposition in one SG $S_G = \max S_i, i = 0, 1, \dots, 60$. Fig.2 shows three orientations in a SG of a SBI for example. Notice that the SBI is rotated along with the basis, too.

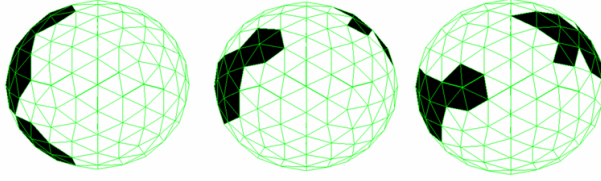


Fig. 2. Three orientations in one symmetrical group, from which we can observe that the trigonal meshes are superposed ($N = 2$)

Secondly, we learn that though rotations and comparison in one symmetrical group can get a nearly approximate matching, the problem hasn't been completely finished, yet. An undoubted fact is that the relation between the SBI and its icosahedron basis is randomly fixed at the beginning, which may create a non-optimal discretization of SBI for matching. To solve this problem, we adopt to experiment on other relations, which will perhaps alter the shape or distribution of the discrete SBIs. Our method is to rotate the icosahedron basis while maintaining the SBI fixed to obtain another SG. To ensure that all SGs are distributed uniformly and able to cover different angles to solve the rotation problem effectively, we adopt the relaxation mechanism proposed by Turk^[6], which intuitively has each directions of a SG push around other ones on the sphere by repelling neighboring directions, and the most important step is to choose a repulsive force and a repulsive radius for the interval.

Suppose we need L different SGs, there are totally $60L$ rotations between the two SBIs. The average maximum error of rotation angle A for two SBIs in longitude and latitude can be roughly estimated using the following formula:

$$\frac{360}{A} \times \frac{180}{A} = 60L \Rightarrow A = \sqrt{\frac{1080}{L}} \quad (1)$$

The calculation is acceptable. Then we can decide the actual similarity between the SBIs as $S_{\max} = \max S_{Gj}, j = 0, 1, \dots, L-1$. Also, we can easily analyze and conclude that the whole time complexity of our algorithm is $O(L * 4^N)$.

Foremost, we evaluate the retrieval performance of these combinations. Assume that the query SBI belongs to the class Q containing k SBIs. The performance of each combination of parameters (N, L) can be evaluated using the percentage of the SBIs from the class Q that appeared in the top $(k-1)$ matches. As the query SBI is excluded from the computation, successful rate is 100% if $(k-1)$ SBIs from the class Q appeared in the top $(k-1)$ matches. In our experiments, two parameters need be decided: N and L . To balance all the influencing facts, we test 18 cases to decide the most appropriate combination in which $N \in \{2, 3, 4\}$ and $L \in \{10, 11, 12, 13, 14, 15\}$. Thus the number of grids for a SBI ranges from 320, 1280 to 5120.

In the experiments, we test various kinds of SBIs and from each kind we choose five SBIs as the query and test the results. Table 1 lists the average performances of the 18 cases, from which we find that when $N=3$ and $L=15$, the arithmetic obtains the best performance. Of course, since there is nearly no acknowledged benchmark and interrelated reports on SBI matching up to now, our experiments and result of performance can only be an attempt.

Table 1. Average Performances (%)

N/L	10	11	12	13	14	15
2	31.3	33.4	33.7	34.1	34.9	35.4
3	34.1	34.9	35.4	36.3	37.1	37.9.
4	33.2	34.1	34.5	35.7	36.4	37.2

As for the results, we make a tersely analysis. Generally speaking, discretization in a high resolution will approach the original SBIs in a more accurate way, but too fine division will arouse the explosion of information and data, also result in general loss of description, and as a result a compromise must be considered. In addition, the performance is certain to improve along with the increase of L , as bigger L leads to more adequate matching.

3 Conclusion and Further Work

In this paper, a tentative method is proposed to match spherical binary images based on superposition degree. Experiments show fairish performances, which preliminarily validates its idea. As for the further work, global descriptors or feature vectors which are analogous to that for planar images had better be extracted in advance to further support off-line matching for mass retrieval.

Acknowledgements. This research has been funded by The National Natural Science Foundation of China (60573146).

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