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A 3D shape descriptor based on spherical harmonics through evolutionary optimization

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ABSTRACT

This paper proposes an optimization approach based on a newly designed parameter set self-evolutionary process. This method improves the discriminability of the original shape descriptor of a 3D model based on spherical harmonics while retaining the efficiency and simplicity of the original shape descriptor. This method captures the critical characteristics, such as the distance, area, and normal distributions of a 3D model extracted along the latitude–longitude directions after the 3D model is normalized in the uniform coordinate frame, and obtains the 3D model's features using a spherical harmonics transform. In order to determine the spherical harmonic basis function relationship, an additional weight (0,1) of each spherical harmonic coefficient as random variable is used to search for the optimal variables based on genetic optimization. The resulting transformed features for these random variables are then used as modified shape descriptors. Retrieval performance is examined using the public benchmarks: the Princeton Shape Benchmark, CCCC and NTU databases, and experiments have shown that the optimized additional weight for shape descriptors based on spherical harmonics results in a significant improvement in discriminability.

1. Introduction

With the general availability of 3D digitizers, scanners, computed tomography (CT), magnetic resonance (MR), stereoscopic vision systems, graphics hardware, and software development, the number of available 3D models has been growing explosively. It has become a great challenge to categorize and retrieve the continuously growing number of 3D models. The traditional retrieval method with keyword annotation cannot meet the retrieval requirements with the explosive growing number of unannotated 3D models. In this context, content-based 3D model retrieval has become an important issue [1–4]. Many researchers have investigated the performance of content-based 3D model retrieval by using shape properties instead of text [5–8]. Several researchers have applied content-based 3D model retrieval in modern industry fields [9,10], such as virtual reality [11], computer-aided design (CAD) [12], medicine [13,14], molecular biology (3D protein models) [15], 3D head [16,17], face recognition [18–20] and entertainment [21].

Among the available shape descriptors, spherical harmonics shape descriptors achieve good retrieval performance [1,4,22–25]. Moreover, spherical harmonics have also been applied in a few practical fields. Papadakis presented a 3D shape retrieval method with spherical harmonics [24]. Abdallah analysed the 3D shape of the heart's left ventricle with a unified parameter and spherical harmonics [26]. Chung presented a cortical asymmetry technique called the weighted spherical harmonics representation for 3D magnetic resonance images (MRI) [27]. Refs. [28,15] adopted spherical harmonics to compute the high resolution structures of the protein and molecule. Ref. [14] proposed 3D particle size and shape distributions for X-ray computed tomography. Ref. [29] applied a spherical parameterization algorithm to retrieval biomedical imaging. Ref. [30] presented an approach with spherical harmonics to retrieve the 3D microscopy image when the topological structure of the model is equivalent to a sphere. However, different shape descriptor extraction approaches have different focuses and limitations. For example, FDCS considers only the distance distribution, while MSEGI pays more attention to the normal distribution. ADCS mainly considers the area distribution.

Spherical harmonics, which are used to transform the functions of a sphere, were first introduced to 3D model retrieval by [31,32]. 3D model retrieval based on spherical harmonics achieves good results. The theory of spherical harmonics holds that any spherical function can be represented as the sum of its harmonics, and each harmonic coefficient is represented as a contribution function on a spherical map. Based on the analysis of the harmonic coefficients of many 3D models, different spherical harmonic basis functions

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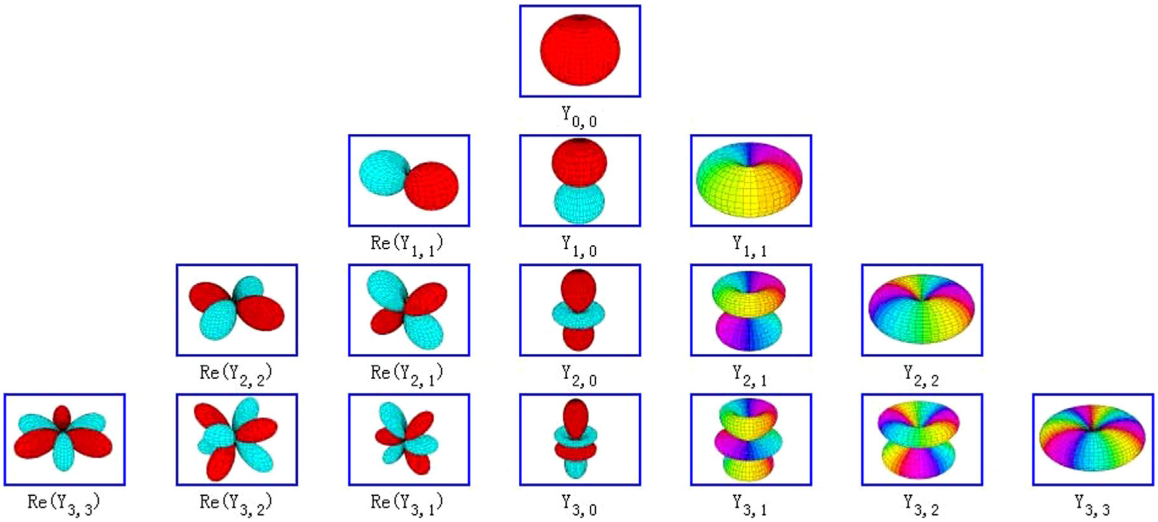

Fig. 1. Examples of spherical harmonics basis functions $Y_l^m(\theta, \phi)$ up to degree 3.

are supposed to play different roles in representing 3D models. How to find the relationship of spherical harmonic basis functions? The proposed approach is to attach a weight to each spherical harmonic coefficient. In general, the first L-order coefficients is represented as 3D models according to the properties of spherical harmonics. Higher-order coefficients represent finer details of the models. In order to represent finer details of 3D models, their dimensions are adopted between 180 and 544. On the assumption that the weight of each spherical harmonic coefficient is between [0, 1] and that the precision is 0.1, the number of candidate resolutions is between 10^{180} and 10^{544}. It is very difficult to directly compute the optimal resolution [33]. This paper proposes the evolutionary algorithm for finding the optimal solution to improve retrieval performance.

This paper proposes a novel retrieval method to capturing 3D geometric relationships on a spherical map as much as possible by combining the parameter set self-evolutionary process with spherical harmonics so that a 3D object is described in as much detail as possible. The spatial features of 3D model include distance, normal and area of mesh. Analyzing previous works, this paper captures the farthest distance on each concentric sphere along longitude and latitude. Then, the harmonic coefficients is obtained by performing spherical harmonics on the distance, normal, and area distributions, which are regarded as composing a feature vector. Further, the properties and coefficients of spherical harmonics are considered that the different harmonic coefficients play different roles in describing a 3D model. Adding different weight coefficients is an effective way. In general, the feature dimensionality of a 3D model is on the order of several hundred. The problem of finding the optimal weight of each harmonic coefficient is known to be NP-hard in general. Here, the parameter set self-evolutionary process is adopted to resolve this problem.

In the next section, the spherical harmonics transform is adopted to extract shape descriptors from 3D models. In Section 3, the 3D model retrieval workflow is presented according to the furthest distance, normal, and area distributions on concentric spheres of extracted shape descriptors, and the parameter set self-evolutionary process is proposed to optimize the descriptors based on spherical harmonics to search for the optimal spherical harmonic coefficients, which serve as more powerful shape descriptors. Section 4 presents the experimental results. The conclusions and future work are addressed in Section 5.

2. Spherical harmonics transform

Spherical harmonics can effectively extract the features of 3D model in spherical mapping [34]. The theory of spherical harmonics states that any spherical function $f(\theta, \phi)$ can be rewritten by the sum of its harmonics:

$$f(\theta, \phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^{m=l} \tilde{f}_{l,m} Y_l^m(\theta, \phi) \tag{1}$$

where $\tilde{f}_{l,m}$ denotes the Fourier coefficient and $Y_l^m(\theta, \phi)$ is the spherical harmonics base calculated by certain products of Legendre functions and complex exponentials. Fig. 1 illustrates the spherical harmonics $Y_l^m(\theta, \phi)$, which are complex functions defined on a sphere, up to degree 3.

$f(r, \theta, \phi)$ denotes the feature vectors which are obtained by spherical harmonic conversion of the mapping of furthest distance, normal, and area on each concentric sphere. Eq. (2) shows $f(r, \theta, \phi)$ while the bandwidth is $N/2$ and l is the degree of the spherical harmonics. According to the theory of spherical harmonics, the larger l means the higher resolution.

$$f(r, \theta, \phi) = \sum_{l=0}^{N/2} \sum_{m=-l}^{m=l} \tilde{f}_{l,m} Y_l^m(r, \theta, \phi) \tag{2}$$

While the value of l is given, the former $l+1$ $(l < N/2)$ rows of coefficients can be used as the feature vectors of 3D model. There are two properties of spherical harmonics on the use of coefficients.

2.1. Property 1

Let $f \in L^2(S^2)$ be a real-valued function, i.e., $f : S^2 \to \Re$. Then, the following symmetry between coefficients exists:

$$\tilde{f}_{l,m} = (-1)^m \overline{\tilde{f}_{l,-m}} \Rightarrow |\tilde{f}_{l,m}| = |\tilde{f}_{l,-m}| \tag{3}$$

where $\tilde{f}_{l,m}$ and $(-1)^m \overline{\tilde{f}_{l,-m}}$ are complex conjugates.

2.2. Property 2

A subspace of $L^2(S^2)$ of dimension $2l+1$, spanned by the harmonics Y_l^m $(-l \le m \le l)$ of degree l, is an invariant with respect to the sphere rotation S^2.