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Watermarking of 3D Meshes using Matlab

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1.INTRODUCTION

Since the 3D watermarking was firstly introduced by Ohbuchi , it is becoming an active research area during the last decade. 3D watermarking is inspired from the image watermarking and video watermarking. The techniques in 2D watermarking can not be directly applied to 3D watermarking. Generally speaking, the 3D watermarking can be classified into transformed domain watermarking and the spatial domain watermarking from the perspective of the embedding domain. Then the transformed domain methods can be further split into spectral methods and multiresolution methods. In this chapter, I will firstly comprehensively survey the transformed domain methods followed by that of the spatial domain methods. We focus mainly on the robust methods and briefly mention the others. Then we introduce the assessment methodology of the 3D watermarking algorithms.

2. Spectral domain algorithms

The methods of mesh spectral analysis are inspired by the development of spectral graph theory , signal processing and the kernel principal component analysis and spectral clustering in the computer vision and machine learning . The mesh spectral analysis of a given mesh object O with N vertices generally has the following three steps in common:

1. A square Laplacian matrix L of size N × N is constructed. The Laplacian matrix which is a discretization of a continuous operator represents a discrete linear operator based on the connectivity of the input mesh.
2. The second step is almost identical for all methods. This consists of to eigen decomposing the matrix L.
3. Process the calculated eigenvalues usually by embedding constraints or by adding noise, i.e. frequency coefficients, and the eigenvectors, i.e.

the ortho normaleigen space. The Laplacian matrix L is a square matrix which characterizes the pairwise information (also called affinity in the literature) between any two vertices on the mesh O, e.g., Li,j reflecting the weight between the ith vertex and the jth vertex.

In the following of this section, the watermarking methods are classified according to the type of basis functions used in the spectral analysis. Methods based on Combinatorial Laplacian are firstly introduced. Most of the spectral 3D watermarking methods belong to this branch. Methods based on manifold harmonics is followed and lastly the other types of spectral methods.

3 Combinatorial Laplacian methods

A combinatorial Laplacian is a matrix operator that solely depends on the connectivity of the mesh. It treats the pairwise relation as a binary delta function, i.e. if vi is connected with vj , the corresponding entry is 1 otherwise, is 0. The idea was firstly introduced by Taubin to approximate low pass filters. Kaini et al compress the mesh geometry making use of the eigenprojections. Zhang studies several variants of combinatorial Laplacian and their properties for spectral geometry processing and JPEG-like mesh compression.

Most of the spectral watermarking methods so far tend to embed the message in the spectral coefficients called eigenprojections in some papers. This is because the basis functions, i.e. eigenvectors, of the combinatorial Laplacian operator are stable and insensitive to the geometry changes since only the connectivity is considered in the matrix. Thus, after watermarking, the connectivity is not changed so the watermarked coefficients can always be detected. Some of the watermarking methods tend to remesh the mesh object ensuring the connectivity is consistent.

4.Theoretical background

We first briefly review the theoretical background of spectral analysis using the combinatorial Laplacian based on the work proposed by Karni et al . Given a mesh object O containing N vertices, the Laplacian matrix of dimension N × N is built according to its connectivity as follows:

$$L_{i,j} = \begin{cases} |\mathcal{N}_{\mathbf{v}_i}| & \text{if } i = j \\ -1 & \text{if } i \neq j \text{ and } \mathbf{v}_i \text{ adjacent to } \mathbf{v}_j \\ 0 & \text{otherwise} \end{cases}$$

where |Nvi | represents the valence of the vertex vi, i.e. the number of its neighbours directly connected to it. Then, the Laplacian matrix is eigen-decomposed as:

$$\mathbf{L} = \mathbf{q}^T \Omega \mathbf{q}$$

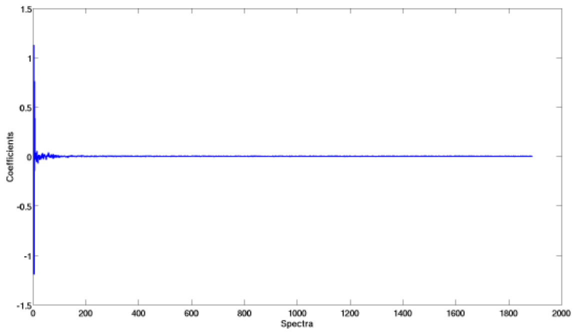
where Ω is the diagonal matrix containing the eigenvalues and q is the matrix consisting of the eigenvectors. The eigenvector matrix q is sorted in the ascending order according to the magnitude of its corresponding eigenvalues in the diagonal matrix Ω . While the eigenvalues in Ω are considered as frequencies, q constitutes an orthonormal basis of the mesh O. The spectral coefficients are calculated by projecting the vertex coordinates on the basis functions defined by the eigenvectors q:

C = qV

where V is the matrix containing the geometry of the vertex coordinates. The spectral coefficients of low frequencies, i.e. the coefficients correspond to the small eigenvalues in Ω , reflects the general shape or the large scale information of the mesh. In contrast, the high frequency coefficients indicate the details or the small scale information of the mesh. Figure 2.1 shows a set of spectral coefficients. 90% of the mesh energy is contained in the low frequency, while the energy in the high frequency is much lower. To reverse the transformation process, the geometry can be recovered as:

$V = q^T C$

Figure 1: A plot of spectral coefficients



Non-blind methods

Ohbuchi et al proposed a non-blind method in 2001 in based on Karni's analysis from . This is the first 3D watermarking method based on the spectral domain. The method applies the spectral analysis employing the basis functions of the combinatorial Laplacian. The message is embedded by slightly modifying the low frequency and medium frequency coefficients. In the detection stage, both the original object and the watermarked object need to be spectrally decomposed. The embedded information is retrieved by comparing the difference of the spectral coefficients between the original and the watermarked ones

In 2002, Ohbuchi et al extended their previous work in three directions. The mesh size was reduced by splitting it into several patches. Each patch is used to carry a set of bits. A more efficient numerical method called Arnoldi is employed to eigen-decompose the Laplacian matrix. The Arnoldi method can calculate the leading spectral coefficients as required, instead of calculating the full set of the eigenvectors. Matrix is identical to the original one. The method proposed in 2002 is resistant to the connectivity alteration attacks like mesh simplification and cropping because the connectivity is enforced to be the same in the detection stage. This method is computationally more efficient as not only the matrix size is reduced but also the numerical routine for eigendecomposition is improved.

All these methods are non-blind and the bit carriers are the low frequency and medium frequency coefficients. The main strength of these methods is the relatively high robustness. Nevertheless, the premises is made that the original object must be present in the message retrieval stage. There are three disadvantages. Firstly, the original object is required to recover the original connectivity. This involves extra steps and computational cost. Secondly, the computational cost is higher than spatial domain methods in general. Thirdly, it is hard to control the distortion.

Blind methods

Cayre and Alface et al proposed a blind algorithm based on the spectral domain in 2003. A mesh object can be considered as a three dimensional signal, i.e. (vx, vy, vz), we can have the corresponding spectral coefficient triplet (Cx,Cy,Cz). Every triplet is considered as an embedding primitive. The triplet is sorted in the ascending order and

the maximum Cmax = max(Cx,Cy,Cz) and minimum value Cmin = min(Cx,Cy,Cz) are regarded as the modulation range.

The mean value Mean = (Cmax + Cmin)/2 is used to distinguish the bits 1 and 0 intervals. When embedding a 1 bit, the medium coefficient is moved into the interval of values corresponding to the bit 1 and vice versa. Figure 2 shows an example of the triplet embedding. The embedding message is inserted repetitively into the low and medium frequency to ensure the robustness. The method is the first blind algorithm based on the spectral domain, but its robustness is very limited.

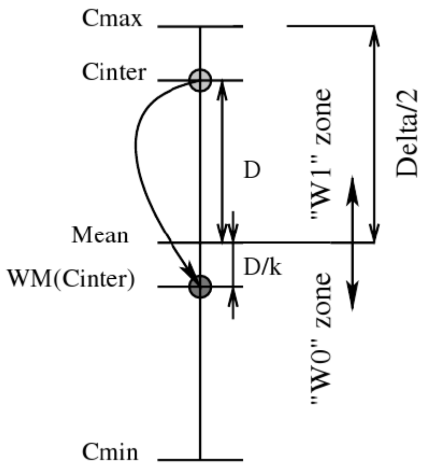


Figure 2: Cinter is moved into the 1 bit interval when embedding 1 bit. Figure is taken from .

Alface et al in 2005 proposed to segment the 3D object into patches for reducing the embedding complexity while the core embedding method is still the same as Cayre's method . Firstly, the feature points are automatically selected through a multi-scale estimation of the curvature tensor field. Then, the algorithm proceeds by partitioning the mesh shape using a geodesic Delaunay triangulation of the detected feature points. Each of these geodesic triangle patches is then parametrized and remeshed by a subdivision strategy to obtain a robust base mesh. The remeshed patches are watermarked in the spectral domain and original mesh points are finally projected on the corresponding watermarked patches. The automatic feature point detection and the patch generation are the main contribution of Alface's method. The core watermarking process is basically identical with Cayre's method. Thus, it suffers from the low robustness problem as well..

Manifold harmonics

Although the combinatorial Laplacian has the perfect reversibility and it is simple to implement, the lack of the geometry information makes it inadequate to describe the feature of an object. There is another kind of discrete Laplacian which deals with the geometry properties of the mesh, called Manifold Harmonics, proposed by Vallet . Its transformation is called Manifold Harmonics Transform (MHT).

The Manifold Harmonics injects the geometry information by calculating the cotangent (cotan) weights of the one ring neighbourhood. The weight between vi and vj is measured by the cotan angle opposite to the edge formed by the two vertices . The cotan weight derived from Finite Element Modeling has been proved a close relationship with the surface curvature . They converge to the continuous Laplacian under certain conditions as explained in . Nonetheless, the cotan weights are calculated by the dual cell area of each vertex, which is nonsymmetric. Thus, the cotan weights can not be used for the spectral analysis directly. L´evy tried empirical symmetrization in Vallet et al clarify these issues based on a rigorous Discrete Exterior Calculus (DEC) formulation and recover symmetry by expressing the operator in a proper basis . The symmetry property ensures its eigenfunctions are both geometry aware and orthogonal as well.

Theory background

In this section, we clarify the theoretical issues of the Manifold Harmonic Transform.

Similar to the Laplace operator in Euclidean space, the Laplace-Beltrami operator

Δ is defined as the divergence of the gradient for functions defined over a manifold

O with its metric tensor. The eigenfunction and the eigenvalue pair (Hk, □k) of Δ

on manifold O satisfy:

$$-\Delta H^k = \lambda_k H^k$$

The above eigen-problem is then discretized and simplified within the finite element modeling framework as the following matrix equation:

$$-Q\mathbf{h}^k = \lambda_k D\mathbf{h}^k$$

where hk = $[H^k_1, H^k_2, \ldots, H^k_n]^T$, the N × N matrix D is diagonal and called lumped mass matrix as:

$$D_{i,i} = \left(\sum_{t \in N_{\mathbf{F}_i}} |t| \right) /3$$

where NFi is the number of neighbouring faces of vertex vi. t is a neighbour of vertex vi. |t| gives the area of the triangle. The matrix Q called stiffness matrix is also of size N × N:

$$\begin{cases} Q_{i,j} = \left(cot(\alpha_{i,j}) + cot(\beta_{i,j})\right)/2 \\ Q_{i,i} = -\sum_j Q_{i,j} \end{cases}$$

where αi,j and βi,j are the two angles opposite to the edge ViVj . The Manifold Harmonics Basis can be calculated by eigen-decomposing the matrix Q in equation . The frequencies are represented by the corresponding eigenvalues. Let us define vector x = (x1, . . . , xN) (respective y and z) containing the x coordinates of the mesh. With the Manifold Harmonics Basis, the kth spectral coefficient can be calculated as:

$$c_k^x = < \mathbf{x}, \mathbf{h}^k > = \sum_{i=1}^{n} x_i D_{i,i} H_i^k$$

Thus, the amplitude of the spectral coefficients is defined as:

$$c_k = \sqrt{(c_k^x)^2 + (c_k^y)^2 + (c_k^z)^2}$$

The object can be exactly reconstructed by using the inverse manifold harmonics transform. For coordinates x (resp. y, z), we have

$$x_i = \sum_{k=1}^{n} c_k^x H_i^k$$

With the geometry information embedded in the operator, the spectrum obtained from the MHT nicely captures shape characteristics of the object. However, on the other hand, the side effect is that when the geometry of the mesh is changed, e.g. watermarked, the approximation matrix Q will be changed. Thus, if we apply the MHT again on the modified mesh, we can no longer retrieve the watermarked coefficients again. The causality problem is the major obstacle of using the MHT to design a watermarking method. People tend to use the iteration methods to recheck the coefficients to ensure a successful embedding .

Another major contribution of Vallet's work is a band-by-band spectrum computation algorithm and an out-of-core implementation that can compute thousands of eigenvectors for meshes with up to a million vertices. These make the spectral analysis directly usable in practice on a large mesh object, besides its common use as a theoretical tool.

Blind methods

Since the Manifold Harmonics Basis incorporates more geometry information of the mesh object, it captures more shape information rather than when considering topology only. The spectrum obtained from the MHT is very stable and consistent for the other object representations. It means that the attacks like mesh simplification, resampling and remeshing, which do not alter the shape of the object, will not affect the spectrum very much. Because this feature of the MHT, it becomes a popular transformation technique to devise robust watermarking schemes. In this section, I will briefly introduce two recent robust and blind algorithm based on the manifold harmonics transform proposed by Vallet et al .

In 2009, Konstantinides et al proposed a blind and robust method based on the Oblate Spheroidal Harmonics. The transform is based on the use of one of the many variants of oblate spheroidal harmonics; namely the Jacobi ellipsoidal coordinates . The algorithm realigns the mesh object by translating the object onto the mass centre, uniformly normalization and PCA rotation. However, the robustness of these traditional alignment methods can be severely affected by attacks. Thus, a smoothing scheme is proposed prior to the alignment.

Multi-resolution methods

The basic idea behind multiresolution analysis is to decompose a complicated function into a "simpler" low resolution part, together with a collection of perturbations, called wavelet coefficients . While in the case of a 3D mesh object, the original 3D mesh itself is considered as a function. The object is analyzed using the so-called lazy wavelet transform In the transform, the object is filtered with a wavelet function. A base mesh is then generated i.e. the base mesh is the analogy of the low-resolution function and it should be a good approximation of the original denser one. The information that is lossy in the base mesh is stored in the wavelet coefficients. Thereafter, the 3D object is iteratively analyzed using the different scale of basis functions. The functions with different scales are orthogonal. The object can be decomposed into different level of details as shown in Figure 2.3. The scheme proposed by Lounsbery et al requires that the mesh must fit a 4-to-1 subdivision connectivity scheme, i.e. a vertex can only connect with six neighbours. Because of the restricted requirement of the mesh,

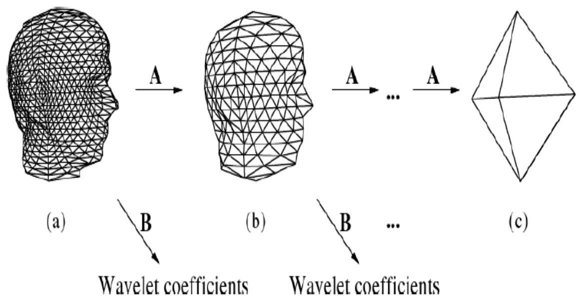


Figure 2.3: Wavelet decomposition

To formulate the wavelet transform in a more rigorous manner, we have:

$$V^j = A^j V^{j+1}$$
$$W^j = B^j V^{j+1}$$

assuming that V^{j+1} denotes the matrix whose row corresponds to the vertex coordinates at the resolution level j + 1. Then V^j is the one level lower resolution. W^j is the wavelet coefficients which is the lossy information from resolution level j + 1 to j. A^j and B^j are called the analysis filters at resolution level j producing the base mesh (base function) and the wavelet (lossy information), respectively. The transform can be reversed by adding the lossy information contained in the wavelet coefficients back to the base mesh as:

$$V^{j+1} = P^j V^j + Q^j W^j$$

where Pj and Qj are called synthesis filters. An interesting mathematical relation
between the synthesis filters and the analysis filters is defined as:

$$\left[\mathbf{P}^j | \mathbf{Q}^j\right] = \left[\frac{\mathbf{A}^j}{\mathbf{B}^j}\right]^{-1}$$

Kanai et al firstly employed the wavelet framework and developed a non-blind 3D watermarking algorithm in 1998. They argue that the human eye is not sensitive to the small geometric changes in the bumpy areas. The watermark is embedded by modulating the norm of the wavelet coefficient vector. The change of the norm is determined by the look up table generated by a secret key.

Robust methods

Benedens et al in 1999 proposed one of the first robust 3D watermarking methods based on the spatial domain in . This method groups the vertex normals as the watermarking bins and each bin is used to carry one bit of message. The message is embedded by carefully modifying the normal distribution of each bin. The experiments show that the algorithm has a good performance against the mesh simplification attack. Because the mesh simplification attack tends to preserve the surface and thus the vertex normals are not likely to be changed a lot. While it is more problematic in the noise attack which randomly modifies the geometry of the surface.

Cho et al in 2007 proposed a similar statistical method combining the ideas of Yu et al and Zafeiriou et al. In this work, the vertices are firstly clustered into groups according to the distance from the vertex to the object centre i.e. ρ component of the (ρ,θ,φ) spherical coordinate system. The observation tells that the distribution of the ρ component is uniform within each bin. Two histogram mapping functions are introduced to modify the mean value and variance value of the distribution respectively as shown in Figure 4. The histogram mapping functions ensure the statistical condition of the distribution is satisfied while the Euclidean movement of the vertex is minimum. The method proposed by Cho et al is probably the most robust 3D watermarking algorithm that does not require the original object to retrieve the watermark.

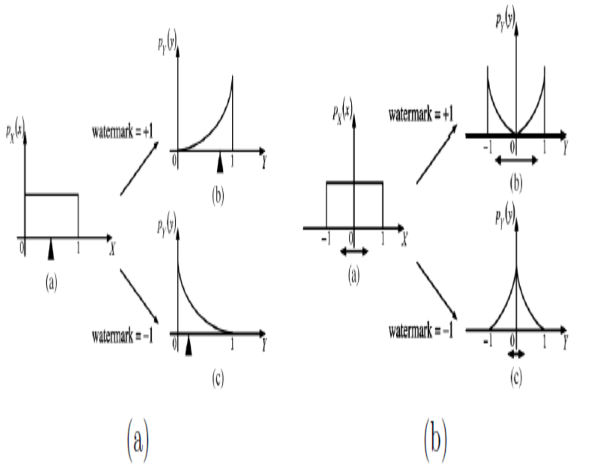


Figure 4: (a) change the mean value of the distribution (b) change the variance of the distribution. .

Except the robust watermarking algorithm, steganography and fragile watermarking are the other two kinds of algorithms in the watermarking family. As we have reviewed in the previous sections, robust watermarking is a technique that aims to detect the embedded information even when the stego medium suffered from a cer tain level of attacks. It is designed for copyright protection purpose. Steganography and fragile watermarking are designed with different motivations in mind.

Steganography is a data transmission and storage technique. In this scenario, the capacity is the most important criteria to evaluate a steganography algorithm but not the robustness. This branch of algorithms usually use every vertex as a embedding primitive. The sequence of the embedded message can be determined by the connectivity . The capacity can be increased by quantization , subdivision , angles and multilayer embedding .

Fragile watermarking, on the contrary to the robust watermarking, is designed that the watermark should disappear when any attacks happens to the stego medium.

Robust 3D watermarking assessment

Figure 1.1 illustrates the three most important aspects in the robust 3D watermarking algorithm: distortion, robustness and the capacity. For a robust and blind watermarking algorithm used for the purpose of copyright protection, most methods accept that the payload of the embedded watermark is 64 bits. Thus, most of the evaluation work are focused on the other two parts i.e. distortion and robustness. In this section, I will present the assessment approaches that are used in the literature.

CONCLUSION

In conclusion, the watermarking methods based on the regular wavelet transform . There are four main advantages of using the wavelet transform.

1. As the norm of wavelet vector implicitly characterize the bumpiness of the local surface, and human eyes are not sensitive to the changes in the bumpy areas,
2. The watermarks can be embedded in different resolution levels. Furthermore, as the low resolution represents the low frequency and high resolution contains more about the high frequency .
3. Not only the wavelet coefficient vector can be watermarked, but also the base mesh. This gives a broader range of the embedding domain.
4. The lazy wavelet transform enables researchers to define a clear geometric relation between the surface distortion and the upper bound of the modification of each wavelet coefficient vector.

LIMITATION

1 The mesh must be in a 4-to-1 subdivision connectivity schemes. Every vertex can only have six neighbours.

2. This class of methods are not robust against any connectivity attacks like mesh simplification, cropping and remeshing etc.

Spatial domain algorithms

There are three characteristics of the spatial domain methods.

1. First of all, it is easy to apply constraints on the mesh and the constraint can be easily recovered and detected blindly.
2. Secondly, because the geometry and connectivity define the appearance of the surface, it enables the user to explicitly control the watermarking distortion on the object surface.
3. Finally, spatial domain method does not have the extra transformation steps, they are much more computationally efficient than the transformed domain methods. These three features determines that the spatial domain is more suitable for blind or fragile watermarking as well as for steganography applications.

From the purpose or the application point of view, the 3D methods can be classified into three sets: 1. Robust watermarking, . Steganography and Fragile watermarking. Almost all transform domain methods are robust watermarking algorithms with a few exceptions of the wavelet methods. In fact, although the wavelet transform analyze the object using a set of orthogonal basis functions, the manipulations are directly on the geometry. On the other hand, spatial domain is used in all the three classes of algorithms. In my research, all my methods are blind and robust watermarking algorithms. Therefore, in this literature review of the spatial domain methods, I will mainly focus on the robust methods in the spatial domain. Steganography and the fragile watermarking will be briefly reviewed for completion.

DISCUSSION

There are various of transformation methods proposed in the last decade such as spectral decomposition, multiresolution analysis, DCT and Radial Basis Function etc. Informally speaking, the methods based on the transformed domain try to analogize the techniques from the 2D data to 3D data. Although the transformed domain algorithms are relatively successful in the conventional data type, they do not gain the same success in 3D. The most important reason is that a 3D object is not regular sampled, the connectivity is not regular either.

So far, the spatial domain has been used in fragile watermarking, steganography and robust watermarking algorithms . There are basically two ways to embed the watermark. The first approach we name it as “single embedding” consists of using a single vertex as an embedding primitive and implement some constraint to carry the message. The second one named “statistical embedding” consists of modifying statistical features. Single embedding is mostly used in the fragile watermarking and steganography because it is not robust to attacks. However, its distortion is low and easy to control. Statistical embedding, on the other hand, consist of using the statistical description as the embedding primitive. So it is generally more robust. The trade-off is the relative high distortion.

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