ADAPTIVE GRAPH FORMULATION FOR 3D SHAPE RECOGNITION

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For More Information

http://tiny.cc/demo3d

@charithmetic

Introduction

- This work aims to develop an optimal model for 3D shape recognition with high level of accuracy, real-time operation and invariant to the angle-of-view changes.
- The current works on 3D shapes recognition, such as, deep learning, model-based, feature-based, shows good improvements in the recognition level. However, high similarities and different angles of view remain a challenge to these recognition methods.
- Graphs and complex networks display useful topological features based on the types of connection between their elements. Such features include degree distribution, clustering coefficient, and hierarchical structure.
- This paper proposes a new method to represent the 3D shapes by capturing local variations into the feature representation.
- The main contributions from this work are:
  - A new method for graph formulation with adaptive connectivity to represent 3D shapes preserving both local and global characteristics of the shape.
  - The proposal of a new set of graph spectral features based on the node distribution of the adaptive graph for 3D shape representation.

The proposed method

The proposed method consists of four stages: 1) shape representation, 2) adaptive graph connectivity modification, 3) feature extraction and 4) the classification process.

1- Shape representation

- A 3D shape consists of a point cloud contain a large number of points on the 3D Cartesian plane.
- Therefore, we use Growing Neural Gas (GNG) to reduce the complexity and to get the same number of pixels for each shape.
- At the end of the training process, the GNG should satisfactory cover the shape regions as can be seen in Fig. 1

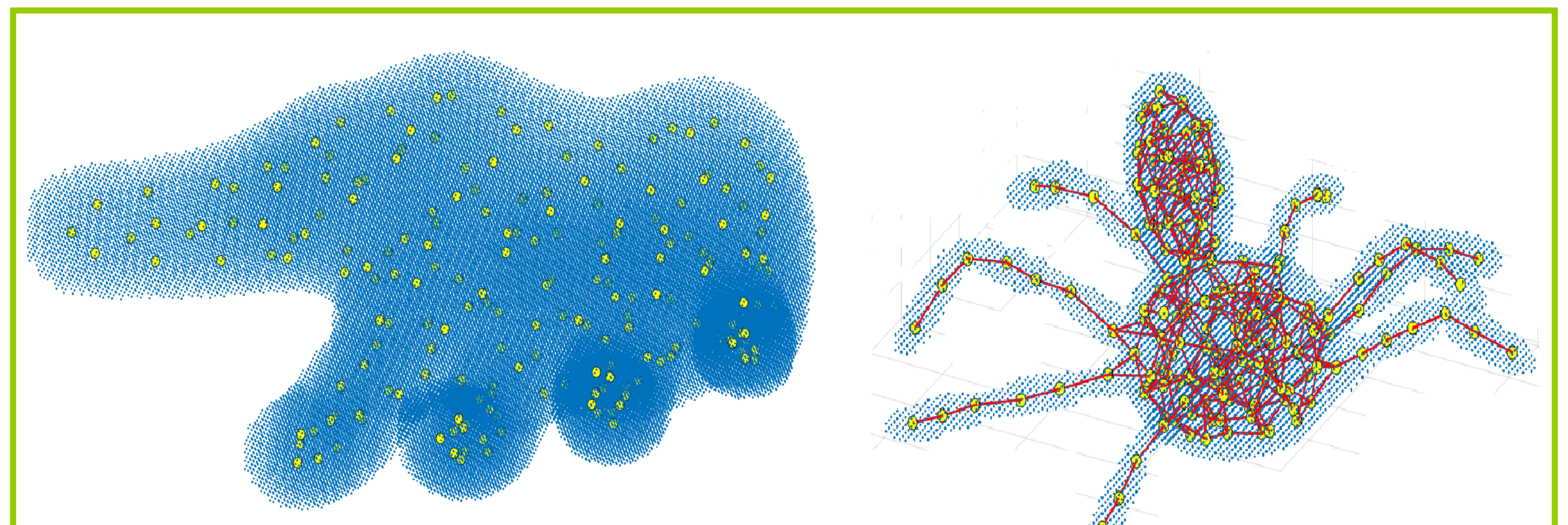

Fig. 1 3D shape representation using Growing Neural Gas.

2- Graph decomposition

We can represent the nodes on the surface as an undirected graph, $\mathcal{G} = \{\mathcal{V}, \varepsilon, A\}$, where $\mathcal{V}$ is the set of N vertices, ε is the set of edges and A is the adjacency matrix with edge weights. We consider ε as the Euclidean distance between nodes because it is invariable to rotation and translational operations. We define the weight, $A_{i,j}$ corresponding to $\varepsilon_{i,j}$ connecting between vertices i and j as follows:

$$A_{i,j} = \begin{cases} \varepsilon_{i,j} & \text{If nodes } i \text{ and } j \text{ are connected} \\ 0. & \text{Otherwise} \end{cases}$$

We also define the signal $r: \mathcal{V} \rightarrow$ R, where i^{th} component represents the Euclidean distance from the centre $(0,0,0)$ to the vertex i in $\mathcal{V}$.

$$r_i = \sqrt{x_i + y_i + z_i}$$

The degree matrix $D_{i,j}$ is calculated as shown.

$$D_{i,j} = \sum_{j=0}^{N-1} A_{i,j}$$

The graph Laplacian matrix is then calculated, as follows:

$$L = D - A$$

Since, L is symmetrically positive, there exists a real unitary matrix, U, that diagonalizes L, such that $U^t L U = \Lambda = \text{diag}\{\lambda_l\}$ is a non-negative diagonal matrix, leading to an eigenvalue decomposition of L matrix as follows:

$$\mathrm{L} = \mathrm{U}^{\mathrm{t}}\mathrm{LU} = \sum_{l=0}^{N-1} \lambda_l\, \mathrm{u}_l \mathrm{u}_l^{\mathrm{t}}$$

u_l is the column vectors of U, and λ_l are a set of orthonormal eigenvectors of L with corresponding eigenvalues, as follows:

$$0 = \lambda_0 < \lambda_1 < \lambda_2 \ldots < \lambda_{N-1} = \lambda_{max}$$

- Initially, a graph is generated over the candidate nodes using GNG.
- We begin with the minimum fully connectivity. Then, we continue increase the links between the nodes as shown in Fig.2 .

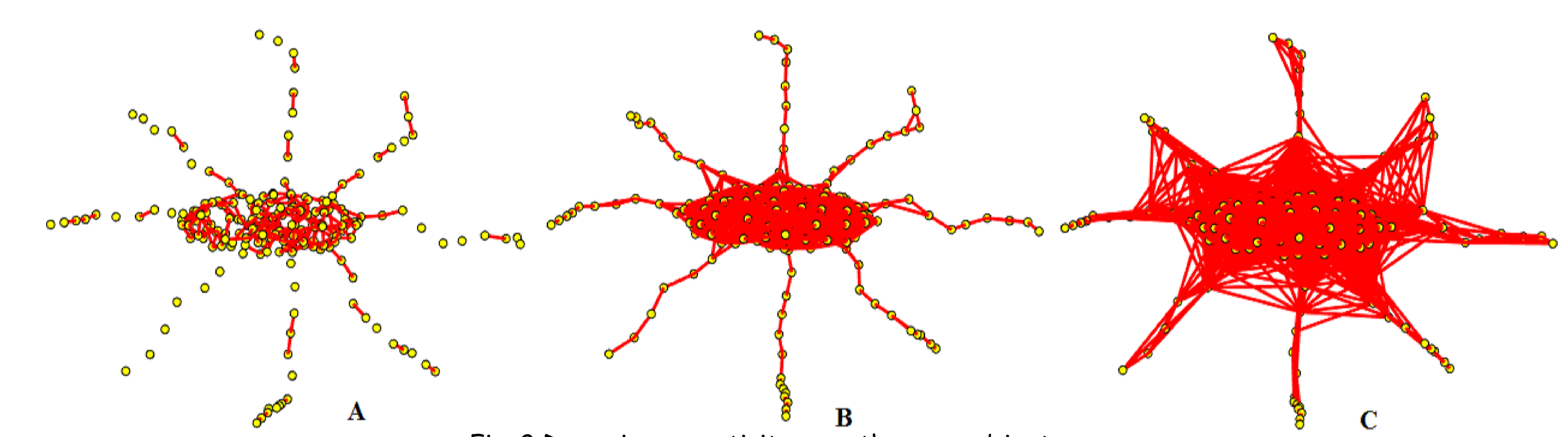

Fig. 2 Dynamic connectivity over the same object.

- At each level, we compute the variance of the node distribution.
- At the end, we take into account the level, which provides the maximum variance as shown in fig. 3

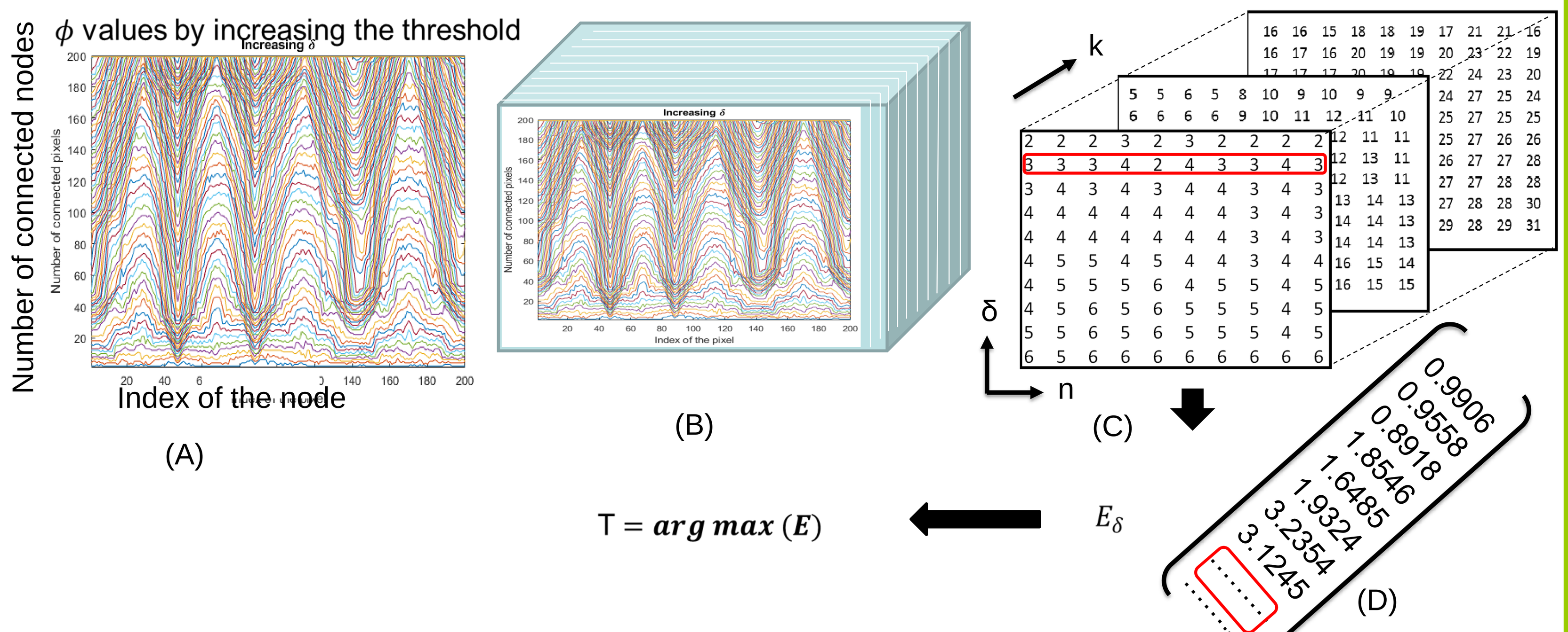

Fig.3 Dynamic evaluations of the adaptive connectivity.

Algorithm 1 also shows how to obtain the optimal connectivity level.

1- **For** $i = 0 : (m-1)$ **do**
2- $P_i \longleftarrow$ Shape representation as (x_i, y_i, z_i).
3- $t \longleftarrow$ Minimum distance to link pixels as a one group.
4- **For** $\delta = 0 : (N-1)$ **do**
5- $\Phi_\delta \longleftarrow$ Compute the node distribution at δ .
6- $B \longleftarrow \frac{\Phi_\delta}{\max(\Phi_\delta)}$
7- $\sigma_\delta^2 \longleftarrow$ Compute the variance of B .
8- **End**
9- $T_i \longleftarrow$ Max (σ^2)
10- **End**

3- Feature extraction

We propose the following three features taking global and local details into account.

$$F_1 = \frac{\Phi_\delta}{\max(\Phi_\delta)} \qquad F_2 = r_i \lambda_i$$

$$F_3 = \left\{ \underbrace{\frac{\sum_0^{N-1} B_i}{N}}_{\text{Mean}},\ \underbrace{\frac{1}{N-1}\sum_1^{N} |B_i - \mu|}_{\text{Variance}},\ \underbrace{\sum_0^{N-1} B_i \log_2 \frac{1}{B_i}}_{\text{Entropy}},\ \underbrace{\sqrt{\sum_0^{N-1} B_i^2}}_{\text{L2-Norm}} \right\}$$

The mean of B

4- Classification

- The total length of the features is (2N + 4).
- In the final step, these features are concatenated and categorised using k-Nearest Neighbour classifier (KNN).

Performance evaluation

- The proposed method was tested on a variety of shapes using artificial 3D shape dataset: A benchmark for 3D mesh segmentation (X. Chen et al (2009)). This dataset contains 19 classes with 20 samples per class giving 380 shapes in total.
- These classes include: Human, Cup, Glasses, Airplane, Ant, Chair, Octopus, Table, Teddy bear, Hand, Plier, Fish, Bird, Mech, Bust, Armadillo, Bearing, Vase, and Four Leg respectively.
- The experiment was implemented using MatLab R2018a Intel processor, CPU@3.6GHz and RAM 16GB.
- We reduce the number of pixels for all shapes into N = 200 using GNG.
- The average speed of the training and testing 380 samples was 6.3 seconds, which is fast for such a large amount of data and the average time for testing a new one sample is 12 milliseconds.
- Compared with the state-of-the-art methods, our algorithm demonstrates a high performance by recording the highest level of accuracy (74.47%) as shown in Table 1.
- Fig.4 shows the confusion matrix of our proposed method. For more details, please visit http://tiny.cc/demo3d

Table.1 Comparison with the state-of-the-art studies.

Method	Classification score (%)
M. Ankerst, et al (1999) (3D shape histogram)	43.42
R. Osada, et al (2002) Shape distribution	67.37
G. E. da Silva and A. R. Backes (2018) Complex network	70.79
The proposed method	**74.47**

Actual \ Predict	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	12	0	0	1	0	0	0	0	0	0	3	0	3	0	0	0	1	0	0
2	0	16	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	1	0
3	0	0	18	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
4	0	0	0	18	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
5	0	0	0	0	18	1	0	0	0	0	0	0	0	0	0	0	0	0	1
6	0	1	0	0	0	17	0	0	0	0	0	0	1	0	0	0	0	0	1
7	0	0	0	0	1	0	16	0	0	0	0	0	0	0	0	0	0	1	2
8	0	1	0	0	0	0	1	13	0	0	0	0	0	1	0	1	0	1	2
9	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	2	11	0	0	1	1	1	0	2	0	1
11	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0
12	0	0	0	1	0	0	0	0	0	0	0	18	0	0	0	0	0	0	1
13	0	0	2	0	0	0	1	0	0	2	0	0	14	0	0	0	0	1	0
14	0	0	0	0	0	0	0	0	2	0	0	0	0	17	0	1	0	0	0
15	0	5	0	0	0	0	0	0	2	1	0	0	0	0	10	2	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	18	0	1	0
17	1	0	0	0	0	0	0	0	0	4	0	1	2	0	0	0	10	1	1
18	0	0	0	0	0	0	0	0	3	2	0	1	0	0	2	3	0	9	0
19	1	0	0	0	2	1	1	0	1	2	0	0	0	2	0	0	0	2	8

Fig. 4 The confusion matrix of the proposed method .

Conclusions

- We have proposed a new 3D shape recognition method based on local details.
- Our approach includes a proposal of a new method for graph formulation with adaptive connectivity to represent 3D shapes preserving both local and global characteristics of the shape .
- This is followed by a new set of graph spectral and node domain features based on the node distribution of the adaptive graph for 3D shape representation.
- The performance evaluation based on one of the most challenging 3D dataset showed that the proposed method exceeded the existing node distribution methods by 4%.