SEGMENTATION OF 3D OBJECTS USING PULSE-COUPLED OSCILLATOR NETWORKS

E. Ceccarelli, A. Del Bimbo, P. Pala

Dipartimento Sistemi e Informatica
University of Firenze
Firenze, Italy
{eva,delbimbo,pala}@dsi.unifi.it

ABSTRACT

Along with image and video libraries, archives of 3D models have recently gained increasing attention. Accordingly, there is an increasing demand for solutions enabling retrieval of 3D models based on global properties as well as properties of object parts.

In particular, retrieval based on object parts relies on segmentation of 3D objects into their constituent parts. This is a challenging task, as the identification of object parts should conform to human perceptual judgement. Therefore, definition of models and solutions that enable decomposition of 3D objects into perceptually relevant parts is a fundamental step to enable effective retrieval based on object parts.

However, a few approaches have been proposed to support segmentation of 3D meshes into perceptually relevant parts. In this paper we propose a model based on pulse-coupled oscillator networks. Preliminary experiments are reported to demonstrate the validity and potential of the proposed solution.

1. INTRODUCTION

Beside image and video libraries, archives of 3D models have recently gained increasing attention for a number of reasons: advancements in 3D hardware and software technologies, their ever increasing availability at affordable costs, and the establishment of open standards for 3D data interchange (e.g. VRML, X3D).

Thanks to the availability of technologies for their acquisition, 3D models are being employed in a wide range of application domains, including medicine, computer aided design and engineering, and cultural heritage.

In this framework the development of techniques to enable retrieval by content of 3D models assumes an ever increasing relevance. This is confirmed by the considerable number of solutions that recently have been proposed to support retrieval of 3D objects based on their appearance and/or structure (the interested reader can refer to [1] for an detailed review).

A common trait of these systems is that they describe objects either in terms of global object features or in terms of an ensemble of local features—typically organized through some graph-like structure. Clearly, description of 3D object based on global object features prevents retrieval based on perceptually *relevant parts* of 3D objects. However, this is also true for systems relying on local descriptors unless the notion of locality grounds on a decomposition of the object into perceptually relevant parts.

Therefore, definition of models and solutions that enable decomposition of 3D objects into perceptually relevant parts is a fundamental step to enable effective retrieval based on object parts.

Mesh segmentation is the process by which a 3D object, represented through 3D meshes, is decomposed into perceptually meaningful parts. Once an object is segmented into parts, each part can be described separately using whichever technique for description of global content of 3D objects.

Generally, recent researches on mesh segmentation [4], [5], [6], [7], [8] follow one of two distinct approaches: primitive based and curvature based. Primitive based approaches rely on the definition of a set of primitive 3D shapes. Each primitive shape is parameterized so as to model the mesh segmentation process as a model fitting problem. Differently, curvature based approaches ground on psychological studies evidencing that a perceptually meaningful decomposition of shapes occurs when parts are cut along minima of the curvature value. This general criterion, also known as *minima rule*, has been implemented through many different techniques commonly used for segmentation of 2D images, including region growing, split&merge and watersheds. Among these, techniques based on watersheds [6], [8] have proved to be particularly effective for segmentation of 3D meshes. However, effectiveness of segmentation by watersheds is limited by high computational complexity and frequent over-segmentations.

In this paper we present a model for segmentation of 3D objects based on the use of pulse-coupled oscillator networks. Pulse-coupled oscillator networks have been used successfully for clustering [12] and image analysis [10]. In the model we present, a network of oscillators is built based on the topology of vertices of a 3D mesh. The dynamics of

0-7803-9332-5/05/$20.00 ©2005 IEEE

each oscillator is determined by an input stimulus and interactions due to coupling with neighboring oscillators. The dynamics of the network is modelled through an iterative process by which oscillators organize into groups of synchronized elements. Organization of oscillators into synchronized groups reflects a decomposition of the original mesh into *homogeneous* parts.

The paper is organized as follows: Sec.2 provide a general review of pulse-coupled oscillator networks; Sec.3 describe how oscillator networks can be used to accomplish segmentation of 3D objects, represented in the form of 3D meshes; finally, in Sec. 4 some preliminary results are presented.

2. OSCILLATOR NETWORKS

Mutual synchronization of coupled oscillators is a well known and studied phenomenon in chemistry, physics and biology. Mutual synchronization occurs when a population of elements—referred to as oscillators—alter their individual rhythms just enough so that they all act in unison. The phenomenon was described for the first time in 1665 by the Dutch physicist Christiaan Huygens, who placed two pendulum clocks side by side on a wall. Within a short time, the pendulums were swinging in perfect synchrony. He altered the movement of one pendulum, but within a half hour the swinging weights had regained synchrony. When one of the clocks was moved to another wall, they gradually fell out of step.

An accurate model of the behavior of coupled oscillators would require the use of a system of differential equations with several degrees of freedom to model the activity of each oscillator as well as the interaction between different oscillators[10]. However, a simplified yet effective solution is to model each element of the population as an *Integrate and Fire* oscillator [9]. The dynamics of each oscillator is characterized by a state variable x that increases monotonically toward a threshold. As this threshold is reached, the oscillator fires a pulse to the other oscillators and resets the value of its state variable. When the oscillators of the network detect a pulse by a firing oscillator, they can update the value of their state variables so as to try to synchronize to the firing oscillator.

Following the same formalism proposed in [12], let $\mathcal{N} = \{O_1, \ldots, O_N\}$ be a network of N oscillators. Each oscillator is characterized by a phase ϕ and a state variable x_i such that $x_i = f(\phi_i)$, being $f : [0,1] \mapsto [0,1]$ a continuous, concave down, monotonically increasing function such that $f(0) = 0$ and $f(1) = 1$. The analytic expression for the state function $x = f(\phi)$ is of the same form used in [11], that is: $f(\phi) = C_\gamma(1 - e^{(-\gamma\phi)})$, with $C_\gamma \in \mathbb{R}$. In order to satisfy the condition $f(1) = 1$, value of C_γ is computed as $C_\gamma = 1/(1 - e^{(-\gamma)})$.

In the absence of any interaction with other oscillators, the phase variable ϕ_i represents the normalized time elapsed since the last firing. In fact, at the beginning, ϕ_i is randomly initialized and it increases linearly until $\phi_i = 1$. When this happens, the oscillator fires and ϕ_i is reset to 0.

When oscillators are arranged into a network, they can interact so that groups of oscillators synchronize with each other. More specifically, oscillators in the network may behave following three different patterns: synchronous, phase-locked and chaotic. In the first case, oscillators progressively change their phases so that within a finite time period they all fire in unison. In the second case, oscillators organize into phase-locked subgroups: oscillators within the same group are synchronized, though oscillators belonging to different groups keep a constant phase difference. The third case models all situations where neither one of the previous two conditions is reached.

Generally speaking, synchronization emerges as a result of mutual interaction between oscillators. This interaction takes place each time an oscillator fires: when oscillator O_i fires, the state variable of a generic oscillator O_j ($i \neq j$) will change by an amount ϵ_{ij}. That is, the phase of oscillator O_j will change from $f^{-1}(x_j)$ to $f^{-1}(x_j + \epsilon_{ij})$. The interaction maybe either excitatory or inhibitory depending on the value of ϵ_{ij}: excitatory if $\epsilon_{ij} > 0$ and inhibitory otherwise.

It can be shown (refer to [12] for details) that under suitable constrains on $f(\cdot)$ and ϵ_{ij} values, oscillators of the network either synchronize or organize into phase-locked subgroups.

3. MESH SEGMENTATION

Mesh segmentation by pulse-coupled oscillators is accomplished by associating each mesh vertex v_i with one oscillator O_i. In this way, a network of N oscillators is defined, being N the number of mesh vertices. The topology of the network is equivalent to the topology of the mesh, that is, two distinct oscillators O_i and O_j are adjacent only if their corresponding vertices on the mesh v_i and v_j are adjacent.

Segmentation is obtained through two distinct steps: mesh preprocessing and network synchronization. In the first step, the mesh is subject to smoothing and polygonal reduction so as to simplify the segmentation process. In the second step, curvature at mesh vertices is used as input to drive synchronization of the network of oscillators into phase-locked subgroups, as described in the following.

3.1. Network synchronization

Curvature at mesh vertices is used to drive synchronization of the network of oscillators into phase-locked subgroups. For this purpose, each oscillator O_i is provided with input information I_i corresponding to mesh curvature at vertex v_i.

Surface curvature in correspondence with vertex v_i of the mesh $\mathcal{M}$ is estimated by considering versor $v_i^{\perp}$, that is, the normal to $\mathcal{M}$ at point v_i. Then, the *platelet* V^{v_i} of vertex v_i is considered. This is defined as the set of all mesh vertices around v_i. Given a generic vertex of the platelet $v_j \in V^{v_i}$ let $v_j^\perp$ be the normal to $\mathcal{M}$ at point v_j. Mesh curvature Γ_{v_i} at vertex v_i is estimated as:

$$\Gamma_{v_i} = \frac{1}{2} \frac{\sum_{v_j \in V^{v_i}} |v_i^\perp - v_j^\perp|}{|V^{v_i}|} \qquad (1)$$

It can be shown that with this definition, the value of Γ_{v_i} is always in $[0, 1]$.

The curvature value Γ_{v_i} of a generic mesh vertex is used as I_i input to the corresponding oscillator O_i. Input values of oscillators determine the amount of interaction that can be established between oscillators. In particular, the amount of interaction between two oscillators should enable partitioning of the N oscillators into K subgroups—and correspondingly, partitioning of the original mesh into K subparts. Oscillators belonging to the same subgroup should be characterized by similar input values and should fire in unison. Differently, oscillators belonging to different subgroups should be characterized by dissimilar input values and should fire with a constant phase difference: they should be phase-locked.

For this purpose, value of ϵ_{ij}, modelling the level of interaction (i.e. coupling) between oscillators O_i and O_j, depends on the distance $d_{ij} = ||I_i - I_j||$ between their input values according to the following formula:

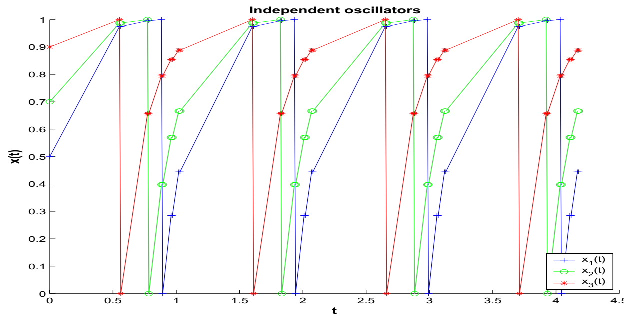
$$\epsilon_{ij} = \epsilon(d_{ij}) = \begin{cases} \epsilon_M & \text{if} \quad d_{ij} \in [0, d_1] \\ \epsilon_M \frac{d_2 - d_{ij}}{d_2 - d_1} + \epsilon_m \frac{d_{ij} - d_1}{d_2 - d_1} & \text{if} \quad d_{ij} \in (d_1, d_2] \\ \epsilon_m & \text{if} \quad d_{ij} \in (d_2, +\infty) \end{cases} \qquad (2)$$

being $d_1 > 0$, $d_2 > d_1$, $\epsilon_m < 0$ and $\epsilon_M > 0$ four control parameters. In the experiments reported in Sect.4 the following control parameter values were used: $d_1 = 0.3$, $d_2 = 0.5$, $\epsilon_m = -0.02$ and $\epsilon_M = 0.02$.

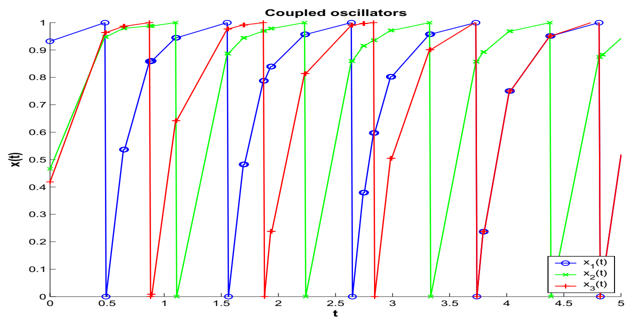
Dynamics of the network of oscillators is modelled through the iterative process summarized below:

1. Randomly initialize the phase ϕ_i of each oscillator
2. Compute the state of each oscillator: $x_i = f(\phi_i)$
3. Detect the first oscillator O_k that will fire: being $k = arg \left\{ \min_i \{1 - \phi_i\} \right\} \; i = 1, \ldots, N$
4. Update the phase of each oscillator O_i to $\phi_i^{(new)} = \phi_i^{(old)} + 1 - \phi_k^{(old)}$
5. Compute the set $\mathcal{C}(k)$ of oscillators that are adjacent to O_k
6. Update the phase of each oscillator $O_i \in \mathcal{C}(k)$: $\phi_i = f^{-1}(x_i + \epsilon(d_{ik}))$
7. if $StopCriterion()$ is not verified repeat from step 3, otherwise stop.

The $StopCriterion()$ is verified if at least one of two conditions is met: *i*) the number of iterations exceeds a predefined threshold τ_{iter}; *ii*) the maximum value of $\epsilon(d_{jk})$



(a)



(b)

Fig. 1. Evolution of a network of independent (a) and coupled (b) oscillators.

computed on a window of ω_{iter} iterations falls below a predefined threshold τ_ϵ.

Fig.1(a)(b) shows the values of the state variables for two sample synchronization processes. In the first case (Fig.1(a)), the network is composed of three independent oscillators: there is no coupling (i.e. interaction) between oscillators. As a result, the time elapsed between consecutive firing keeps constant. Differently, in Fig.1(b) results for a network of three coupled oscillators are shown. Coupling between oscillator pair $O_1 - O_3$ is excitatory. Differently, coupling between oscillator pairs $O_1 - O_2$ and $O_2 - O_3$ is inhibitory. It can be noticed that, within a few iterations, oscillators O_1 and O_3 synchronize (they fire in unison) whereas oscillator O_2 is phase locked with O_1 and O_3.

4. EXPERIMENTAL RESULTS

Based on the proposed model for segmentation of 3D objects using pulse-coupled oscillators a prototype system has been implemented in c language. The prototype system has been tested on a set of VRML object models. Approximately 120 models were collected to build the test set. These comprise three classes of models: taken from the web, manually authored (with a 3D CAD software), and variations of the previous two classes (obtained through deformation or application of noise, which caused surface points to be moved from their original locations).

Fig.2 shows a few steps of the iterative process corre-

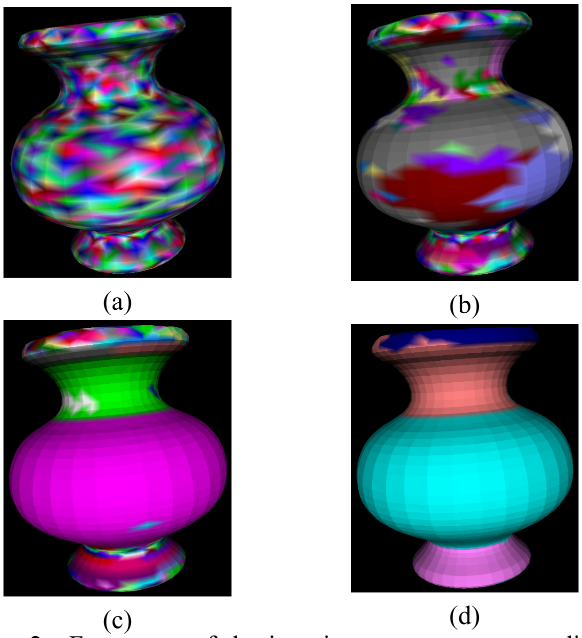


Fig. 2. Four steps of the iterative process corresponding to the segmentation of a vase: synchronized oscillators are evidenced with the same color. (a) Random initialization of oscillators; (b)(c) intermediate synchronization steps; (d) final segmentation.

sponding to the segmentation of a simple vase. At the beginning, each oscillator is initialized with a random state variable. As the synchronization process is iterated, oscillators characterized by similar values of the input variable (vertex curvature) organize into phase locked subgroups. When the synchronization process completes, the mesh is partitioned along vertices characterized by a strong local change of curvature values. Results of the segmentation of a vase and a bunny models are shown in Fig.3.

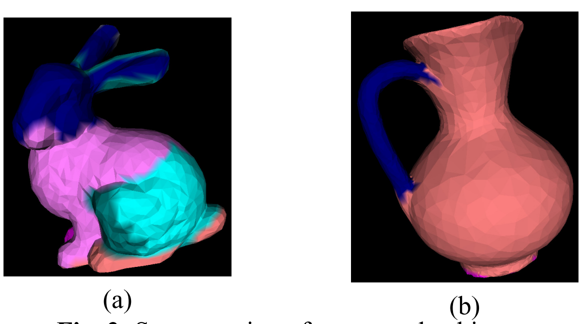


Fig. 3. Segmentation of two sample objects.

Results of the segmentation of 15 sample models have been compared with groundtruth data obtained by asking a group of 20 people to judge segmentation results. Judgement was expressed as a boolean value to be assigned to each part of the segmented object. In particular, parts were labelled *true* if they corresponded to perceptually relevant parts; *false* otherwise. Comparison with this groundtruth showed that 85% of parts automatically detected by the segmentation process corresponded to perceptually relevant parts for 97% of interviewed people.

5. REFERENCES

[1] J. Assfalg, G. D'Amico, A. Del Bimbo, P. Pala. "3D content-based retrieval with spin images". *In Proc. of IEEE Int. Conf. on Multimedia and Expo* (ICME'2004), Taipei, Taiwan, June 27th - 30th, 2004.

[2] J. Assfalg, A. Del Bimbo, P. Pala, "Curvature Maps for 3D CBR", in *Proc. of Int'l Conf. on Multimedia and Expo (ICME'03)*, Baltimore (MD), July 2003.

[3] M. Elad, A. Tal, S. Ar, "Content Based Retrieval of VRML Objects - An Iterative and Interactive Approach", *EG Multimedia*, September 2001, 97-108.

[4] B. Falcidieno, M. Spagnuolo. Polyhderal surface decomposition based on curvature analysis. In T. L. Kunii and Y. Shinagawa, editors, Modern Geometric Computing for Visualization, pages 5772. Springer-Verlag, 1992.

[5] N. S. Sapidis, P. J. Besl. Direct construction of polynomial surfaces from dense range images through region growing. ACM Transactions on Graphics, Vol.14, n.2, pp.171-200, Apr.1995.

[6] K. Wu, M. D. Levine. 3D part segmentation using simulated electrical charge distributions. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, n.11, pp.1223-1235, Nov. 1997.

[7] Y. Yu, A. Ferencz, J. Malik. Extracting objects from range and radiance images. IEEE Transactions on Visualization and Computer Graphics, Vol.7, n.4, pp.351-364, 2001.

[8] D.L. Page, A.F. Koschan, M.A. Abidi. "Perception-based 3D triangle mesh segmentation using fast marching watersheds". *In Proc. Int. Conf. on Computer Vision and Pattern Recognition 2003*, Vol.2, pp.27-32, June 2003.

[9] J. Bélair. Periodic Pulsatile Stimulation of a Nonlinear Oscillator. Jour. Math. Biology, Vol.24, pp.74-85, 1988.

[10] K. Chen, D. Wang, X. Liu. "Weight Adaptation and Oscillatory Correlation for Image Segmentation", *IEEE Transactions on Neural Networks*, vol. 11, no. 5, 2000, 1106-1123.

[11] R.E. Mirollo, S.H. Strogatz. "Synchronization of pulse-coupled biological oscillators", *SIMA Journ. Applied Mathematics*, vol.50, pp.1645-1662, 1990.

[12] M.B.H. Rhouma and H. Frigui. "Self-Organization of Pulse-Coupled Oscillators with Application to Clustering", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 2, 2001, 180-195.