ADAPTIVE CONTOUR SAMPLING AND CODING USING SKELETON AND CURVATURE

F. Jaillet, Y.M. Ghamri Doudane, M. Melkemi and A. Baskurt

LIGIM (Computer Graphics, Image and Modelisation Laboratory)
EA 1899, University Claude Bernard, Lyon 1
Bât. 710, 43 bd du 11 novembre 1918, 69622 Villeurbanne cedex FRANCE

ABSTRACT

This paper presents a new binary shape sampling and coding method. Within the framework of MPEG-4 standard, the binary shapes in Video Object Plans have to be coded with a near to lossless approach in order to obtain a perfect spatial and temporal localization. For this purpose, a new sampling method based on the object skeleton is developed. The ”r-sampling” is defined function of the Local Feature Size (LFS) which is the distance between a shape point and the closest point on the medial axis of this shape. A weighting convex function φ depending on the local curvature is also introduced to increase the local adaptiveness of the sampling (”the r&c-sampling”). This new approach is tested on contours presenting high level details. The first results obtained are satisfactory in terms of both the reduction of samples and the reconstruction error.

1. INTRODUCTION

The MPEG-4 standard [1] provides the means to encode audio-visual material as objects with their relations in time and space. This standardization effort has revived great interest for object video compression techniques in recent years. Within this framework, a video sequence is treated as a collection of disjoint video object plans (VOP). Each VOP is encoded as independent texture, motion and shape information.

The shape information can occupy a large part of the bit stream associated to a VOP, especially for very low bit rate applications. Otherwise, as the eye is quite sensitive to the localization of edges in time and space, the shape data is to be encoded with a ”near to lossless” strategy.

A review on shape coding techniques in MPEG-4 framework can be found in [2]. The main idea remains the extraction of a subset of points from the original shape (the coding process) and the interpolation (linear, spline,..) of the selected points for reconstructing the approximated shape (the decoding process). The methods differ by the “intelligent” way to select characteristic points in order to obtain an optimal description of the original contour in a rate/distortion sense.

This paper addresses a new shape coding method based both on the skeleton of the object and on the local curvature of the object contour.

2. ADAPTIVE CONTOUR SAMPLING AND CODING

The proposed method is based on an adaptive sampling of a binary shape based on the object medial axis. The adaptability here consists in having less points for the regular parts where we have less details than for the areas having more significant details.

2.1. Local Feature Size (LFS) and the r-sampling

Let F be a smooth curve and $S \subset F$ a finite set of samples in F. We use a fairly generous and well-defined sampling condition in S. Precisely, we consider the notion of Local Feature Size (LFS) function which is used in computational geometry literature on mesh generation. This term was first introduced by Ruppert [3]. Based on this measure which depends on a proximity nearby feature for a point $p \in F$, the sampling condition quantifies the local “level of details” at a point p on a smooth curve. Formally, the LFS and the sampling condition named r-sampling are defined as follows (Fig. 1):

Definition 1 *LFS(p) of a point $p \in F$ is the Euclidean distance from p to the closest point m on the medial axis of F (Fig. 1).*

Definition 2 *The curve F is r-sampled by a set of samples S if every point $p \in F$ is within the distance*

$$r.LFS(p)$$

of a sample $s \in S$:

$$d(s,p) \leq r.LFS(p) \text{ with } r \leq 1 \tag{1}$$

The r-sampling is used in [4] as a condition for curve reconstruction from unorganized points. In next, we present a new binary shape coding algorithm based on the r-sampling adapted to the case of spatially organized points belonging to a given shape.

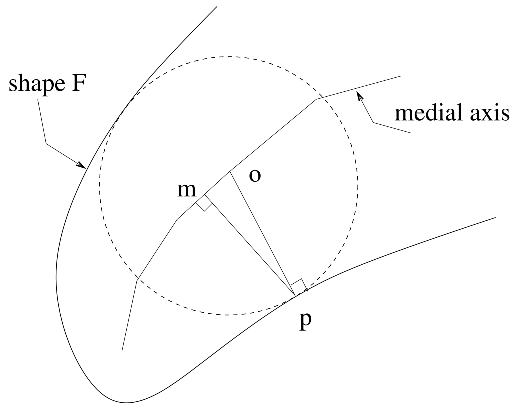

Fig. 1. LFS(p) is the distance d(p,m), not the perpendicular distance d(p,o) to the center of the largest empty tangent ball at p.

2.2. Weighting LFS with a Local Curvature Function and the r&c sampling

The introduction of a weighting function which depends on the local curvature c at a point p, brings an additional local information for sampling the shape. The idea using a convex function φ is to move away the sampling points when $c(p)$ is low and to take them closer when $c(p)$ increases. In [5], Davis studied such a scheme selecting points with high curvature as vertices of a polygonal approximation. This is illustrated by Fig. 2.

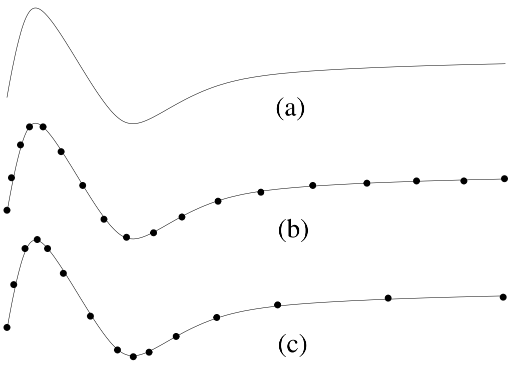

Fig. 2. Different sampling schemes: (a) original curve, (b) r-sampling, (c) r&c sampling.

The new sampling condition takes into account the curvature $c(p)$ at the considered point p using a weighting function φ. The **r&c-sampling** is defined as:

Definition 3 *The curve F is* **r&c-sampled** *by a set of samples S if every point $p \in F$ is within the distance*

$$r.\varphi(c(p)).LFS(p)$$

of a sample $s \in S$:

$$d(s,p) \leq r.\varphi(c(p)).LFS(p) \textit{ with } r.\varphi(c(p)) \leq 1$$
$$\varphi : [-\pi, \pi] \rightarrow [V_{min}, V_{max}] \tag{2}$$
$$\textit{and } \varphi(c(p)) = (V_{max} - V_{min})cos\left(\frac{c(p)}{2}\right) + V_{min}$$

A fast algorithm is developed to implement the r&c-sampling. We exploit the spatial organization of the points to improve the sampling process. The process is initialized with s_0 which is chosen among the points with a null LFS value. For each point $p \in F$, we check $d(s_0, p)$ until condition (2) is false. The following step is the search of the next sampling point s_1. For this, we march the contour from p, and for each candidate point s_1, we test the condition (2) until it is false. Once s_1 has been chosen, we have to check whether every point of F between p and s_1 fits the r&c-sampling condition given by definition 3. Let now s_0 be s_1 and iterate this process (Fig. 3). The set of consecutive points s forms the r&c-sampling set.

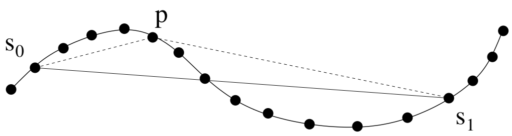

Fig. 3. Finding the r&c-sampling vertices.

2.3. Displacement vector coding

Once the representative points have been extracted from the original shape, their spatial positions have to be encoded. These points belong to a natural boundary and so the consecutive points are closely spaced. This indicates that there is a profit in encoding the points by a second order predictive scheme [2, 6]. The model used here is a simple predictive scheme in which the difference between the consecutively extracted points (the displacement vectors) are coded with an arithmetic coder, except the first absolute point position.

3. RESULTS

The r&c-sampling has been tested on various shapes and compared to the B-spline approach. On synthetic and natural smooth shapes, these two approaches give equivalent sampling results. Fig. 4(a) shows the original contour of Australia (1730 points) presenting details with quite high resolution, as well as its internal and external skeletons. Fig. 4(b) and 4(c) show the sampled contour for different values of $r.\varphi(c(p))$ superimposed on the original one. Note that we choose this contour because of its complex aspect presenting high level details. The number of sampled points as well as the computed errors can be found in Table 1.

In order to measure the distortion between the original and approximated shapes, two different and complementary error metrics are considered: the mean square error (MSE) and the infinity norm error. The reduction of samples obtained (Table 1) is satisfactory associated to a quite low reconstruction error for the two measures. This is also confirmed by the visual quality of Fig. 4(b) and 4(c).

Table 2 resumes the errors when the reconstruction of the Australian map is obtained using cubic B-spline curves. In order to compare the results, the number of control points for B-spline curves are fixed the same as the number of selected samples obtained with the r&c sampling (Table 1). When the expresion $r.\varphi(c(p))$ is low (≤ 1), the r&c-sampling leads to quite small MSE values. This corresponds to a reconstruction with high level details (high resolution). In this case, the infinity norm error is similar for both approaches. When the expression $r.\varphi(c(p))$ increases, the performance of B-spline curves becomes better. This is essentially due to the high reconstruction errors localized on the smooth parts of the contour (Fig. 4(c)) for the r&c-sampling method. However, it is possible to reduce these local errors by increasing the influence of the local curvature weight $\varphi(c(p))$ in expression (2).

The first results obtained with this new binary shape sampling and coding technique are encouraging. The optimization of the parameter r and the function φ as well as the comparison of the results with other techniques [2], especially with the baseline method [7] and the block-based context arithmetic encoding retained for MPEG-4, are under investigation.

4. REFERENCES

[1] R. H. Koenen, F. Pereira, and L. Chiariglione, "Mpeg-4: context and objectives," *Image Communication*, vol. 9, pp. 295–304, 1997.

[2] A. K. Katsagellos, L. Kondi, F. W. Meier, J. Ostermann, and G. M. Schuster, "Mpeg-4 and rate distortion based shape coding techniques," *Proceedings of IEEE*, pp. 1126–1154, June 1998.

[3] J. Ruppert, "A new and simple algorithm for quality two-dimensional mesh generation," in *ACM SIAMES Symposium and discrete Algorithms*, 1993, pp. 83–92.

(a) Original contour and its skeletons

(b) Comparison between original and approximated contour with $r.\varphi(c(p)) = 0.5$

(c) Comparison between original and approximated contour with $r.\varphi(c(p)) = 5.0$

Fig. 4. Experimental results using the Australian map with 1730 original samples.

$r.\varphi(c(p))$ for r&c-sampling	**Selected samples**	**MSE**	**Infinity norm error**
0.1	908	0.02	1.0
0.3	749	0.12	1.4
0.5	574	0.19	2.1
0.7	554	0.31	3.7
1.0	444	0.37	4.4
3.0	194	1.15	7.9
5.0	143	1.65	15.5
10.0	108	2.25	13.4

Table 1. Number of sample points and reconstruction errors obtained for different values of $r.\varphi(c(p))$ (Australian map with 1730 original samples).

Number of control points for B-spline curves	**MSE**	**Infinity norm error**
908	0.23	1.0
749	0.26	1.2
574	0.30	1.5
554	0.31	1.7
444	0.34	1.8
194	0.57	2.5
143	0.69	3.1
108	0.92	4.2

Table 2. Reconstruction errors obtained using cubic B-spline curve with different numbers of control points (Australian map with 1730 original samples)

[4] N. Amenta, M. Bern, and D. Eppstein, "The crust and the beta-skeleton: combinatorial curve reconstruction," *Graphical Models and Image Processing*, vol. 60/2, no. 2, pp. 125–135, 1998.

[5] L. Davis, "Understanding shape : angles and sides," *IEEE Transaction on Computers*, vol. 26, no. 3, pp. 236–242, 1977.

[6] R. Nygaard, J.H. Husøy, and D. Haugland, "Compression of image contours using combinatorial optimization," in *Proc. of ICIP'98*, Chicago, Il, Oct. 1998.

[7] S. H. Lee, D.-S. Cho, Y.-S. Cho, S. Son, E. S. Jang, J.-S. Shin, and Y. S. Seo, "Binary shape coding using 1-D distance value from baseline," in *Special session on shape coding, ICIP'97, Santa Barbara, CA*. IEEE, Oct. 1997, vol. I, pp. 508–511.