SHREC’08 Entry: Multi-view 3D Retrieval using Multi-scale Contour Representation

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ABSTRACT
We describe in this paper a method for 3D shape indexing and retrieval that we apply on three data collections of the SHREC-SHape Retrieval Contest 2008: Stability on watertight, CAD and Generic 3D models. The method is based on a set of 2D multi-views after a pose and scale normalization of the models using Continuous PCA and the enclosing sphere. In all views we extract the models silhouettes and compare them pairwise. To compute the similitude measure we consider the external contour of the silhouettes, we extract their convexities and concavities at different scale levels and we build a multiscale representation. The pairs of contours are then compared by elastic matching achieved by using dynamic programming.

1 INTRODUCTION
We proposed a 2D/3D method for the 3D Shape Retrieval Contest 2008. It is based on a multi-view approach which keeps 3D model coherence by considering simultaneously a set of 2D images in specific view directions. The various silhouettes of a model being strongly correlated, using a set of them help to better discriminate one model among others.

First of all, we have to get a robust normalization of the model pose and model scale in order to remain invariant to various geometrical transformations (translation, rotation, scaling). We used a Continuous Principal Component Analysis [4] and the smallest enclosing sphere [3] to solve these problems.

The approach is based on a multiscale representation of the external closed contour of non rigid 2D shapes presented in [1]. We capture a set of views of a model and for each view we extract and normalize the external border of the silhouette. Then we build a multi-scale shape representation of the contour where for each contour point we store information on the convexities and concavities at different scale levels. We then search the optimal elastic match between each pair of silhouettes by minimizing the distance between matched contour points and we integrate the distance over the silhouettes pairs.

Section 2 presents the normalization method for the 3D models. Section 3 presents the contour convexities and concavities approach. Experimental results are shown in section 4.

2 MODEL NORMALIZATION
Before comparing 3D models we need to proceed to a robust normalization of their pose and scale in order to remain invariant to various geometrical transformations (translation, rotation, scaling). For the center and the scale, we use the smallest enclosing sphere $S$ [3]. The normalization then becomes:

$$x = \frac{x - c_x(S)}{d(S)}, \quad y = \frac{y - c_y(S)}{d(S)}, \quad z = \frac{z - c_z(S)}{d(S)}$$

where $d(S)$ is the diameter of $S$ and $c_i(S)$, $i = x, y, z$ are the i-th coordinates of its centre. The use of the smallest enclosing sphere has several advantages: it is fast to calculate, it allows maximizing the model size inside the unit sphere and then its silhouette size in any view direction, with the guaranty that the silhouette remains inside the unit disc inscribed in the image domain associated to this view (no risk of accidental cropping of the silhouette).

For the normalization of the model pose we use the Continuous Principal Component Analysis [4] which defines and orientates the three principal axis of a model in a robust way and at a very reasonable computation cost.

3 CONTOUR CONVEXITIES/CONCAVITIES DESCRIPTOR
3.1 Signature extraction
After the above model normalization, some errors in 3D pose alignment may remain which result from the limitation of Continuous Principal Component Analysis. To rectify these possible errors we compute the 48 possible poses of an object corresponding to the $(3! =) 6$ possible permutations of the 3 PCA axis (rotations) multiplied by $(2^3 =) 8$ possible orientations of the PCA axis (mirrors).

In 2D/3D methods 3D object coherence is reinforced by considering simultaneously a set of images in specific view directions. The various silhouettes of an object being strongly correlated, using a set of them help to better discriminate one object among others [2]. For this, we can use any set of view directions regularly distributed in space. We consider here two sets, the first one is represented by the three orthogonal views along the oriented principal axis with parallel projections. The second one is represented by the three first one plus their six bissectors.

Figure 1: Smallest enclosing sphere.
We choose an image size of 256x256 for each silhouette. This resolution gives a good precision and a reasonable computation time. The descriptor of a silhouette contour $C$ is obtained by normalizing the contour length with $N=100$ sampled contour points and by extracting convexity/concavity information at each sampled contour point and at $K=10$ scale levels [1]. The representation can be stored in the form of a $K*N$ matrix where the columns correspond to contour points (parameter contour $u$) and the rows correspond to the different scale levels $\sigma$. The position $(u, \sigma)$ in this matrix contains information about the degree of convexity or concavity for the contour point $u$ at scale level $\sigma$. The simplified boundary contours at the different scale levels are obtained via a curve evolution process. It should be noted that we use the same number of sample contour points at each scale. Let the contour $C$ be parameterized by arc-length $u : C(u) = (x(u), y(u))$, where $u \in [0, N-1]$. The coordinate functions of $C$ are convolved with a Gaussian kernel $\phi_\sigma$ of bandwidth $\sigma \in \{1, 2, ..., \sigma_{max=K}\}$. The resulting contour $C_\sigma$ becomes smoother with increasing $\sigma$ value, until it becomes convex for a sufficiently large $\sigma$.

The convexity/concavity of the curve is defined as the displacement of the contour between two consecutive scale levels. If we denote the contour point $u$ at scale level $\sigma$ as $p(u, \sigma)$, the displacement $d(u, \sigma)$ of the contour between two consecutive scale levels at point $p(u, \sigma)$ is defined as the Euclidian distance between locations of $p(u, \sigma)$ and $p(u, \sigma-1)$.

$C(u) = (x(u), y(u))$, $u \in [0, N-1]$.

The distance between two models is first defined as the sum of the distances of contour points along the three (or nine) pairs of silhouettes, one pair per view direction:

$$d(A, B) = \sum_{\text{views}} \sum_{u_A = u_B = 0}^{N-1} d(u_A, u_B)$$

To find the best pose of the query object, we compute the distance between the object B and each 48 pose of the query object. So, we keep the pose with the minimal distance.

With the silhouettes of the best pose of the query object we use a dynamic programming method with an $N * N$ distance table to conveniently examine the distances between corresponding contour points on both shapes. The columns represent contour points of one shape representation $u_A$ and the rows represent the contour points of the other $u_B$. Each row/column entry in the table is the distance $d(u_A, u_B)$ between the two corresponding contour points calculated according to the previous equation.

Finding the optimal match between the columns corresponds to finding the lowest cost diagonal path through the distance table.

3.2 Signature matching

When comparing two contours A and B, it is necessary to examine the distance between each sampled contour point of both contours. If two contour points $u_A$ and $u_B$ are represented by their multi-scale features $d_A(u_A, \sigma)$ and $d_B(u_B, \sigma)$ respectively, then the distance between the two contour points can be defined as:

$$d(u_A, u_B) = \frac{1}{K} \sum_{\sigma=1}^{K} |d_A(u_A, \sigma) - d_B(u_B, \sigma)|$$

The distance between two models is first defined as the sum of the distances of contour points along the three (or nine) pairs of silhouettes, one pair per view direction:

$$d(A, B) = \sum_{\text{views}} \sum_{u_A = u_B = 0}^{N-1} d(u_A, u_B)$$

Figure 2: Example of extracting the MCC shape representation: (a)-original shape image, (b)-filtered versions of the original contour at different scale levels, (c)-final MCC representation for 100 contour points at 14 scale levels.

Figure 3: Matching of two MCC representations by using dynamic programming.

4 EXPERIMENTAL RESULTS

We propose two runs for the each track of SHREC’08. The contour convexities and concavities descriptor with pose invariance (rotations and mirrors) have been computed with 3 silhouettes (Run1) and 9 silhouettes (Run2).

5 CONCLUSION

We have tested the contour convexities and concavities descriptor on the SHREC’08 contest. We observe that we obtain good results for this approach. We can notice that this method is very robust with small deformations of an object. However the method needs important computation time (Run1 / Run2: descriptors extraction for one model = 0.18s / 0.24s, time per pair matching = 0.025s / 0.074s, on a P4, 3.2GHz, 2Go Ram). This weakness could be partly reduced by optimizing the source code.

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REFERENCES


