Middle East Technical University
Department of Computer Engineering

A dynamic procedure for forming shape categories from skeletal shape trees

Aykut Erdem

METU-CENG-TR-2007-04

July 2007

Department of Computer Engineering
Middle East Technical University
İnönü Bulvarı, 06531, Ankara
TURKEY

The first version of this METU-CENG Technical Report is published previously as an internal report of Image Processing and Pattern Recognition Lab. in Dec. 2006.

Abstract

This report presents a dynamic procedure for the formation of category trees from a collection of skeletal shape trees. It overcomes several shortcomings of the formation procedure proposed by Baseski [4]. Unlike the method in [4], the structure of a category tree is not fixed at the beginning and can be updated in a dynamic way as a new example is considered. By this way, the true nature of category concept that is *flexibility* can be achieved.

1 Introduction

As a well studied problem in pattern recognition and computer vision literature,*categorization* refers to the action of grouping together similar objects. After obtaining this information, how to represent each category is an interrelated and open issue. Strongly depending on object *representation* [10], different computational models are proposed [13]. The most common ones can be grouped into two as *feature* and *similarity* based approaches. While the feature based methods tries to distinguish common features (or primitives) and represent categories with them [11, 6, 14, 19, 8], the similarity based methods examines ways of describing a category with a few number of representative members (or prototypes [12]) based on computed similarities [5, 7, 3, 15].

In [4], Baseski proposed a compact way of representing shape categories. The major novelty lies on the representation used to describe shapes. Once a coarse skeleton of a shape is extracted by the method of Aslan and Tari [2, 1], the shape can be expressed as a rooted, ordered, depth-1 tree (Figure 1). The nodes of that tree structure hold certain skeletal attributes (*i.e.* location where the skeleton branch terminates,branch length and branch type (positive or negative, corresponding either a protrusion or an indentation respectively)).

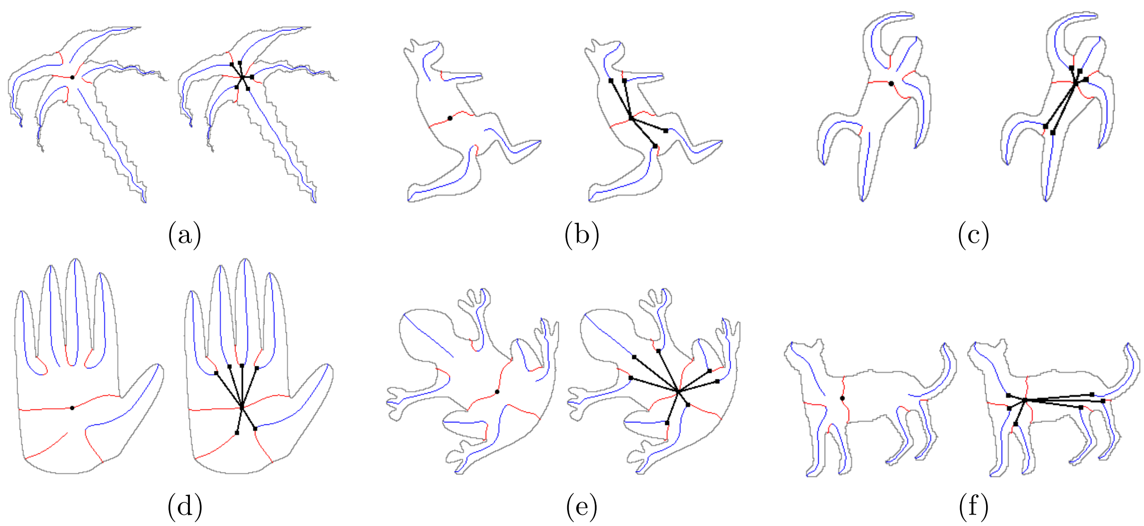


Figure 1: (a)-(f) Some shapes and the corresponding shape trees from the extracted skeleton structures. Positive skeleton branches are shown in blue whereas negative ones are shown in red.

Given two shape trees, in order to match these structures more efficiently, the nodes are labeled according to an ordering of branches. The ordering can be started with either one of the negative branches that reach the shape center. In this respect, multiple descriptions of a shape is obtained and stored for each such choice (Figure 2) [4]. Note that for a shape having n-fold symmetry, there are n possible major negative branches [4]. Since the depth of shape trees is always one, shape matching process is simply reduced into string matching process and a tree edit based algorithm is adopted for that purpose [16].

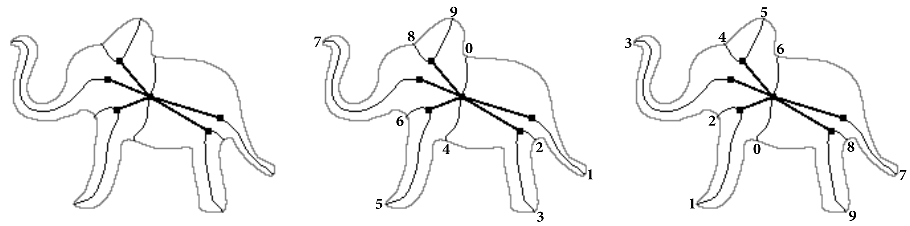


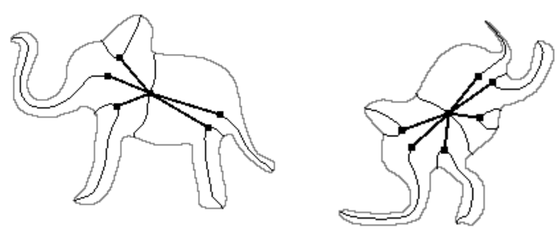
Figure 2: Multiple descriptions obtained using two different orderings of skeleton branches. Notice that the symmetry is two-fold at the center.

As described in [4], shape categories can also represented with the same compact data structure, *i.e.* they are also expressed as depth-1 trees. In this respect, a category tree is a union of shape trees whose nodes hold a list of attributes collected from the category members. The previously proposed method for forming category trees is based on a static view. Given a collection of shape trees, the structure of the corresponding category tree is fixed at the beginning and it is formed by using all the existing samples at once. Hence, observing a new member may require a re-formation of the category tree from scratch.

In this report, an alternative, dynamic way of constructing category trees is presented. Thus, by the proposed method, we overcome the shortcomings of the previous formation procedure and this will open up new possibilities for use of category tree structure. In Section 2, I summarize and make a critique of Baseski's formation procedure of category trees [4]. In Section 3, the proposed dynamic formation procedure is introduced. Lastly, Section 4 is the concluding remarks and discussion.

2 Baseski's procedure for forming category trees

In devising his procedure, Baseski's key observation is that shape tree representations of shapes in the same category do not always have equal number of nodes (*i.e.* skeleton branches). In some cases, some extra branches may appear. This is either due to within category variability or due to an artifact of shape deformations (Figure 3).



(a) (b)

Figure 3: Shape trees of two elephant shapes having (a) ten leaf nodes (b) twelve leaf nodes.

Consequently, the previously proposed formation procedure is as follows: Given a set of shape trees, first, the shape tree having the maximum number of nodes is selected. Referred as the *base tree*, that shape tree simply specifies the structure of the category tree. Afterwards, the remaining shape trees are all matched with this base tree and the category tree is formed based on the correspondences among nodes.

However, this procedure has some shortcomings. First, the structure of the category tree is fixed and addition of a new shape may require a re-formation from scratch. Second, this procedure does not guarantee the inclusion of all the available information. An illustration is given in Figure 4.

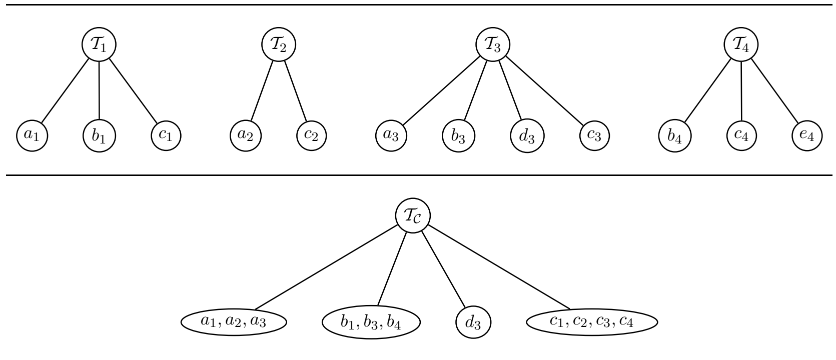


Figure 4: Static formation of a category tree. $\mathcal{T}_3$ is the base tree. Correspondences among nodes are specified by labeling the matched nodes with identical letters. Node e_4 in $\mathcal{T}_4$ is eliminated in forming the category tree $\mathcal{T}_\mathcal{C}$ since it matches to none of the nodes of the base tree.

3 A dynamic procedure for forming category trees

The alternative formation procedure, proposed in this report, is as follows: Given a set of shape trees, at first pairwise dissimilarities are computed. The tree having the minimum total dissimilarity is thought to be the most representative shape tree for a given set. Then, the category tree is enlarged incrementally by merging it with the remaining trees in ascending order of total dissimilarities. In matching, removing a node from the category tree is prohibited by setting a large value for the cost of `remove` operation and merging with trees having smaller dissimilarities first increases the accuracy of obtained correspondences. An illustration is given in Figure 5). This process is dynamic in the sense that the structure of the category tree is modified on the fly and can be updated as new shapes are acquired.

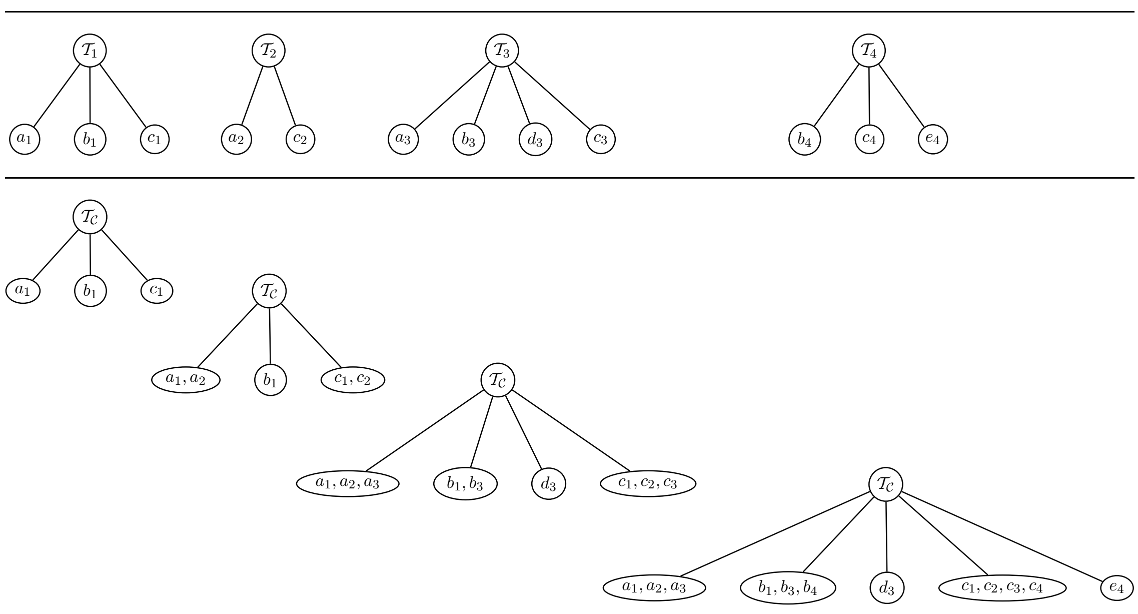


Figure 5: Dynamic formation of a category tree. The category tree $\mathcal{T}_\mathcal{C}$ is enlarged sequentially with the shape trees $\mathcal{T}_1$, $\mathcal{T}_2$, $\mathcal{T}_3$ and $\mathcal{T}_4$.

4 Concluding remarks and discussion

This report presents an alternative way of forming category trees from skeletal shape trees. This newly proposed method is free of the shortcomings of the previous method [4]. Since the procedure is based on a dynamic view, it brings *flexibility* into category trees and we hope this will open new possibilities for the utilization of category tree data structure.

Additionally, it should be noted that the proposed procedure resembles construction of *tree unions* from shock trees [17]. However, unlike category trees, the union of two shock trees [15, 9] may not naturally result in a tree structure but it may be a graph as well. Torsello and Hancock introduced additional heuristics to overcome this issue. However, in conceptual term, the main distinction lies in the utilization of the resulting tree structures. A tree-union provides an embedding of shock trees in a pattern space where each of its node corresponds to a dimension of the pattern space. By this way, each shock tree is represented with a fixed length vector in this space. Lately, tree-unions are also utilized for unsupervised learning of shape categories [18]. On the other hand, category trees are container structures used to represent shape categories.

References

[1] C. Aslan. Disconnected skeleton for shape recognition, May 2005. M.Sc. thesis, Dept. of Computer Engineering, Middle East Technical University.

[2] C. Aslan and S. Tari. An axis-based representation for recognition. In *ICCV*, pages 1339–1346, 2005.

[3] S. Duvdevani Bar and S. Edelman. Visual recognition and categorization on the basis of similarities to multiple class prototypes. *IJCV*, 33(3):201–228, 1999.

[4] E. Baseski. Context-sensitive matching of two shapes, July 2006. M.Sc. thesis, Dept. of Computer Engineering, Middle East Technical University.

[5] R. Basri. Recognition by prototypes. In *CVPR*, pages 161–167, 1993.

[6] I. Biederman. Recognition-by-components: A theory of human image understanding. *Psychological Review*, 94(2):115–147, 1987.

[7] R. P. W. Duin, D. Ridder, and D. M. J. Tax. Experiments with a featureless approach to pattern recognition. *Pattern Recognition Letters*, 18(11):1159–1166, 1997.

[8] R. Fergus, P. Perona, and A. Zisserman. Object class recognition by unsupervised scale-invariant learning. In *CVPR*, volume 2, pages 264–271, 2003.

[9] P. N. Klein, T. B. Sebastian, and B. B. Kimia. Shape matching using edit-distance: an implementation. In *Symposium on Discrete Algorithms*, pages 781–790, 2001.

[10] D. Marr. *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information.* W. H. Freeman San Francisco, 1982.

[11] D. Marr and H. K. Nishihara. Representation and recognition of the spatial organization of three-dimensional shapes. *Royal Society of London Proceedings Series B*, 200:269–294, 1978.

[12] E. Rosch. *Principles of Categorization*, pages 189–206. Hillsdale NJ: Erlbaum 1978. (Reprinted in Concepts: Core Readings. Edited by E. Margulis and S. Laurence. Cambridge MA: MIT Press, 1999.

[13] Edelman S. Computational theories of object recognition. *Trends in Cognitive Sciences*, 1:296–304, 1997.

[14] E. Sali and S. Ullman. Combining class-specific fragments for object classification. In *BMVC*, 1999.

[15] T. B. Sebastian, P. N. Klein, and B. B. Kimia. Shock-based indexing into large shape databases. In *ECCV*, volume 3, pages 731–746, 2002.

[16] D. Shasha and K. Zhang. Approximate tree pattern matching. In *Pattern Matching Algorithms*, pages 341–371. Oxford University Press, 1997.

[17] A. Torsello and E. R. Hancock. Shape-space from tree-union. In *ICPR*, volume 1, page 10188, 2002.

[18] A. Torsello and E. R. Hancock. Learning shape-classes using a mixture of tree-unions. *IEEE Trans. Pattern Anal. Mach. Intell.*, 28(6):954–967, 2006.

[19] P. Viola and M. Jones. Rapid object detection using a boosted cascade of simple features. In *CVPR*, pages 511–518, 2001.