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Shape Classification Using Tree -Unions

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Abstract

In this paper, we proposed a novel approach to shape classification. A new shape tree based on junction nodes can represent the global structure in a simple way. The statistic distribution of junctions can be learned by merging the shape trees. In the process of learning, context of a junction node is obtained to improve the rate of classification. We illustrate the utility of the proposed method on the problem of 2D shape classification using the new shape tree representation.

1. Introduction

Classification has been an important goal in image analysis and pattern recognition. The supervised learning of shape from a set of training examples is considerably of practical importance in the field of computer vision. One problem remains to be how to represent shape variants. Usually, contour and skeleton are used to describe shapes. Contour-based approaches, however, cannot well deal with structural variation and articulation [9, 10, 11]. In our paper, therefore, we use skeleton-based model, since skeleton combines geometrical and topological features of the objects [3]. The basic idea is that junction nodes contain plenty of local structural information (see Fig.1). Hence, the proposed method combines junction nodes and Bayesian classifier together.

As for the learning part, we use the tree-union model proposed in [2], even though our shape tree is different from [2]. Tree-union integrates all variability within a shape class and therefore can represent a shape class well. In addition, trees are frequently used to represent the hierarchical arrangement of the parts of shape-primitives [12]. The main obstacle for tree-based matching is, however, that it is difficult to extract feature vectors from trees to learn shape-classes. To overcome this problem, the aim in this paper is to develop a novel method to learn a tree-based model from a set of example trees.

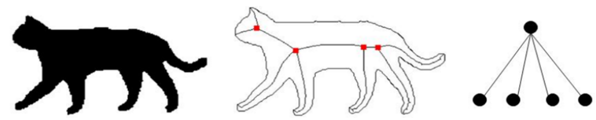

Figure 1. A shape tree for a skeleton.

We conclude our contributions into two aspects. The first contribution is the new shape tree which consists of junction nodes. Junction nodes connect several main skeleton paths and contain the main structure. Trees based on junction nodes can well represent the hierarchical arrangement of parts of shapes. The second contribution is that we improved our rate of classification by learning the context of nodes in the shape trees.The context of a node can help recognize the range of distances between a shape class. And the penalty function based on the learned context can greatly improve the rate of classification.

2. Learning the tree union

2.1 Shape representation

In this paper, all the skeletons of shapes are extracted and pruned by the method introduced in [15]. In Fig.1, we show a typical skeleton including critical points and shortest paths between junction points and endpoints. These concepts are introduced in [14]. In this paper we consider skeleton paths from junction points to skeleton endpoints. Let sp denotes a skeleton path. We sample the path sp with M equidistant points, which are all skeleton points. Let R and R' denote the vectors of radii of two paths sp and sp' respectively, L and L' denote the lengths of sp and sp' respectively, then the path distance between sp and sp' is:

$$pd(sp, sp') = \sum_{i=1}^{M} \frac{(r_i - r_i')^2}{r_i + r_i'} + \lambda \frac{(l_i - l_i')^2}{l_i + l_i'} \quad (1)$$

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where λ is a weight factor. In order to make the representation scale invariant, the path lengths and radii are normalized. Let v denote a junction node of a shape tree. Since junction nodes are very important to our model, it is essential to find the correspondence of junction nodes. Assume the number of paths connected with a junction node v_i is K, and the number of paths connected with another junction node v'_j is N, then we have a matrix of path distances: Then we apply OSB algorithm to the matrix, we can get the distance of two junction nodes:

$$Jd(v_i, v'_j) = OSB(pathdis(v_i, v'_j)) \tag{2}$$

2.2 Learning a tree union

For each shape class, we can construct a tree union that integrates some useful knowledge from all the labeled shapes of the class. Given two tree models T_1 and T_2, we wish to construct a union whose structure respects the hierarchical constraints present in both T_1 and T_2. Posed as the merge of two structures, the correspondence problem is reduced to finding the set of nodes in T_1 and T_2 that are common to both trees. Here we apply a simple rule to solve this problem. Assume a base tree has a set of critical nodes, in this case skeletal junction nodes $V = \{v_1, v_2, \ldots, v_L\}$, and a critical node v' of another tree needs to be matched. Then the matched node to v' is:

$$matched\{v'\} = \arg\min_{v_i}\{Jd(v_i, v'_j)\}, v_i \in V \tag{3}$$

Note that this simple rule cannot guarantee a one-to-one correspondence. The main function of this matching rule is to compute the nodes' probability of being matched which will be used in later classification. After the correspondence of junction nodes is found, we can merge shape trees to a base tree in the same class. Fig. 2 provides an example of the process of merging a shape tree to a base tree. After merging shape trees to a base tree, the nodes that represent features have a greater probability while nodes that are less common have smaller probability. In Fig 2, nodes which have greater probability are darker in color.

Let m_i denote the number of nodes v_i that are matched to nodes of the base tree including itself, the probability of is defined as:

$$prob(v_i) = \frac{m_i}{\sum m_i} \tag{4}$$

The idea behind the probability of junction nodes is that nodes of greater probability are features of the shape skeleton and can well represent the structural information of the shape while other nodes of smaller probability are more likely to be structural noise. In the process

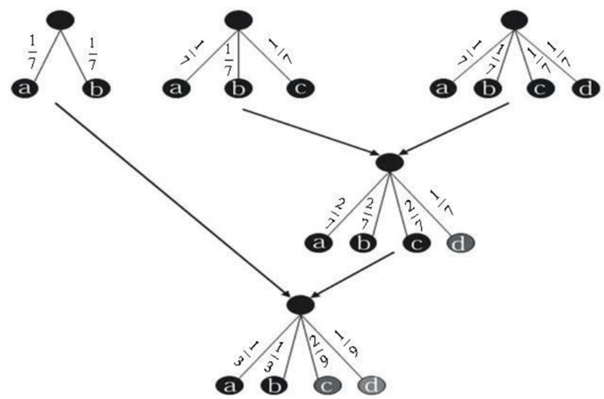

Figure 2. Example of merging shapes trees to a base tree.

of constructing a tree union, we can collect additional information that will help classification. A union of shape trees can provide a context that will set a scope of dissimilarity between critical nodes within a class. For each nodes of the base tree of a certain class, we can store every distance between it and some other nodes that are matched to it. Therefore, a node of a base tree can hold a list of attributes collected from the construction of a tree union. These attributes are the observed ranges for the dissimilarity of nodes (d_{max} and d_{min}) and the frequency of the node. These attributes will be very useful in the classification later.

3. Bayesian classification using tree unions

Compared to the method in [13], which uses skeleton to perform a classification task, our method uses critical nodes. In [13], all paths are assumed to have equal probability and therefore the method is susceptible to noise. However, our method relies on learned critical nodes probabilities and therefore nodes that are noise will have little impact on the result of Bayesian classifier. Furthermore, through supervised learning we can achieve a context that will be very helpful to accurate classification. For a given query shape and a given shape class, we aim to compute the probability that shape belongs to the class. This step is repeated for all shape classes, and then the query shape is assigned to the class with the highest probability.

Given a query shape w', we construct a shape tree $\Gamma(w')$ as the input of Bayesian classifier. For a query shape tree, we assume the number of critical nodes is n, and the number of nodes of a base tree of a shape class is m. We use the Gaussian distribution to compute the similarity of two critical nodes:

$$p(v'|v) = \frac{1}{\sqrt{2\pi\alpha}} \exp(-\frac{Jd(v',v)^2}{2\alpha}) \tag{5}$$

This probability is high for two different junction nodes with small dissimilarity. Different shape classes may use a different α. To improve this formula we utilize the learned context of junction nodes of a base tree and defined a penalty γ as:

$$\gamma = \begin{cases} \beta\frac{Jd(v',v)}{d_{min}(v)} & \text{if } Jd(v',v) < d_{min}(v) \\ 1 & \text{if } d_{min}(v) < Jd(v',v) < d_{max}(v) \\ \frac{1}{\beta}\frac{d_{max}(v)}{Jd(v',v)} & \text{if } Jd(v',v) > d_{max}(v) \end{cases} \tag{6}$$

Here β is a weighted factor. In our paper, we use $\beta = 2$. Thus, the probability p that a given junction node v' is similar to a junction node v of a base tree is:

$$p(v'|c_i) = \sum_{v\in\Gamma(c_i)} p(v'|v)p(v|c_i) \tag{7}$$

The class-conditional probability of observing v' given that w' belongs to class c_i is: Here $p(v/c_i)$ is learned through the construction of a tree union of a shape class. According to the probability that the query shape belongs to a given class, the posterior probability of a class given that junction node $v' \in \Gamma(w')$ is determined by Bayes rule:

$$p(v') = \sum p(v'|c_i)p(c_i) \tag{8}$$

We assume there are M shape classes, and all the shape classes are equiprobable which means $p(c_i) = 1/M$ and we have

$$p(c_i|v') = \frac{p(v'|c_i)p(c_i)}{p(v')} \tag{9}$$

Through the above formulas, we can get the posterior probability of all junction nodes of $\Gamma(w')$ By summing the posterior probabilities of a class over the set of junction nodes in the query shape tree, we obtain the probability that it belongs to a given shape class.

$$p(c_i|\Gamma(w')) = \sum_{v'\in\Gamma(w')} p(c_i|v') \tag{10}$$

Obviously, the input shape belongs to the class C_m that has the greatest probability

$$C_m = \arg\max_i p(c_i|\Gamma(w')) \tag{11}$$

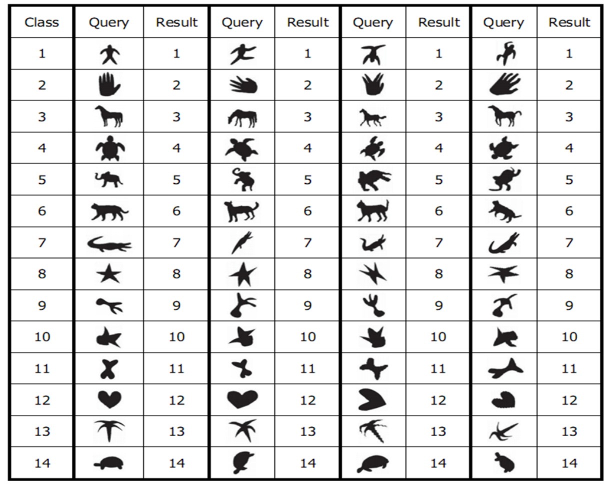

Figure 3. Results of the proposed method on Aslant and Tari' 56 database. There is no error.

4. Experiments

In this section, we test the proposed method of classification on the database of Aslan and Tari [4]. This database consists of 14 classes of articulated shapes of large variations with 4 shapes in each class. We use each shape in this database as a query, and the other 3 shapes to learn and construct a shape tree union. Fig. 3 shows the classification result of our system. The first column of the table in Fig. 3 represents the class of each row. For each row, there are four experimental results which belong to the same class. If the classification result is correct, it should be the same with the first column of the row. Since there are no errors in 56 classification results, the classification accuracy by this measure is 100%. Hence we can conclude that our method is very successful in this database.

We compared our method to the methods presented by X. Bai et al [13] and by Sun and Super [6]. They used the same Bayesian classifier but based on paths and contour parts respectively. We also compare our method to the inner distance [5] on this data set. As Table 1 shows, our method is better than other methods on this database. We also applied the proposed method to a larger database which includes 30 classes with 6 shapes in each class. To our encouragement, we also achieve no errors in the 180 classification results.

In addition, we also tested our method on the Kimia data set [11], which includes 18 classes, and each class consists of 12 shapes. In each experiment, we removed the query shape from the database, leaving others to

Table 1. Comparison of different algorithms on the database of Aslan and Tari.

ALGORITHM	IDSC	BAI'S	SUN'S	OURS
ACCURACY	94.64%	98.2%	92.8%	100%

Table 2. Comparison of different algorithms on the kimia 216 database.

ALGORITHM	BAI'S	SUN'S	OURS
ACCURACY	94.1%	97.2%	97.7%

learn and construct a tree union. Since there were only 5 errors in 216 classification results, the classification accuracy is 97.7%. We illustrate some of the results in Fig. 4 . We also show the 4 incorrect results in Fig. 4 which are marked in red. On this data set, we also compared our method to the methods presented by Xiang Bai [13] and by Sun and Super in [6].Table 2 shows the result of comparison. It takes about 1.5, 5 and 8 min to classify 56, 180 and 216 shapes on Core Duo i7-920 processor, respectively.

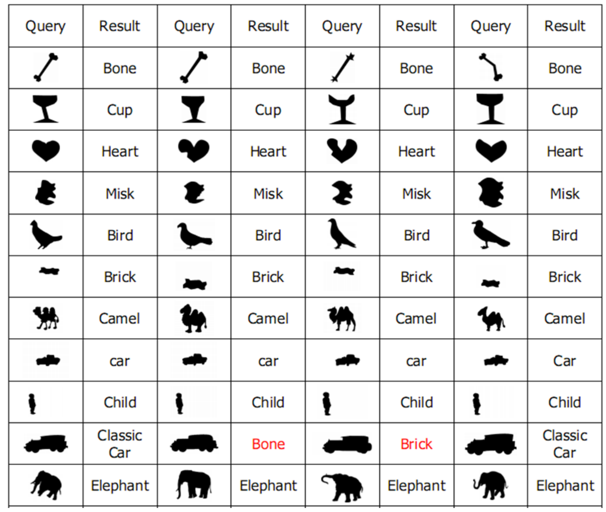

Figure 4. Part of classification results on Kimia 216 dataset, the errors are marked in red.

5. Conclusion

In this paper, we have presented a novel method to shape classification based on statistics of distances of junction nodes. As critical points of a skeleton, the junction nodes contain structural information of a shape. By constructing and learning a tree-union, we had improved the accuracy of Bayesian classification.In the future, our work will focus on combining the junction nodes and end nodes to construct a classifier and providing a more accurate matching method which takes consideration of the structures of skeleton.

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