TEXTURE SEGMENTATION WITH ANTS

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1. Overview

In this work, a novel algorithm for texture classification is presented. The proposed algorithm employs dyadic Gabor filter banks for extracting discriminant features from images containing multiple textures not known to the algorithm. The clustering of feature space is inspired by the self-assembling behavior observed in real ants and builds trees based on similarity of feature vectors. Self-assembly behavior is observed in biological ants when building live structures with their bodies. We show that the feature data can be hierarchically organized in a tree, resembling the self-assembly behavior in real ants, where each artificial ant represents a feature vector and is attached to one of the tree branches depending on its similarity with the ants on the branches. Classification results using our ant clustering algorithm are shown to be comparable to the commonly used *k*-means clustering algorithm using the same feature data. A major disadvantage of *k*-means is that it can get stuck in local minima in high-dimensional vector spaces. The proposed algorithm uses similarity scope for partitioning the feature data and uses a probabilistic approach to avoid local minima. The results thus obtained show promise of the algorithm.

2. Ant Tree Model

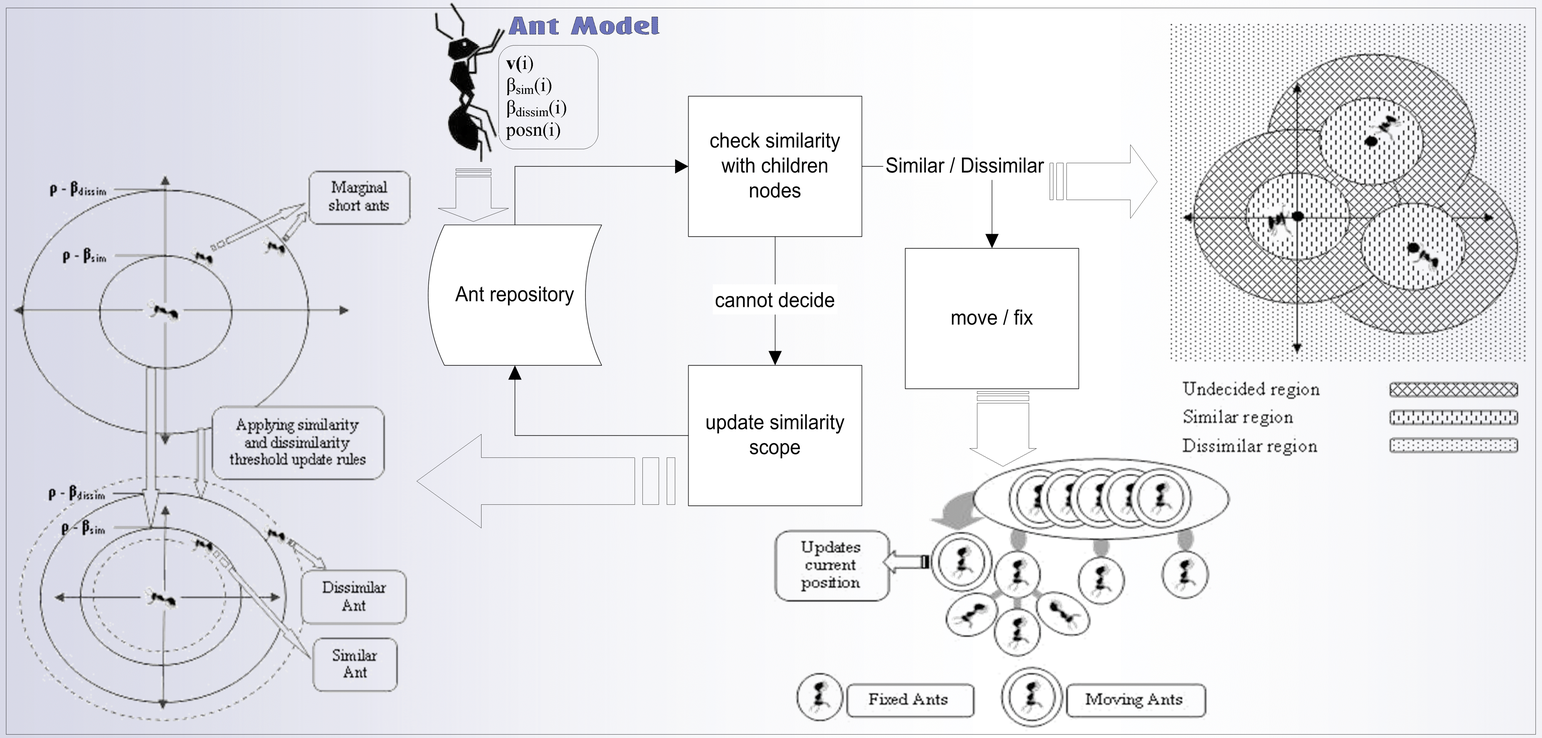

Figure 1. Ant Tree Construction Model

3. Similarity Estimation

$$\xi(i,j) = \rho - \sqrt{\frac{1}{M}\left(\sum_{k=1}^{M}(v_{ik} - v_{jk})^2\right)}$$

Here, ξ is the similarity measure between ants *i* and *j*, *M* is dimensionality of feature vectors *v*, ρ is the similarity scope value and is used to allow the ant *j* to consider all those ants that lie in the range of ρ units, as similar to it and can be grouped together.

4. Threshold Update

$$\beta_{sim}(i) \leftarrow \beta_{sim}(i) \times 0.9$$

$$\beta_{dissim}(i) \leftarrow \beta_{dissim}(i) + 0.01$$

Here, *i* represents the ants whose threshold is being updated. The β_{sim} and β_{dissim} are initialized with the values $\rho/2$ and 0 respectively, where ρ is the similarity scope.

5. Similarity and dissimilarity rules

Following rules are used to define similar and dissimilar ants:

1. If $\xi(i,j) > \beta_{sim}(i)$, then ant i is similar to ant j.
2. If $\xi(i,j) < \beta_{dissim}(i)$, then ant i is dissimilar to ant j.
3. If $\xi(i,j) \geq \beta_{dissim}(i)$ and $\xi(i,j) \leq \beta_{sim}(i)$, then ant i is neither similar nor dissimilar to ant j and needs further processing.

6. Convergence

All immediate children of the tree root are grouped together with their respective descendants to form data partitions. Centroids of all groups (or partitions) are calculated and are used in the following iteration as artificial ants connected to the tree before any other ants. The algorithm stops when the centroids converge. Centroids of the partitions are used for classification purposes in the nearest-centroid sense.

7. Results

Image	*k*-means	ATC	μ_1*	μ_2*	μ_3*
Nat-5c	**7.94**	7.95	11.50	24.10	17.20
Nat-5v	**14.07**	14.08	27.20	44.00	33.60
Nat-5v2	17.00	**16.88**	25.90	38.70	33.50
Nat-5v3	23.77	**23.71**	31.10	41.00	33.20
Nat-5m	20.68	**20.59**	24.70	41.10	30.30
Nat-16c	**38.01**	39.39	47.80	51.10	50.70
Nat-16v	56.78	**44.60**	54.40	62.70	58.20

Table 1. Classification error (%) for some of the test images in [3]
. * μ_1, μ_2, and μ_3 denote the average classification error in [3] using the following mixtures of filtering techniques:
. μ_1 - Heuristically designed texture feature extractor
. μ_2 - Optimized texture feature extractor
. μ_3 - Wavelet, Gabor, and QMF full-rate filter bank

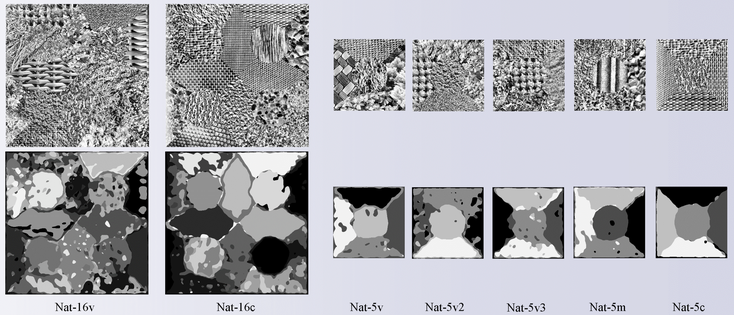

Figure 2. Visual result for texture segmentation with ants

8. References

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