Classification of Synthetic and Real Images Using Pattern Features

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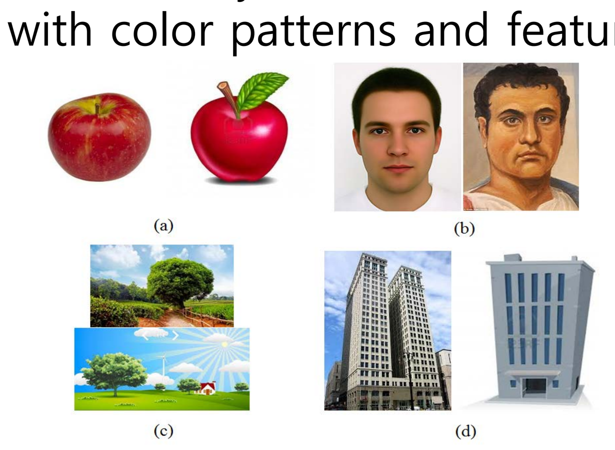
ABSTRACT

We propose, in this paper, an automatic image classification algorithm applicable to synthetic and real motion pictures so that a user's intention can be fully reflected in the image search and classification. Feature-based or edge-based histogram descriptors produce poor results when applied to classification of synthetic and real images because this is inter-class classification. The algorithm proposed in this paper obtains feature vectors of color distribution pattern in motion pictures to classify synthetic and real images.

INTRODUCTION

- The majority of image classification algorithms focus on intra-class classification methods.
- we propose an algorithm for both synthetic and real images by combining widely used feature descriptors with color patterns and feature distribution analysis.

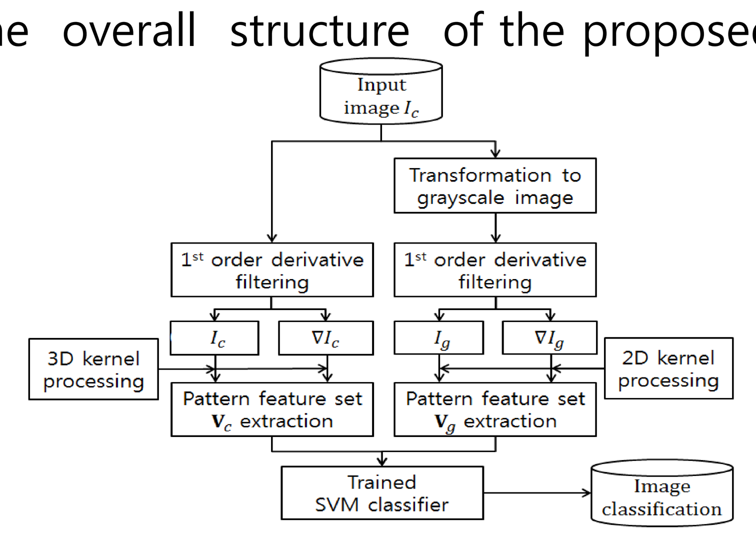


[Figure 1] Example of inter-class classification

- Pattern features are based on information about how the distribution of texture features takes place within a particular local region of the image.

FLOWCHART

- An illustration of the overall structure of the proposed algorithm



[Figure 2] Flowchart of Algorithm for Synthetic / Real Image Classification

METHODS 1

1. Two-dimensional Pattern Extraction

$$f_{3,1} = \begin{bmatrix} -1 & 1 & -1 \\ 1 & -1 & 1 \\ -1 & 1 & -1 \end{bmatrix}, f_{3,2} = \begin{bmatrix} -1 & 2 & -1 \\ 2 & -4 & 2 \\ -1 & 2 & -1 \end{bmatrix}, f_{3,3} = \begin{bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}, f_{3,4} = \begin{bmatrix} -1 & -2 & 0 \\ -2 & 0 & 2 \\ 0 & 2 & 1 \end{bmatrix}, f_{3,5} = \begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{bmatrix}, f_{3,6} = \begin{bmatrix} 0 & -2 & -1 \\ 2 & 0 & -2 \\ 1 & 2 & 0 \end{bmatrix}$$

- To find the pattern vector $\boldsymbol{V_g}$, $\mathbf{f}_w \in \{f_{w,1}, f_{w,2}, \dots, f_{w,6}\}$ is defined.

$$I_{g,x}(u,v) = I_g(u,v) - I_g(u+1,v), \qquad I_{g,y}(u,v) = I_g(u,v) - I_g(u,v+1)$$
$$\nabla I_g = I_{g,x} + I_{g,y}$$

- In order to reflect a wide range of characteristics in the images, first-order differential image ∇I_g for the black-and-white image I_g is calculated.
- In order to obtain pattern features from two images of I_g and ∇I_g , f_w is applied, which can be in one of three different forms.

$$\boxed{b_{1,i} = I_g * f_{w,i} \qquad b_{2,i} = \nabla I_g * f_{w,i}}$$

- The first form is applied to the ith element of f_w, or $f_{w,i}$ as a convolution calculation

$$\boxed{b_{3,i}(u,v) = \frac{1}{w^2} \sum_{\lceil x \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \sum_{\lceil y \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \hat{I}_g(u,v;x,y), b_{4,i}(u,v) = \frac{1}{w^2} \sum_{\lceil x \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \sum_{\lceil y \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \nabla \hat{I}_g(u,v;x,y)}$$
$$\hat{I}_g(u,v;x,y) = I_g(u+x, v+y) f_{w,i}(u+x, v+y)$$

- The definition of the kernel weight product $\hat{I}_g(u,v;x,y)$ on the pixel position (u,v) is as above.
- f_w is used for extracting the weighted average for the ith element $f_{w,i}$.

$$\boxed{b_{5,i}(u,v) = \left(\frac{1}{w^2} \sum_{\lceil x \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \sum_{\lceil y \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \left(\hat{I}_g(u,v;x,y) - b_{3,i}(u,v) \right)^2 \right)^{\frac{1}{2}} \quad b_{6,i}(u,v) = \left(\frac{1}{w^2} \sum_{\lceil x \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \sum_{\lceil y \rceil = -\frac{w}{2}}^{\lfloor w/2 \rfloor} \left(\nabla \hat{I}_g(u,v;x,y) - b_{4,i}(u,v) \right)^2 \right)^{\frac{1}{2}}}$$

- f_w is used for extracting the weighted standard deviation for the ith element $f_{w,i}$.

2. Adaptive Pattern Feature Extraction

$$\begin{cases} P(I_g, \nabla I_g; u, v) & \text{if } k > \alpha \\ \emptyset & \text{otherwise} \end{cases}, k = \left\lceil \frac{\max z - \min z}{h} \right\rceil \qquad \tilde{I}_g(u,v) = \frac{1}{l^2} \sum_{\lceil x \rceil = -\frac{l}{2}}^{\lfloor l/2 \rfloor} \sum_{\lceil y \rceil = -\frac{l}{2}}^{\lfloor l/2 \rfloor} I_g(u+x, v+y)$$

- α is a parameter that determines the processing sensitivity for texture information. It is used to determine whether pattern feature extraction is performed in the background of an image or in an area where texture information does not exist excessively.

METHODS 2

1. Three-dimensional Pattern Feature Extraction

- The only difference compared to two-dimensional pattern feature extraction is that it uses three-dimensional kernel cubes.
- A set of 72-dimensional pattern vectors are extracted for specific positions (u, v) of the image.

2. Three-dimensional Adaptive Pattern Feature Extraction

- The process of extracting three-dimensional adaptive pattern features is conceptually the same as the method performed in three-dimensional.

3. Support Vector Machine

$$\max_{\boldsymbol{\alpha}} L(\boldsymbol{\alpha}) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2\lambda} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i y_i)(\alpha_j y_j) \mathbf{K}(b_i, b_j)$$
$$\text{s.t. } \mathbf{y}\boldsymbol{\alpha} = 0, 0 \le \alpha_i \le \frac{1}{n}$$

- The b represents the feature vector of the extracted pattern feature.

EXPERIMENTAL RESULT

- Comparison result of classification accuracy of synthetic image and real image

apple	real	synthetic	precision
Real	144	66	0.686
synthetic	137	73	0.348
recall	0.512	0.525	0.517
			0.519

face	real	synthetic	precision
real	189	21	0.9
synthetic	89	121	0.576
recall	0.68	0.852	0.738
			0.766

landscape	real	synthetic	precision
real	127	83	0.605
synthetic	139	71	0.338
recall	0.477	0.461	0.471
			0.469

building	real	synthetic	precision
real	169	41	0.804
synthetic	124	83	0.41
recall	0.577	0.677	0.607
			0.627

HoG [8]	real	synthetic	precision
real	679	161	0.808
synthetic	576	679	0.314
recall	0.541	0.621	(p) 0.561
			(r) 0.581

[Table 1] Precision-recall for HoG features

SIFT [4]	real	synthetic	precision
real	730	110	0.869
synthetic	621	730	0.2607
recall	0.5403	0.665	(p) 0.564
			(r) 0.603

[Table 2] Precision-recall for SIFT features

Proposed m ethod	real	synthetic	Precision
real	629	211	0.749
synthetic	489	351	0.418
Recall	0.563	0.623	0.583
			0.594

[Table 3] Precision-recall for pattern features

- To evaluate the performance of the algorithm, 5-fold cross validation is performed by collecting a total of 100 synthetic / real images of each class.
- The classifier is trained using a total of 80 synthetic / real images and tested using a total of 20 synthetic / real images.
- As shown in [Tables 1,2,3], the proposed algorithm showed the highest performance in overall average precision compared to HoG and SIFT, and the average precision of the synthetic image was the highest.

CONCLUSIONS

In this paper, we propose a kernel-based pattern feature for classifying images, and the pattern feature is a texture-based feature to improve the classification accuracy in the class, unlike the existing feature points and edge-based features.

FUTURE WORK

It is possible to extract features using extended patterns, and to explore other statistical features that can be utilized within a specific regional domain.