NOVATEUR PUBLICATIONS
INTERNATIONAL JOURNAL OF INNOVATIONS IN ENGINEERING RESEARCH AND TECHNOLOGY [IJIERT]
ISSN: 2394-3696
VOLUME 4, ISSUE 10, Oct.-2017

TEXTURE CATEGORIZATION WITH BIOLOGICALLY INSPIRED FEATURES AND RANDOM FORESTS

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ABSTRACT
Texture classification is used extensively in computer vision application and images analysis. The aim of this paper was to use biologically inspired mechanisms for features extraction and random forests as a classifier to enhance the texture classification. These mechanisms were implemented by multi channels Gabor filter and multi-scale difference of Gaussian, which were combined efficiently using local binary pattern histograms. These histograms were computedin none overlapped window and classified by ensemble random forests. The experiments results demonstrate that the proposed method improves classification rates. The proposed method achieves higher classification rates compared to other methods.

INTRODUCTION
Texture classification plays an important role in computer vision tasks and images analysis. Such tasks include classification, segmentation, image retrieval and object recognition, only to name a few. Texture classification includes two major steps, feature extraction, and classification.
A lot of methods have been proposed in the literature for feature extractions, including statistical[1], and model based methods[2] to manipulate the texture spatial interaction. Moreover, structural methods focus on the regularity of basic texture primitive[1]. In addition to that, filter based methods process texture using either frequency or spatial domain filtering, or spatial-frequency filtering to solve the problem of localization as the case in Gabor filter[3, 4]. The goal of all these methods is to extract stable textural features to be invariant to rotation, scale, and gray scale.
The goal of the classification is to compare the described textural features of a new sample with those of the training samples and assign a label to the new sample.
Many algorithms have been proposed to solve the problem of scale, rotation, and gray scale invariance, while achieving a high performance [2, 3, 5]. Still, the problem of texture classification remains challenging. Recently VU[5], showed the ability of biologically inspired on/off-center mechanism in texture classification, but they ignore the multi-scale processing. In this study, a texture classification method was proposed, based on a combination of biologically inspired mechanisms, the on/off-center with multi-scale processing and Gabor filter bank. The outputs of these two type of filters were converted to local binary pattern and classified with random forests classifier.
The proposed method was tested on three texture databases and shows that multi-scale on/off-center performs better than Gabor filter. Although when the two filtering were merged together can further enhance the classification rates.

LITERATURE REVIEW
Prior works haveshown the efficiency of biologically inspired mechanisms in texture classification and discriminations.Since Gabor filter resembles the simple cells in visual cortex[6], it has been used extensively in texture analysis. For example, Manjunath[7], proposed a method for image retrieval based on texture analysis using Gabor filter. Hammouda[4], proposed a method for texture segmentation based on image decomposition using Gabor filter bank. Riaz[3], proposed a texture classification method that arranges the output of Gabor filter into amatrix, then utilized the shift invariance property of the Fourier transform to achieve rotation and scale invariance recognition.

With thedevelopment of the deep learning, researchers started using convolution neural network (CNN) in texture analysis. For example, Andrearczyk[8, 9], demonstrate the performance CNN in texture segmentation using theresponse of filter bank at various depths.

However, recently Vu[5], demonstrated the efficiency of on/off-center mechanism combined with LBP in texture classification, but they ignore multi scale processing which might enhance the classification rates.

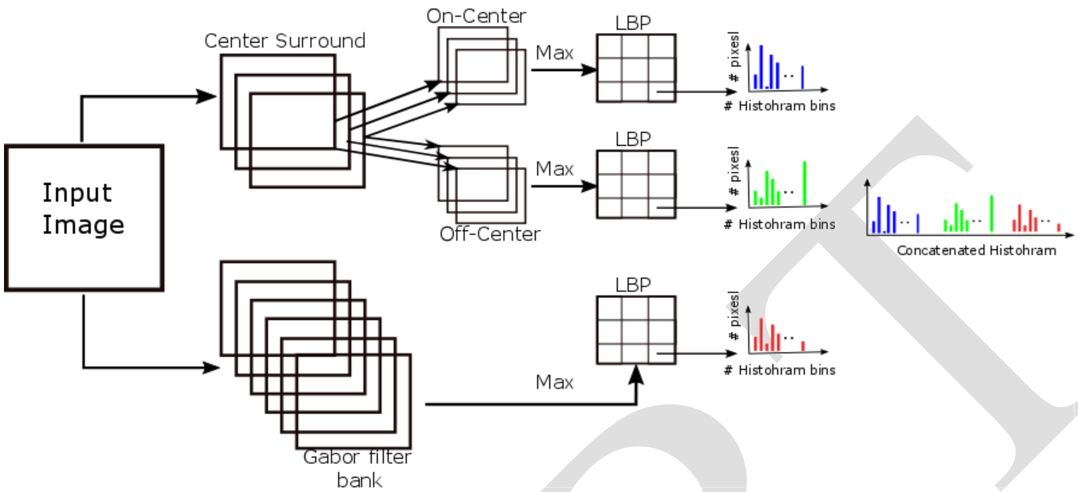

Figure 1: The proposed model

THE PROPOSED MODEL

The proposed model uses the biologically inspired features for texture categorization as shown in figure (1). The model uses two type of filtering; multi-scale on/off-center and multi-channels Gabor filter which is used frequently in texture analysis.

ON/OFF-CENTER

The on/off-center is approximated by applying the difference of Gaussian filterson an input image. In this work, six scale Gaussian filters with $(\sigma_1,\sigma_2,\sigma_3,\sigma_1+2,\sigma_2+2,\sigma_3+2)$ were used to filter the input image. The differences between each two pairs of filters with (σ_s,σ_s+2) were computed to generate three feature maps, the positive responses represent the on-center while the negative responses represent the off-center. The max operation was applied on all on-center and on all off-center responses separately to get one on-centerresponse and one off-center response.

$$DoG = \frac{1}{2\pi\sigma_1^2}e^{-\frac{x^2+y^2}{2\sigma_1^2}} - \frac{1}{2\pi\sigma_2^2}e^{-\frac{x^2+y^2}{2\sigma_2^2}}$$

Where σ_1 and σ_2 represent the standard deviation of the two Gaussian function. The input image $I(x,y)$ was convolved with the DoG filter.

$$Oc = DoG * I(x,y)$$

The output of the convolution $Oc$was separated into two maps, the positive maps which represents the on-center responses and the negative maps which represents off-center responses.

GABOR FILTER

Gabor filter bank with multiple scales and orientationis frequently used in texture analysis[7]. In this work, the Gabor filterwith 4 scales and 8 orientationswas used. The Gabor filter in spatial domain given by

$$g_{\lambda\theta\psi\sigma\gamma}(x,y) = \exp(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2})cos(2\pi\frac{x'}{\lambda}+\psi)$$

Where

$$x' = xcos(\theta) + ysin(\theta)$$
$$y' = ycos(\theta) - xsin(\theta)$$

In this equation, λ represents cosine factor wavelength, θ represents the orientation, γ represents the aspect ratio, σ represents the standard deviation of the Gaussian function which determines the size of the receptive field, and ψrepresents the phase offsets.
The Gabor filter convolved with input image $I(x, y)$at all scale and orientation.

$$Gr = g_{\lambda\theta\psi\sigma\gamma} * I(x, y)$$

The convolution resulted in 32 features maps, a max operation was applied on all the maps to only one response.

LBP Histogram

The DoG filtering generates two features maps the on-center and the off-center, and the Gabor filter generates one features map. Each map was partitioned into asmall disjoint region, and the histogram of LBP was computed for each region in each map separately based on[10], and the resulting three histogramswere concatenated to form the final feature vector.

RANDOM FOREST

Random forest is a set of trees that grow randomly[11]. Each leaf node in the tree learns a class posterior distribution. The tree internal nodes take a decision to branch left or right according to a binary function learned from features vectors.
Each tree is trained on subsets $I' \subseteq I$ of the training data I selected randomly. During learning the training data I_n is divided into two subsets right I_r and left I_l based on a threshold of the binary function applied to the features vector. The threshold is generated randomly and the one maximize the information gain is selected. The information gain is specified by

$$\triangle E = -\frac{I_r}{I_n}E(I_r) - \frac{I_l}{I_n}E(I_l)$$

Where$E()$, is the entropy function. The above test is recursively applied at each nonterminal node until no more possible information gain or the tree reaches a maximum depth.
A texture feature vector is passed down through each tree towards leaf nodes. The posterior probability of the leaf nodes are averaged and the arg max represents the class of the feature vector.

EXPERIMENTS & RESULTS

The proposed method was evaluated on three datasets, UIUC[12], CUReT[13] and Outex[14], using the setup as in [5].
The UIUC texture database contains 25 texture classes, with 40 samples per class. All images are 640x480 pixels and in grayscale JPG format. **Error! Reference source not found.**, shows the obtained results for two training patches with 20 and 15 images per patches.

Table 1: Classification obtained results on UIUC database

Training size	20	15
CS+CLBP_S/M/C	92.00%	88.30%
GB+CLBP_S/M/C	89.04%	86.00%
CS+GB+CLBP_S/M/C	93.60%	89.70%
Result obtained by [5]	91.47%	87.41%

CUReT texture database contains 61 classes with 98 images per class. Two training samples were used 40 and 20 to train the method, and the remaining images were used as test samples. **Error! Reference source not found.**, shows the obtained results.

Table 2: Classification results obtained on CUReT database

Training size	40	20
CS+CLBP_S/M/C	97.3%	94.10%
GB+CLBP_S/M/C	94.2%	91.00%
CS+GB+CLBP_S/M/C	97.7%	95.00%
Result obtained by [5]	97.2%	93.89%

Outex database contains large sets of textures images, in the form natural scenes and surface textures. The model was tested on two test suite of the database (TC10, TC12t). As shown in**Error! Reference source not found.**, the proposed model achieve the best results.

Table 3: Classification results obtained on Outex database

Test Suite	TC10	TC12t
CS+CLBP_S/M/C	97.60%	96.00%
GB+CLBP_S/M/C	93.14%	90.54%
CS+GB+CLBP_S/M/C	97.90%	96.70%
Result obtained by [5]	97.40%	95.28%

As clear from the results, the multi-scale on/off-center filtering performs better than Gabor filter banks. However, the multi-scale on/off-center when combined with Gabor filter bank enhance the classification rate.

CONCLUSION

In this study, we demonstrated the effectiveness of biologically inspired on/off-center and multi-channel filtering in texture processing. An extension to the on/off-center method was proposed, by incorporating the multi-scale processing and combined it with Gabor filter. The experiments results showed that better classification rates could be achieved by using multi-scale on/off-center. Although the performance of Gabor filter compared to the on/off-center was very weak, nonetheless when the two methods were combined further enhancement was achieved.

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