DEEP DECOMPOSITION OF CIRCULARLY SYMMETRIC GABOR WAVELET FOR ROTATION-INVARIANT TEXTURE IMAGE CLASSIFICATION

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Introduction

In recent years, deep learning technique has been studied extensively and got success in computer vision [8, 9] which shows that the good internal image representation is hierarchical. Motivated by deep learning, we propose Deep Decomposition of Circularly Symmetric Gabor Wavelet (DD-CSGW) based on CSGW which are rotation-invariant filters designed by Porter and Canagarajah [11] according to Gabor filters. Furthermore, we capture the dependence structure at each layer of DD-CSGW by using copula model to improve the classification performance.

For classification, the energies and standard deviations of DD-CSGW subbands, as well as the parameters of copula models based on DD-CSGW are used as the features of texture image. SVM is utilized as the classifier for texture recognition. Experiments on texture databases show our method is effective compared with the state-of-the-art rotation-invariant methods

CSGW

CSGF

$$g_C(x,y)=\frac{1}{2\pi\sigma}\mathrm{e}^{-\frac{1}{2}\left(\frac{x^2+y^2}{\sigma^2}\right)}\mathrm{e}^{-2\pi jW\sqrt{x^2+y^2}}$$

CSGW

$$g_m(x,y)=\lambda^{-m}h_C(x',y')$$

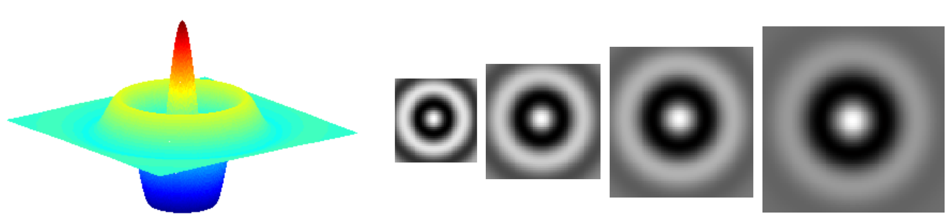


Fig.1 CSGW with four different scales

Properties

(1) CSGW can represent images on different scales

(2) CSGW is rotational invariant

Copula

Copulas have been employed in wavelet domain and achieved success for image analysis[12]. Copula theorem states that if *H*(x) is a multivariate cumulative distribution function of a random vector *x* ($x=[x_1,\ldots,x_n]$), then it can be expressed by the margins $F_1(x_1)$, …, $F_d(x_d)$ and a *d*-dimensional copula.

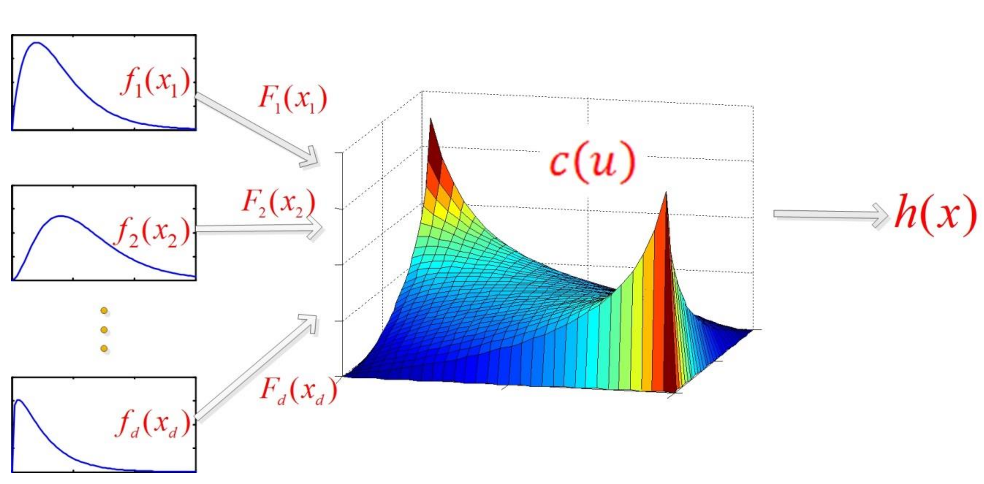
$$H(x\mid\Theta)=C(F_1(x_1\mid\delta_1),\cdots,F_n(x_n\mid\delta_n))$$

Model CSGW subbands

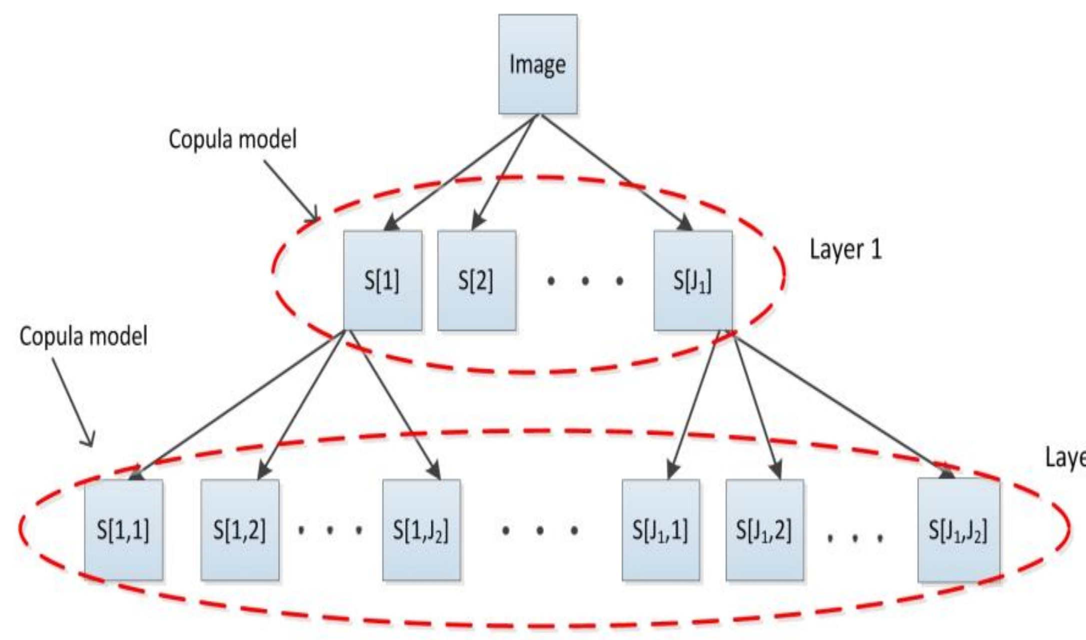
(1) There exist strong dependencies between the subbands of CSGW

(2) Each subband can be model by a univariate distribution

(3) Copula is used to join these univariate distributions into a multivariate distribution



DD-CSGW



Deep decomposition of CSGW (DD-CSGW) refers to the iterative and hierarchical decompositions by using CSGW. With DD-CSGW, the coarser-scale subbands of CSGW are continually decomposed into several finer-scale subbands.

$$S[i]=\left|g_m(x,y)*I(x,y)\right|,$$

$$S[i,j]=\left|g_m(x,y)*S[i]\right|,$$

$$S[i,j,\cdots,k,l]=\left|g_m(x,y)*S[i,j,\cdots,,k]\right|$$

Results

To evaluate the performance of DD-CSGW combining with copula model, we carried out several classification experiments on Outex and UIUC databases. The proposed method is compared with several popular descriptors including LBP[17], LTP[18], CLBP[19], and CLBC[20].

Table 1. Classification rate on Outex database (%)

Method	Outex TC 00010	Outex TC 00012	
		t184	horizon
LBP	97.84	85.76	84.54
LTP	98.2	93.59	89.42
CLBP	99.38	94.98	95.51
DD-CSGW(L1)	96.11	93.24	94.32
DD-CSGW(L2)	97.86	97.84	98.38
DD-CSGW(L3)	**99.64**	**98.82**	**98.91**

Table 2. Classification rate on UIUC database (%)

LBP	73.60
CLBP	90.60
DD-CSGW (Layer-3)	**90.80**

Copula model in DD-CSGW

$$h(x\mid\Theta)=c\left(F_1(x_1\mid\delta_1),\cdots,F_n(x_n\mid\delta_n)\mid\theta\right)\bullet\prod_{i=1}^{n}f_i(x_i\mid\delta_i)$$

Copula PDF

Gaussian copula PDF

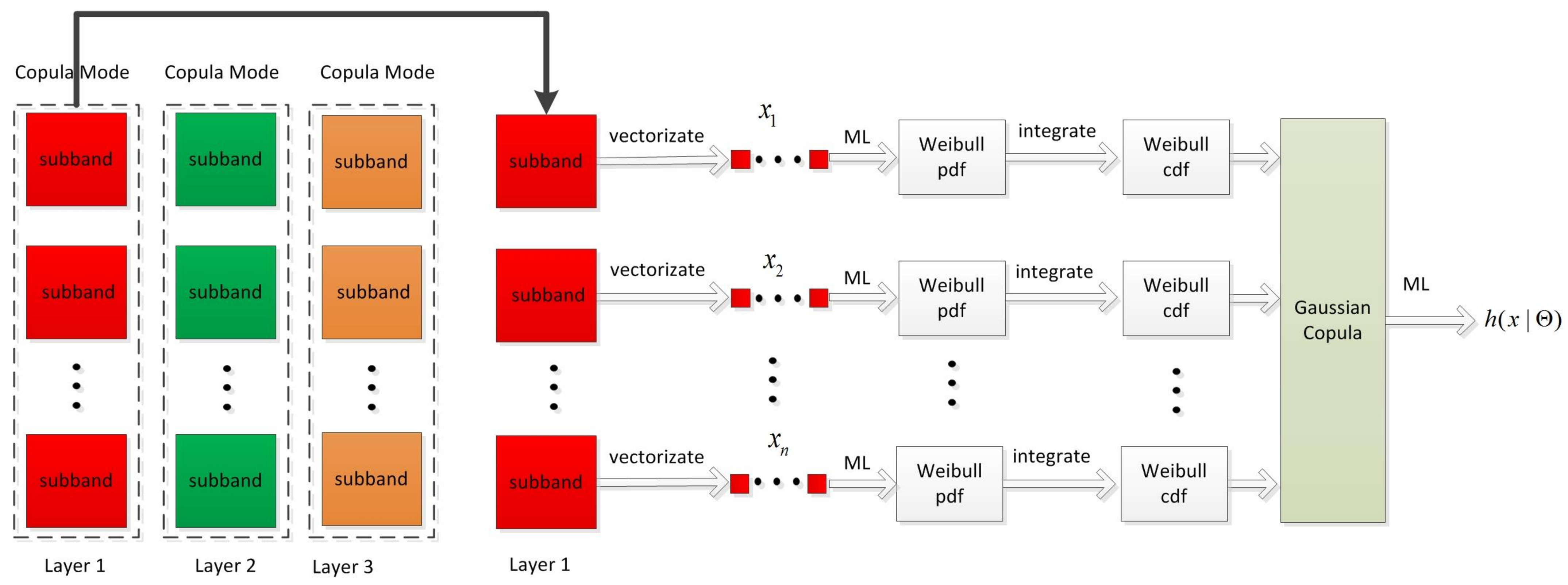
$$g(u\mid R)=|R|^{-1/2}\exp\left(-\frac{1}{2}\xi^T(R^{-1}-I)\xi\right)$$

Margin CDF

$$F_{WFL}=1-e^{-(x/\beta)^{\alpha}}$$

Margin PDF

$$f_{WBL}(x\mid\alpha,\beta)=\frac{\alpha}{\beta}(x/\beta)^{\alpha-1}e^{-(x/\beta)^{\alpha}}$$



(a) Organizing subbands (b) The implementation of the Gaussian copula model at layer 1

Classification

FEATURES

$$X=\left[X_{CP},X_{en}\right],$$

$$X_{CP}=\left[\cdots,\alpha_k^l,\beta_k^l,\cdots,r_{i,j}^l,\cdots\right]_{l=1}^{L},$$

$$X_{en}=\left[\cdots,m_k^l,e_k^l,s_k^l,\cdots\right]_{l=1}^{L}$$

X_{CP} : parameter feature set of copula model

X_{en} : feature set (energy and standard deviation features)

m_k^l : norm-1 energy features

e_k^l : norm-2 energy features

s_k^l : standard deviation features

Classifier

We use Support Vector Machine (SVM) [14] as the classifier in our method.

Conclusion

DD-CSGW shows good performance for image representation compared to the state-of-the-art local descriptors. Deep decomposition is the highlight in this work, which remarkably improved the representation performance of CSGW and it can be applied into other undecimated wavelets such as Gabor wavelet.

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