A Distinct Discriminant Canonical Correlation Analysis Network based Deep Information Quality Representation for Image Classification

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Motivation

- The deep-level feature representation is a data-driven solution, maybe leading to failures on the small scale data sets.
- One potential solution to balancing the small scale and deep-level feature representation is to integrate the multi-view representation and the deep cascade structure effectively.
- In this paper, a distinct discriminant canonical correlation analysis network (DDCCANet) based deep-level feature representation and extraction is proposed for image classification.
- The proposed DDCCANet mainly possesses three different components, including the DDCCA filters, the pooling operation, and the information quality representation.

Distinct Discriminant CCA (DDCCA)

DDCCA aims to find the discriminant information by the within-class and between-class correlation matrices across two data sets instead of the scatter matrix, it is able to explore more discriminant representation especially in multi-feature spaces.

$$\arg\max_{\omega_1,\omega_2} \rho = {\omega_1}^T \tilde{C}_{x_1x_2} \omega_2,$$

subject to

$${\omega_1}^T C_{x_1x_1} \omega_1 = {\omega_2}^T C_{x_2x_2} \omega_2 = 1$$

Then Lagrange multiplier and GEV algorithms are utilized to find the solution.

DDCCA Filters

Based on the aforementioned analysis on DDCCA, DDCCA filters aims to accomplish the task of 2D convolution by vectors based product operator, which is drawn graphically in Figure. 1.

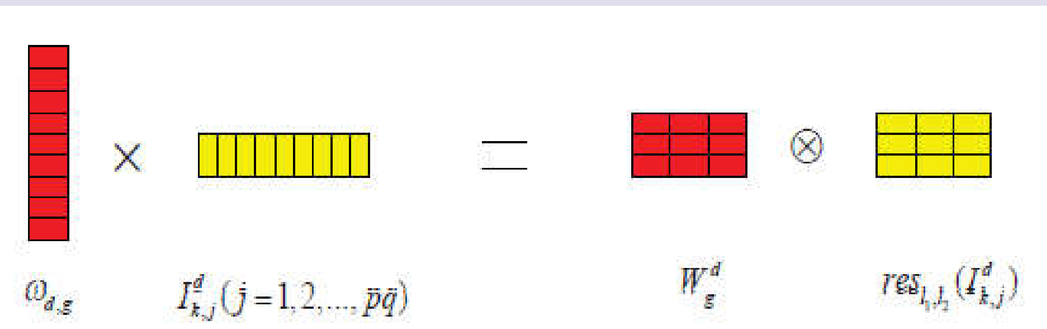

Figure 1. The representation of DDCCANet filters

Pooling Operation

Then outputs from DDCCA filters are binarized based on Hashing transform as follows

$$S\{I^{out}_{d,k,g} \otimes W^d_\ell\}(\ell = 1, 2, .., L_{i+1}),$$

where

$$S(x) = \begin{cases} 1, & (x > 0) \\ 0, & others. \end{cases}$$

After that, the vector of ` binary bits is considered as a decimal number, resulting in a single integer-valued "image".

Information Quality Representation

Information quality (IQ) instead of histogram is employed to generate the deep-level feature representation as follows

$$H(p(t)) = -log(p(t))$$

Therefore, in the DDCCANet, the deep level representation of the kth sample in the dth view is written

$$o_{k,d} = [H(Q_{d,k,1}), ..., H(Q_{d,k,L_i})]^T \in R^{(2^{L_{(i+1)}} L_i A)}.$$

$$o_k = [o_{k,1}; o_{k,2}] \in R^{(2^{L_{(i+1)}+1} L_i A)}.$$

Results and Conclusions

THE PERFORMANCE WITH DIFFERENT ALGORITHMS ON THE ORL DATABASE

Methods	Performance
DDCCANet	**97.50%**
AOS+VGG [12]	93.62%
CDPL [13]	95.42%
ANFIS-ABC [14]	96.00%
SOLDE-TR [15]	95.03%
GDLMPP [16]	94.50%
CNN [6]	95.00%
PCANet [17]	96.50%
CS-SRC [18]	96.00%
ANFIS [11]	96.00%
LCCA [19]	95.50%

THE PERFORMANCE WITH DIFFERENT ALGORITHMS ON THE ETH80 DATABASE

Methods	Performance
DDCCANet	**91.67%**
CCANet [9]	91.45%
PCANet [17]	91.28%
RandNet-1 [20]	78.50%
RandNet-1 [20]	83.51%
DCC [21]	86.25%
LEML [22]	84.25%
PML [23]	89.00%
SDNN [26]	82.80%
MFD [27]	86.91%
ALP-TMR [28]	84.86%
CERML [29]	85.00%

THE PERFORMANCE WITH DIFFERENT ALGORITHMS ON THE CIFAR10 DATABASE

Methods	Performance
DDCCANet	**62.05%**
DCCANet [10]	60.00%
CCANet[9]	53.50%
PCANet [17]	58.01%
DCTNet [24]	56.23%
RandNet [20]	45.11%
LDANet [25]	51.42%
Wide ResNet [30]	60.00%
VGG-16 [31]	56.00%

- The proposed DDCCANet is capable of improving the quality of feature representation from original images.
- Experimental results demonstrates the superiority of DDCCANet on image classification vs state-of-the-art.