Class-specific Coders for Hyper-spectral Image Classification

Sanatan Sharma[1], Akashdeep Goel[1], Omkar Gune[2], Biplab Banerjee[2], Subhasis Chaudhuri[2]

[1]Indian Institute of Technology Roorkee, India
[2]Indian Institute of Technology Bombay, India

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Hyper-spectral Image (HSI) Classification

- Visible images have only three bands as red, green and blue.
- HSI: Captures information using many bands of electromagnetic spectrum
- Applications

  Environmental monitoring, target detection, homeland security

Representation Learning of HSI

- High dimensional features due to many bands
- Robust representation with dimension reduction techniques needed
  - PCA, ICA
  - Auto-encoders
- We focus on auto-encoder based technique.

Issues with representation Learning using auto-encoder

- Designed for sample reconstruction and not classification
  e.g. denoising auto-encoder, sparse auto-encoder

- Representations may not be discriminative

- Class-encoder (CEC[1]): issue with class imbalance

We propose Class-specific Coders (CSC) for HSI classification.

[1] Learning Descriminative Features with Class-encoders, CVPR Workshop'16

Class-specific Coders (CSC)

- One coder (encoder-decoder framework) for each object class
- Coder trained on every input-output sample pair for a given class

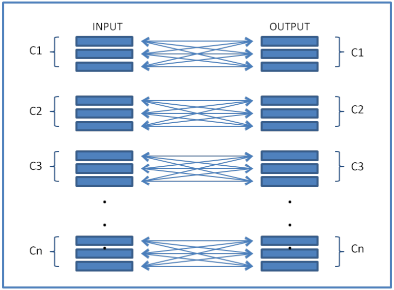

Figure 1: Class-specific coders

Class-specific Coders (CSC)

- Base loss function

$$\sum_{j=1}^{N_c}\sum_{k=1}^{N_c}\|x_k^c W^c W^{cT} - x_j^c\|_2^2 + \Omega(W^c)$$

x_k^c, x_j^c : Class C input and reconstructed sample

W^c, W^{cT}: Encoder and decoder weights of class C-coder

N_c: number of samples of class C

$\Omega(\cdot)$: regularization function

Training CSC with Orthogonality Constraints

- Loss function

$$\arg\min_{W^c, H^c} \{ \|H^c - \tilde{X}^c W^c\|_F^2 + \|\overline{X}^c - H^c {W^c}^T\|_F^2 + \alpha \|W^c\|_F^2 + \beta \|H^c {H^c}^T - I\|_F^2 \}$$

H^c: Matrix of latent representations of inputs samples in $\tilde{X}^c$

$\overline{X}^c$: Matrix containing reconstructed sample

$W^c, {W^c}^T$: Encoder and decoder weights of class C-coder

I: Identity matrix

α, β: Regularization constants

Feature Encoding using CSC

- Concatenate latent/hidden representations from each CSC
- Proposed feature descriptor has dimension of nh where n is number of classes and h is dimension of latent feature of each CSC.

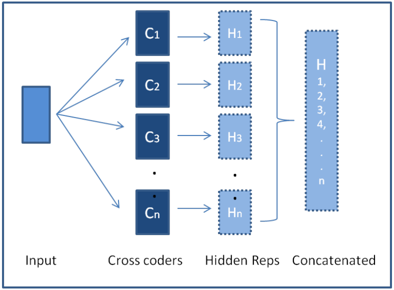

Figure 2: Feature encoding using CSCs

Results on HSI Datasets

Feature Encoding	Botswana	Indian Pines
PCA + NN based classifier	93.9	89.5
Auto-encoder (AE)	90.8	85.8
Class-encoder (CEC)	91.2	90.4
Sparse AE	85.5	82.2
Denoising AE	37.1	45.5
CSC (Ours)	**94.5**	**91.2**

Table 1: Comparison of classification accuracy (%) of different auto-encoder features (latent) and CSC feature encoding.

Conclusions

- CSC: Novel encoder-decoder framework
- CSC maps the sample to the mean of a class
- Simple but effective feature encoding scheme of concatenation of latent representations
- Improved performance on HSI classification over existing AE models