Learning Component-Level Sparse Representation Using Histogram Information for Image Classification

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Introduction

- A novel **dictionary learning** framework is presented with an energy minimization formulation that jointly optimizes :
  - both the **sparse dictionary** and
  - the **component-level importance** within one framework.
- An **iterative reweighted update process** to give a more discriminative representation for image groups.

Motivation

- An image group contains **main object/subject**. It also includes **irrelevant object** & **cluttered background**.
  - distinguish **distinctive** bins from those **noisy** ones

Contribution

- The **main novelty** of the proposed approach is
  - to incorporate component-level importance into the sparse representation by optimizing the reconstruction errors for the image groups.
- **In constrast to the previous methods** :
  - **Feature-type level weight assignment** (feature dimensions of the same type have the same weight)
  - **Component-level importance measure**. In proposed method, each feature dimension has its own weight.

Method Overview

- **Component Importance Measure :**
  - The objective function enforces the large reconstruction error in one component to have a smaller importance value.
  - The penalty term is for the minimal reconstruction error computed from dictionaries of other classes.

$$R^{(p)}\left(X^{(p)}\right)=\sum_{i=1}^{n_p}\left|x_i^{(p)}-D^{(p)}\alpha_i^{(p)}\right|,\quad R^{(p)}\left(X^{(p)}\right)\in R^m,$$

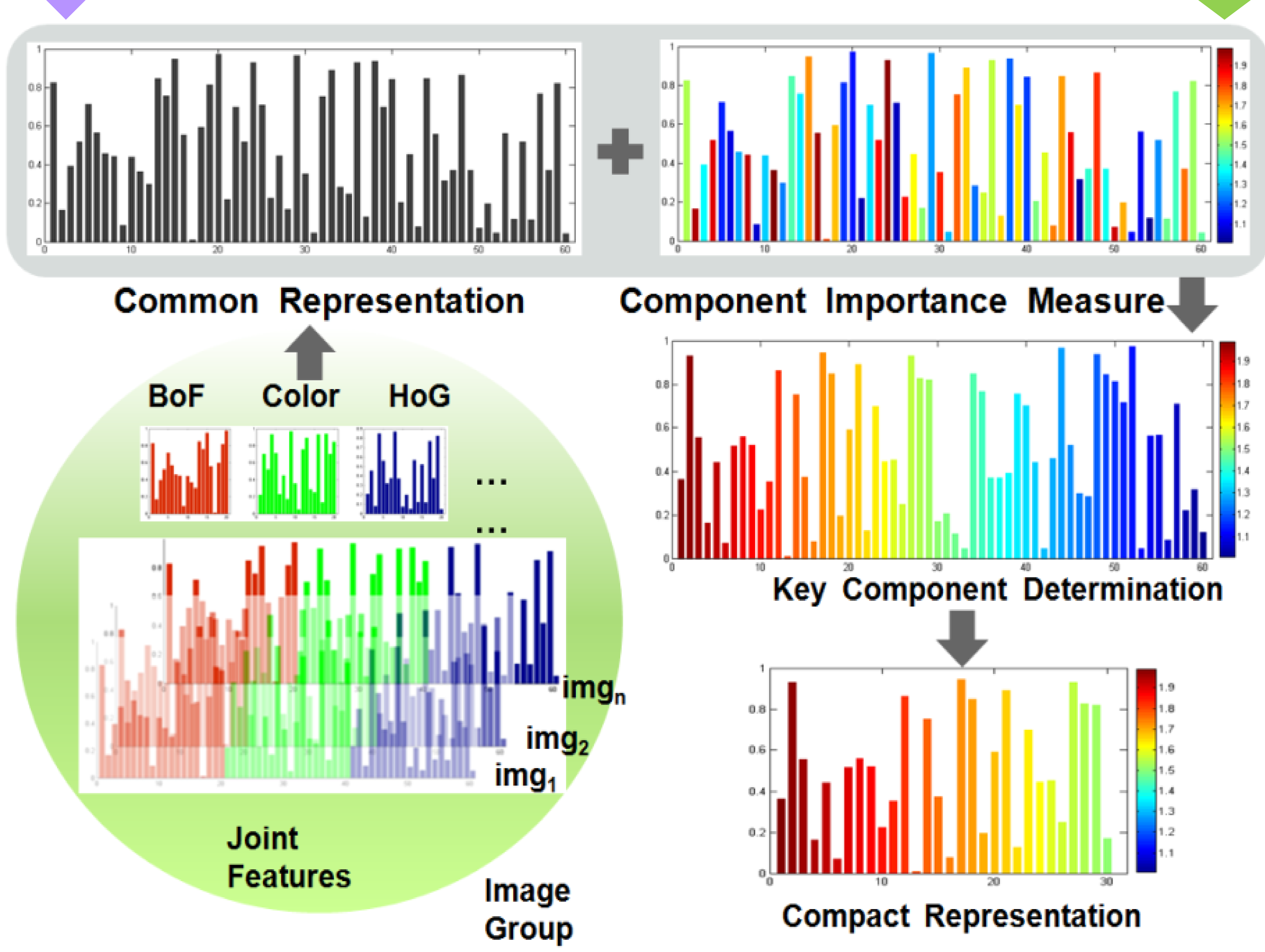
$$\min_{\beta^{(1)},\beta^{(2)},\dots,\beta^{(C)}}\sum_{p=1}^{C}\left((\beta^{(p)})^T R^{(p)}\left(X^{(p)}\right)-(\beta^{(\hat{c})})^T R^{(\hat{c})}\left(X^{(p)}\right)\right)$$

$$\text{subject to}\quad 0\le\beta_j^{(p)}<1,\quad \sum_{j=1}^{m}\beta_j^{(p)}=1,\quad \hat{c}=\arg\min_{\{q,q\neq p\}} R^{(q)}\left(X^{(p)}\right)$$

- **Common Representation :**
  - Sparse representation by dictionary learning.
  - Employed orthogonal constraint.

$$\hat{f}_t(D)\overset{\Delta}{=}\frac{1}{t}\sum_{i=1}^{t}\frac{1}{2}\left\|x_i-D\,\alpha_i\right\|_2^2+\lambda\left\|\alpha_i\right\|_1$$

$$\Theta=\left\{D=[d_1,d_2,\dots,d_k]\in R^{m\times k}\;\middle|\;\forall j=1,\dots,k,\quad d_j^T d_j\le 1\right\}$$



Iterative Reweight Update

1. **Initialization**: Set $t\leftarrow 1$. Choose the training set X^p as dictionary $D^{p,1}$ for image group p.
   $w^{p,0}\in R^m,\ w_i^{p,0}=1,\ R_i^{p,0}\left(X^{p,0}\right)=0,\ \beta_j^{p,0}=1.$
2. **repeat** { Main loop}
3. $D^{p,t}\leftarrow D^{p,1}\ .*\ w^{p,t-1}$, **Dictionary update**
4. Solve $\alpha^{p,t}$ by X^p and $D^{p,t}$, $\forall p,q\in\{1\dots C\},\ q\neq p$,
5. Calculate $R^{p,t}(X^p)$, $R^{q,t}(X^p)$, **Importance measure**
6. Solve $\beta^{p,t}$, **Termination condition**
7. $\Delta R=\sum_{p=1}^{C}\left(\left(\beta^{p,t}\right)^T R^{p,t}\left(X^P\right)-\left(\beta^{p,t-1}\right)^T R^{p,t-1}\left(X^P\right)\right)$
8. $\delta^{p,t}\leftarrow w^{p,t-1}\ .*\ \beta^{p,t-1}$, **Decision criterion**
9. $w_j^{p,t}=\begin{cases}\beta_j^{p,t} & \text{if } \beta_j^{p,t}<\rho\\ 1 & \text{otherwise}\end{cases}$ **Calculate new weight**
10. $w^{p,t}\leftarrow w^{p,t-1}\ .*\ w^{p,t}$, **Weight update**
11. $t\leftarrow t+1$,
12. **until** $\Delta R<\varepsilon$ or $t<T$

Experimental Results

- Classification accuracy (%) on (a) **Oxford 17 Category Flower Dataset** (b) **Oxford 102 Category Flower Dataset** (c) **Caltech 101**

Accuracy	Color	BoW	HOG	ALL
NN	36.47	44.63	35.96	39.56
SRC [33]	36.91	49.71	41.18	58.82
MCLP [60]	42.62	50.38	42.33	66.74
KMTJSRC [39]	44.80	51.72	44.51	69.95
HCLSP	45.15	52.34	43.38	63.15
HCLSP_ITR	50.15	55.68	46.76	67.06

(a)

Accuracy	Color	BoW	HOG	ALL
NN	33.52	22.76	19.39	36.27
SRC [33]	24.43	18.05	19.58	37.85
MCLP [60]	36.74	29.49	30.96	58.68
KMTJSRC [39]	36.67	30.16	29.14	57.00
HCLSP	37.37	29.73	31.58	51.77
HCLSP_ITR	44.53	32.35	39.01	60.14

(b)

Accuracy	Color	BoW	HOG	ALL
NN	29.65	51.26	44.85	38.83
SRC [33]	14.06	53.39	47.61	52.64
MCLP [60]	33.68	57.15	55.34	65.77
KMTJSRC [39]	18.14	48.93	46.25	53.21
HCLSP	35.12	56.03	58.12	60.49
HCLSP_ITR	35.43	58.24	59.94	68.41

(c)