Improved Deep Classwise Hashing With Centers Similarity Learning for Image Retrieval

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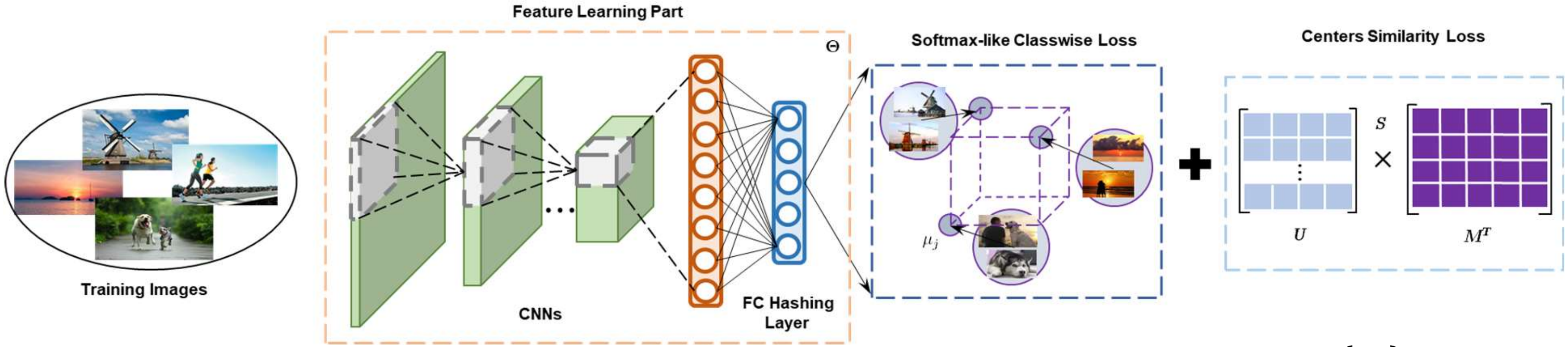

Fig. 1. An overview of proposed IDCWH. It learns network parameters Θ and class centers $M = \{\mu_j\}$ simultaneously. Here, $U = \{u_k\}_{k=1}^{Z}$ are estimated binary centers of each unique label in a mini-batch data and S is similarity indicator matrix.

Motivation

Existing pairwise/triplet labels-based deep supervised hashing suffers from tremendous computation cost and insufficient utilization of data similarity relation. Recently, class labels-based methods were proposed with better retrieval performance. However, the centers of these methods are either predefined or periodically updated from the deep features, where the semantics information of the class centers are not fully explored to generate more compact and discriminative hashing codes.

Two-step Centers Similarity Learning

$$\min_{\Theta,M} L_{clw} = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ji}\log\frac{\exp\{-0.5\|h_i-\mu_j\|^2/\sigma^2\}}{\sum_{j=1}^{C}\exp\{-0.5\|h_i-\mu_j\|^2/\sigma^2\}}$$

$$s.t.\ h_i = b_i, \quad h_i \in \mathbb{R}^l, \quad b_i = \{-1,1\}^l$$

We treat $M = \{\mu_j\}$ as learnable parameters and design a L_{csl} as a regularization term to enlarge the Hamming distance between pairwise class centers for a separable inter-class distribution.

a. ***Intra-class samples clustering****:* Dynamically attract each class center to concentrate on corresponding intra-class samples.

b. ***Center-sample concentration and repelling****:* Minimize the distance between estimated center and learnable class center while maximizing the distance between intra-class samples and centers belonging to other classes.

$$\min_{M} L_{csl} = -\sum_{s_{ij}\in S}\left(s_{ij}\theta_{ij} - \log(1+e^{\theta_{ij}})\right)$$

where $\theta_{ij} = 0.5l\cos\left(u_i, \mu_j\right)$ and l is code length. Relax h_i to be continuous and introduce $L_{quant.}$ between $b_i = \mathbf{sgn}(h_i)$ and h_i:

$$L_{quant.} = \beta\sum_{i=1}^{N}\|b_i - h_i\|_2^2$$

Finalized loss function:

$$\min_{\Theta,M} L_{clw} + \gamma L_{csl} + \beta L_{quant.}$$