INCORPORATING INTRA-CLASS VARIANCE TO FINE-GRAINED VISUAL RECOGNITION

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ABSTRACT

Fine-grained visual recognition aims to capture discriminative characteristics amongst visually similar categories. The state-of-the-art research work has significantly improved the fine-grained recognition performance by deep metric learning using triplet network. However, the impact of intra-category variance on the performance of recognition and robust feature representation has not been well studied. In this paper, we propose to leverage intra-class variance in metric learning of triplet network to improve the performance of fine-grained recognition. Through partitioning training images within each category into a few groups, we form the triplet samples across different categories as well as different groups, which is called Group Sensitive TRiplet Sampling (GS-TRS). Accordingly, the triplet loss function is strengthened by incorporating intra-class variance with GS-TRS, which may contribute to the optimization objective of triplet network. Extensive experiments over benchmark datasets CompCar and VehicleID show that the proposed GS-TRS has significantly outperformed state-of-the-art approaches in both classification and retrieval tasks.

Index Terms— Fine-grained visual recognition, Metric learning, Intra-class variance

1. INTRODUCTION

Fine-grained visual recognition aims to reliably differentiate fine details amongst visually similar categories. For example, fine-grained car recognition [1,2] is to identify a specific car model in an image, such as “Audi A6 2015 model”. Recently, more research efforts in fine-grained visual recognition have been extended to a variety of vertical domains, such as recognizing the breeds of animals [3,4,5], the identities of pedestrians [6,7,8] and the types of plants [9,10,11], etc. The challenges of fine-grained visual recognition basically relate to two aspects: inter-class similarity and intra-class variance. On the one hand, the instances of different fine categories may exhibit highly similar appearance features. On the other hand, the instances within a fine category may produce significantly variant appearance from different viewpoints, poses, motions and lighting conditions.

To mitigate the negative impact of inter-class similarity and/or intra-class variance on the fine-grained visual recognition, lots of research work has been done [12,13,14]. Various part-based approaches [12,13] have been proposed to capture the subtle “local” structure for distinguishing classes and reducing the intra-class variance of appearance features from the changes of viewpoint or pose, etc. For example, for fine-grained birds recognition in [13], zhang et al. proposed to learn the appearance models of parts (i.e., head and body) and enforce geometric constraints between parts. However, part-based methods rely on accurate part localization, which would fail in the presence of large viewpoints variations. In addition, recently, more promising methods [14,15,16] based on metric learning, which aims to maximize inter-class similarity distance and meanwhile minimize intra-class similarity distance, have been proposed. In particular, a sort of triplet constraint in [14] is introduced to learn a useful triplet embedding based on similarity triplets of the form “sample A is more similar to sample P in the same class as sample A than to sample N in a different class”.

On the other hand, some methods [17,18] utilize multiple labels, which are meant to denote the intrinsic relationship of properties in images, to learn a variety of similarity distances of relative, sharing or hierarchical attributes. In [17], multiple labels are leveraged to inject hierarchical inter-class relationship of attributes into learning feature representation. Lin et al. [18] utilized bipartite-graph labels to model rich inter-class relationships based on multiple sub-categories, which can be elegantly incorporated into convolutional neural network. However, those methods focus on the inter-class similarity distance, whereas the intra-class variance and its related triplet embedding have not been well studied in learning feature representation. When a category exhibits high intra-class appearance variance, intra-class triplet embedding is useful to deal with the complexity of feature space.

In this paper, we propose a novel Group Sensitive Triplet Sampling (GS-TRS) approach, which attempts to incorporate the modeling of intra-class variance into triplet network. A so-called grouping is to figure out a mid-level representation within each fine-grained category to capture the intra-class
and finally we conclude this paper in Section 5. In Section 3, we present the proposed GS-TRS class variance into triplet embedding for fine-grained visual recognition. In Section 3, we formulate the problem of injecting the modeling of intra-class variance into triplet network learning, which can significantly improve the performance of triplet embedding in the presence of considerable intra-class variance.

Our main contributions are twofold. Firstly, we incorporate the modeling of intra-class variance into triplet network learning, which can significantly mitigate the negative impact of inter-class similarity and/or intra-class variance on fine-grained classification. Secondly, by optimizing the joint objective of softmax loss and triplet loss, we can generate effective feature representations (i.e., feature maps in Convolution Neural Network) for fine-grained retrieval. In extensive experiments over benchmark, the proposed method outperforms state-of-the-art fine-grained visual recognition approaches.

The rest of this paper is organized as follows. In Section 2, we formulate the problem of injecting the modeling of intra-class variance into triplet embedding for fine-grained visual recognition. In Section 3, we present the proposed GS-TRS approach. Extensive experiments are discussed in Section 4, and finally we conclude this paper in Section 5.

2. PROBLEM STATEMENT

2.1. Problem Formulation

Let $S_{c,g}$ denote a set of instances of the $g$th group in fine-grained category $c$, and $S_n$ are a set of instances not in category $c$. Assume each category $c$ consists of $G$ groups, where the set of distinct groups may represent intra-class variance, and each individual group may represent intra-class invariance. The objective of preserving intra-class structure in metric learning is to minimize the distances of samples in the same group for each category when the distances of samples from different categories exceed a minimum margin $\alpha$.

$$\min \sum_{g=1}^{G} \sum_{i,j \in S_{c,g}} \|x_i - x_j\|^2$$
$$s.t. \sum_{i \in S_{c,g}} \sum_{k \in S_n} \|x_i - x_k\|^2 \geq \alpha, \tag{1}$$

where samples $x_i$ and $x_j$ from category $c$ fall in the same group $g$; $x_k$ is from the other category; and $\alpha$ is the minimum margin constraint between samples from different categories.

Equation (1) can be optimized by deep metric learning using triplet network. The remaining issue is to model the intra-class variance of each fine-grained category and properly establish triplet units to accommodate the variance structure.

2.2. Triplet Learning Network

Our proposed GS-TRS approach works on a triplet network model. The main idea of triplet network is to project images into a feature space where those pairs belonging to the same category are closer than those from different ones. Let $<x^a, x^p, x^n>$ denote a triplet unit, where $x^a$ and $x^p$ belong to the same category, and $x^n$ belongs to the other category. The constraint can be formulated as:

$$\|f(x^a) - f(x^p)\|^2 + \alpha \leq \|f(x^a) - f(x^n)\|^2, \tag{2}$$

where $f(x)$ is the feature representation of image $x$, $\alpha$ is the margin between positives and negatives. If the distances between positive and negative pairs violate the constraint in (2), then loss will be back propagated. Thus, the loss function can be defined as:

$$L = \sum_{i=1}^{N} \frac{1}{2} \max\{\|f(x^a) - f(x^p)\|_2^2 + \alpha - \|f(x^a) - f(x^n)\|_2^2, 0\}. \tag{3}$$

However, there exist two practically important issues in triplet network. First, triplet loss constrains samples of the same class together, while the class-inherent relative distances associated with intra-class variance cannot be well preserved, as illustrated in Fig. 1(a). Second, triplet loss is sensitive to the selection of anchor $x^a$, and improper anchors can seriously degrade the performance of triplet network learning.

3. GS-TRS APPROACH

The proposed GS-TRS incorporates intra-class variance into triplet network in which the learning process involves: (1) clustering each category into groups, (2) incorporating intra-class variance into triplet loss, (3) a multiple loss function.

3.1. Intra-class Variance

To characterize intra-class variance, grouping is required. Unlike category labels, intrinsic attributes within a category are
latent or difficult to precisely describe (e.g. lighting conditions, backgrounds). Here, we prefer an unsupervised approach to grouping images for each category.

Firstly, we feed image instances in each fine-grained category into the VGG-CNN-M_1024 (VGGM) network obtained by pre-training on ImageNet dataset. Then, we extract the last fully-connected layer’s output as the feature representation, followed by Principal Component Analysis (PCA) based feature dimension reduction. Finally, K-means is applied to perform clustering:

$$\arg\min \sum_{g=1}^{G} \sum_{x=1}^{N^g} \| f(x) - \mu_g \|^2,$$

where $G$ is the number of cluster center $\mu_g$ (i.e., group num). $N^g$ is the number of samples contained in $S_{c,g}$. Each image instance is assigned a group ID after clustering. As illustrated in Fig. 2, grouping often relates to meaningful attributes.

3.2. Mean-valued Triplet Loss

An anchor in triplet units is often randomly selected from positives. To alleviate the negative effects of improper anchor selection, we determine the anchor by computing the mean value of all positives, and formulate a mean-valued triplet loss. Given a positive set $X^p = \{x^p_1, \cdots, x^p_{N^p}\}$ containing $N^p$ positive samples and a negative set $X^n = \{x^n_1, \cdots, x^n_{N^n}\}$ containing $N^n$ samples from other categories. Thus, the mean-valued anchor can be formulated as:

$$c^p = \frac{1}{N^p} \sum_{i=1}^{N^p} f(x^p_i),$$

where $1 \leq i \leq N^p$ and $1 \leq j \leq N^n$. Rather than using randomly selected anchors, the proposed mean-valued triplet loss function is formulated as follows:

$$L(c^p, X^p, X^n) = \sum_i^{N^p} \frac{1}{2} \max \{\|f(x^p_i) - c^p\|_2^2 + \alpha - \|f(x^n_i) - c^p\|_2^2, 0\},$$

where $x^n_i$ is the negative closest to anchor $c^p$. It is worthy to note that, although the mean value of positives is considered as an anchor, the backward propagation needs to get all the positives involved. The advantage will be demonstrated in the subsequent experiments. When the anchor is computed by all of the positives, the triplet $< c^p, x^p_i, x^n_j >$ may not satisfy the constraints $\|f(x^p_i) - c^p\|^2 + \alpha \leq \|f(x^n_j) - c^p\|^2$. Hence, all the positives involving mean value computing are enforced to perform backoward propagation. The partial derivative of positive sample $x^p_i$ is:

$$\frac{\partial L}{\partial f(x^p_i)} = f(x^p_i) - c^p + \frac{1}{N^p}(f(x^n_i) - f(x^p_i)).$$

The partial derivative of other positives $x^p_k$ ($k! = i$) is:

$$\frac{\partial L}{\partial f(x^p_k)} = \frac{1}{N^p}(f(x^n_j) - f(x^p_k)).$$

The partial derivative of negative samples is:

$$\frac{\partial L}{\partial f(x^n_j)} = c^p - f(x^n_j).$$

3.3. Incorporating Intra-Class Variance into Mean-valued Triplet Loss

To enforce the preservation of relative distances associated with intra-class variance, we introduces Intra-Class Variance loss (ICV loss) into triplet learning. Let $c^p$ denote a mean center (the mean value of samples) in category $c$ and $c^{p,g}$ denote a group center that is the mean value of samples in group $g$ of category $c$. For each category $c$, there are one mean center $c^p$ and $G$ group centers $c^{p,g}$. As illustrated in Fig. 1(b), each black dot represents the center of a group.

In terms of intra-class variance, $x^p_i, x^n_j$ denote two samples from different groups within $c$. In terms of inter-class relationship, $x^p_k \in c$ are positives, and $x^n_i \not\in c$ are negatives. To incorporate the intra-class variance into triplet embedding, we formulate the constraints as:

$$\|c^p - f(x^p_i)\|^2 + \alpha_1 \leq \|c^p - f(x^n_i)\|^2,$$

$$\|c^{p,g} - f(x^p_i)\|^2 + \alpha_2 \leq \|c^{p,g} - f(x^n_j)\|^2,$$

where $\alpha_1$ is the minimum margin between those samples from different categories, and $\alpha_2$ is the minimum margin between those samples from different groups within the same category. Accordingly, we formulate the ICV incorporated mean-valued triplet loss as follows:

$$L_{ICV, Triplet} = L_{inter}(c^p, x^p_i, x^n_j) + \sum_{g=1}^{G} L_{intra}(c^{p,g}, x^p_i, x^n_j)$$

$$= \sum_{k=1}^{N^g} \max \{\|c^p - f(x^p_k)\|^2 + \alpha_1 - \|c^p - f(x^n_j)\|^2, 0\}$$

$$+ \sum_{g=1}^{G} \sum_{i=1}^{N^g} \max \{\|c^{p,g} - f(x^p_i)\|^2 + \alpha_2 - \|c^{p,g} - f(x^n_j)\|^2, 0\}.$$
the solely ICV triplet loss based learning incurs much slower convergence than classification. Secondly, as the triplet loss works on similarity distance learning rather than hyperplane decision, the discriminative ability of features can be improved by adding the classification loss to the learning objective. Hence, we propose a GS-TRS loss to jointly optimize the ICV triplet combinatin loss and softmax loss in a multi-task learning manner. A simple linear weighting is applied to construct the final loss function as follows:

\[ L_{\text{GS-TRS}} = \omega L_{\text{softmax}} + (1 - \omega) L_{\text{ICV triplet}}, \]  

(12)

where \( \omega \) is fusion weight. Fig. 3 illustrates the triplet network. Optimizing this multi-loss function helps accomplish promising fine-grained categorization performance as well as discriminative features for fine-grained retrieval. We will investigate the effects of ICV triplet loss with or without mean-valued anchor on GS-TRS loss in the experiments.

4. EXPERIMENTS

4.1. Experiments Setup

**Baselines** To evaluate and compare the triplet network based fine-grained visual recognition methods, we setup baseline methods as follows: (1) triplet loss \([16]\), (2) triplet + softmax loss \([15]\), (3) mixed Diff + CCL \([19]\), (4) HDC + Contrastive \([20]\), (5) GS-TRS loss without a mean-valued anchor for each group, i.e., a randomly selected anchor (GS-TRS loss W/O mean), (6) GS-TRS loss with a mean-valued anchor for each group (GS-TRS loss W/ mean). We select the output of L2 Normalization layer as feature representation for retrieval and re-identification tasks. For fair comparison, we adopt the base network structure VGG\_CNN\_M\_1024 (VGG\_M) as in \([19]\). The networks are initialized with the pre-trained model over ImageNet.

**DataSet** Comparison experiments are carried out over benchmark datasets VehicleID \([19]\) and CompCar \([1]\). VehicleID dataset consists of 221,763 images with 26,267 vehicles (about 250 vehicle models) captured by different surveillance cameras in a city. There are 110,178 images available for model training and three gallery test sets. The numbers of gallery images in small, medium and large sets are 800, 1,600 and 2,400 for retrieval and re-identification experiments. CompCar is another large-scale vehicle image dataset, in which car images are mostly collected from Internet. We select the Part-I subset for training that contains 431 car models (16,016 images) and the remaining 14,939 images for test. Note that all the selected images involve more or less backgrounds. We conduct retrieval and ReID experiments on VehicleID dataset, and retrieval and classification experiments on CompCar dataset.

**Evaluation Metrics** For retrieval performance evaluations, we use mAP and mean precision \( @ K \). For ReID evaluation, we apply the widely used cumulative match curve (CMC). For classification evaluation, we use the mean percentage of those images accurately classified as the groundtruth.

![Image](image.png)

Fig. 4. Exemplar Top-10 retrieval results on CompCar dataset. The images with a dashed rectangle are wrong results. The GS-TRS loss with grouping yields better results in (a) than the traditional triplet loss without grouping in (b).

4.2. Performance Comparison on VehicleID Dataset

**Retrieval** Table 1 lists the retrieval performance comparisons. Note that during the training stage, unlike \([8, 19]\) treating each vehicle model as a category, we treat each vehicle ID as a class (i.e., 13,134 vehicles classes). As listed in Table 1 directly combining softmax and triplet loss has outperformed Mixed Diff+CCL \([19]\) with significant mAP gain of 19.5% in the large test set. Furthermore, our proposed GS-TRS loss
without mean-valued anchors can consistently achieve significant improvements across three different scale subsets. In particular, the additional improvement on large test set reaches up to 4.6% mAP. Compared to [19], the improvement on large set has been up to 23.9% mAP. Moreover, GS-TRS loss with mean-valued anchors can further obtain about 2% mAP gains since using mean values of positives from multiple groups within a category yields more reliable anchors, which contributes to better triplet embedding.

**Table 1.** The mAP results of vehicle retrieval task.

| Methods                   | Small | Medium | Large |
|---------------------------|-------|--------|-------|
| Triplet Loss [8]          | 0.444 | 0.391  | 0.373 |
| Mixed Diff+CCL [19]       | 0.492 | 0.448  | 0.386 |
| Softmax Loss              | 0.546 | 0.481  | 0.455 |
| HDC + Contrastive [20]    | 0.625 | 0.609  | 0.580 |
| Triplet+Softmax Loss [15] | 0.655 | 0.631  | 0.575 |
| GS-TRS loss W/O mean      | 0.731 | 0.718  | 0.696 |
| GS-TRS loss W/ mean       | 0.746 | 0.734  | 0.715 |

**4.3. Performance Comparison on CompCar Dataset**

**Retrieval** Table 3 lists the TopK precision comparisons. The incorporation of intra-class variance into triplet embedding can achieve more than 5.6% precision gains at top-500. Overall, the modeling of intra-class variance and its integration into triplet network can significantly improve the discriminative power of feature representation which plays a significant role in fine-grained image retrieval. Fig. 4 gives the retrieval results of an exemplar query over CompCar dataset before and after injecting GS-TRS into triplet embedding.

**Classification** We train a VGGM network with single softmax loss and set initial learning rate = 0.002 and total iteration = 80K, and then yield 78.24% classification accuracy. Further fine-tuning with triplet+softmax loss can bring about 0.7% classification accuracy improvement, while GS-TRS loss with mean-valued anchors can yield more accuracy improvement of 1.6% (i.e., the classification accuracy is 79.85%). Such improvements demonstrate that preserving intra-class variance is beneficial for fine-grained categorization as well.

**5. CONCLUSION**

We have proposed a novel approach GS-TRS to improve triplet network learning through incorporating the intra-class variance structure into triplet embedding. The multi-task learning of both GS-TRS triplet loss and softmax loss has significantly contributed to fine-grained image retrieval and classification. How to further optimize the grouping strategy as well as the selection of anchors with respect to meaningful and effective groups is included in our future work.

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