Place Clustering-based Feature Recombination for Visual Place Recognition

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Abstract—Visual place recognition is an important problem in both computer vision and robotics, and image content changes caused by occlusion and viewpoint changes in natural scenes still pose challenges to place recognition. This paper aims at the problem by proposing novel feature recombination based on place clustering. Firstly, a general pyramid extension scheme, called Pyramid Principal Phases Feature (Tri-PF), is extracted based on the histogram feature. Further to maximize the role of the new feature, we evaluate the similarity by clustering images with a certain threshold as a 'place'. Extensive experiments have been conducted to verify the effectiveness of the proposed approach and the results demonstrate that our method can achieve consistently better performance than state-of-the-art on two standard place recognition benchmarks.

Index Terms—Visual Place Recognition, Pyramid Principal Phases, Place Clustering

I. INTRODUCTION

VISUAL place recognition is an important basic component in computer vision [1], [2], [3], [4], [5], [6], [7], [8] and robotic community [9], [10], [11] which has attracted a significant amount of attention working on it in recent years. In the complex outdoor environment, the change of illumination, viewpoint and partial occlusion leads to visual place recognition is a still difficult subject.

Given a query image, visual place recognition has always been an instance retrieval task [7], [8], which aims to find the most matching image by querying a large geo-tagged database[3], [12], [13]. In general, there are two steps to achieve place recognition: (1) Training a geo-tagged database model by extracting local or global features; (2) Estimation of optimal matching by extracting the feature using the identical architecture in the training phase[14], [15], [16].

The solution to visual place recognition can be summarized into two generations: traditional handcrafted features, such as Bag of Words (BoW)[17], [18], [19], [20], Fisher Vectors[21], [22], [23], [24], Vector of Locally Aggregated Descriptors (VLAD)[1], [25], and features automatic learning from the neural network[7], [8], [26], [27], [28], [11], [29], [30]. In this paper, we try to investigate whether the improvement of visual place recognition performance can be bridged by analyzing the CNN representation traditionally. To this end, the following problem should be considered. Can we select the most important local features from the place, and then recombine them to construct a new feature to represent the place? To address the question, we put forward the following three new ideas.

In this work, we first defined a histogram bin as a phase, statistical probability matching on different phases is the substantive characteristics of a histogram-like feature framework, such as BoW and NetVLAD[7]. It is necessary to explain the phase-matching here, the phase is the bin of histogram, the reason we don’t just call it bin but the phase is that phase information also plays a role in matching results. We consider retaining the most important phases of the image and suppressed others by the fact that an image can only match a subset of the pre-trained visual dictionary. Then we extend the retained phases in the form of pyramids. Each pyramid component is matched separately, and then the optimal component is selected and recombined into a virtual completion pyramid feature. Figure 1 shows the basic idea.

We defined the place as a larger region to maximize the role of Tri-PF. In the previous paragraph, there was a priori knowledge that was different from the previous approach, in the traditional process of place recognition, the optimal matching is obtained through rough matching against individual images[1], [7], [8], this is so-called Image-to-Image (I2I) matching. To achieve feature recombination, the place is defined as a larger region[14]. More specifically, all the images around the same position and adjacent positions are clustered into a new place.

Finally, we designed a variant weakly supervised triplet loss function, which is inspired by the traditional triplet loss function but is designed to adapt to our feature framework and clustering place, then we developed an end-to-end learning procedure for place recognition tasks.
II. RELATED WORK

In this section, we briefly review previous methods, including traditional and CNN solutions for visual place recognition, we also review the different definitions of a place.

Traditional framework for visual recognition. Before the popularization of the deep solution, the traditional methods adopted a two-step framework, including extracting manual features and training classifiers. Extracting discriminative image features have led the core Computer Vision research for almost twenty years[31], [32], [33], [34], and classifiers such as Support Vector Machine[35] or Boosting[36] were trained using those local features. In particular, BoW has been proved to be less sensitive than local features. Later, the histogram-based features were extended to VLAD and Fisher Vectors, which establish higher-order statistic models of local image features.

Deep neural network for place recognition. Inspired by the success of deep learning in AlexNet[37], deep learning solutions have attracted amount of attention in image retrieval[38], [39], [40], [22], [41], [2], [42] and place recognition[43], [44], [9], [45], [46], [7], [8]. Torii et al. developed a representation to deal with repetitive image structures for visual place recognition in urban environments[6]. A derivative of VLAD was proposed[5] to combine view synthesis with dense VLAD for robust recognition. [47], [48], [7] investigated the effectiveness of the triplet ranking loss to fine-tune pre-trained CNN models in image retrieval and visual place recognition task, [7] implemented VLAD in a learning strategy, and significantly outperformed the non-learned image representations. However, the same scenario category from different locations may degrade the representation performance of NetVLAD.

Place definition. Whether in the traditional method or the CNN framework, the definition of a place is a basic problem. [14] reviewed the common definitions of a place. The definition of a place depends on the navigation context and may either be considered as a precise position—a place describes part of the environment as a zero-dimensional point’, or as a larger area—‘a place may also be defined as the abstract of a region’[14]. In our work, we define the place in the latter but a variant way. Images from different viewpoints from the same location and images within a certain threshold are clustered to a new place.

III. AN OVERVIEW OF THE PROPOSED METHOD

Instead of defining a single image as a place, we cluster all images with adjacent geometric positions into a new place. The key advantage is that the surrounding information will also be seen as a contribution to current place recognition. We believe that images can only hit a few words in the dictionary-based features, which means that there are main phases in the features and these phases contribute the most. We only retain
the principal phases feature and then extend it in a pyramidal way.

Figure 2 is an overview of our visual place recognition framework. Tri-PF module produces $S$ components for each image. Given a query image, we first extract the CNN local features, any pre-trained CNN models can be used in this step, VGG is used in our experiments, and then we cluster those local features to $K$ centers to obtain a histogram feature with $K$ phases or bins. After scoring each phase by a certain rule, the phases with a high score are the principal phases, are left and others are set to zero. Finally, to suppress the interference caused by some principal phase features, the pyramid extension strategy is used to increase the robustness of the features. In the process of place recognition, the minimum distance corresponding to each component is estimated, and then Image-to-Place (12P) distance is the sum of the $S$ minimum distances and is used as the final distance from the query to the place.

IV. METHOD

In this section, we introduce the details of Tri-PF and the proposed place definition. We first introduce Tri-PF generation from the histogram-like NetVLAD and then explain how to cluster places and, finally introduce the 12P distance and a variant weakly supervised triplet loss to implement an end-to-end network. Our trainable network is shown in Figure 3.

A. Tri-PF

**Histogram-like descriptor.** Locally aggregated descriptor NetVLAD is used as our baseline, after an image $p^{W \times H}$ goes through the network, we treat the activation of the last convolution layer as a tensor of $F^w \times h^W \times c$, which is generally regarded as a set of $c$-dimensional local features with $N = W \times H$ numbers: $X = \{x_i | \mathbb{N} \times \{1, 2, \ldots, n\}$. As a member in the dictionary-feature family, locally aggregated descriptor module encodes the local features into $K$ clusters, each cluster is assigned with the number of features falling into it. Unlike BoW, NetVLAD stores the sum of residuals of each word. The aggregated descriptor is computed as follow:

$$v_k = \sum_{i=1}^{c} a_k(x_i)(x_i - b_k),$$  \hspace{1cm} (1)

where $b_k$ is the $k$-th visual word and $a_k(x_i)$ denotes the membership of descriptor $x_i$ to $b_k$, i.e. it is 1 if $b_k$ is the closest cluster to descriptor $x_i$ and 0 otherwise. The whole aggregated descriptor is formatted as:

$$v = [v^T_0, v^T_1, \ldots, v^T_{K-1}]^T.$$  \hspace{1cm} (2)

In the standard VLAD formalism, these assignments $a_k(x_i)$ are binary, in the context of deep learning, these assignments can be relaxed and expressed for differentiability as follows:

$$a_k(x_i) \approx e^{-\alpha \|x_i - b_k\|^2} \sum_{k=1}^{K} e^{-\alpha \|x_i - b_k\|^2}.$$  \hspace{1cm} (3)

As suggested in [7] and [4], to adapt VLAD descriptors to new datasets, we decouple the soft assignment $a_k(x_i)$ from the visual word $b_k$, we re-write Eq. 3 as:

$$a_k(x_i) = \frac{e^{-\alpha \|x_i - b_k\|^2}}{\sum_{k=1}^{K} e^{-\alpha \|x_i - b_k\|^2}}.$$  \hspace{1cm} (4)

where $s_k = 2ab_k$ and $h_k = \alpha \|b_k\|^2$ are treated as independent learning parameters. A histogram feature with $K$ phases for each image is extracted from NetVLAD.

**Tri-PF generation.** To determine which phases are important and which are not, we need to design a rule to score each phase. Specified to NetVLAD, we use the following rules to score each phase:

1. The more features of a phase, the higher the score is.
2. The smaller the cumulative residual error of a phase is, the higher the score is.

To balance the above two criteria, the score of the $k$-th phase is estimated as:

$$r_k = \alpha e^{-c_k} (1 - a_k) e^{-err_k},$$  \hspace{1cm} (5)

where $c_k$ and $err_k$ represent the feature count falls into the $k$-th phase and cumulative residual error of the $k$-th phase respectively, $a$ is the coefficient to balance two factors.
In the NetVLAD framework, the local features of the image only hit a subset of visual words. Inspired by[49], we take the top-$M$ phases with higher score as the principal phases, retain them and suppress others to zero as:

$$v^* = [0, ..., v^T_{p1}, ..., v^T_{pk}, 0]^T,$$

where $v^T_{pk}$ is the $k$-th principal phase, $v^T_{p1}, ..., v^T_{pk}$ are the principal phases feature and has $K$ dimension.

We further analyze the principal phases feature, we believe that the main features, such as buildings, generally remain the same, and those lights, billboards often change. Matching with the principal phase features, the factors that often change can be suppressed.

Based on the principal phases feature, we continue to expand the feature in a pyramidal way to improve the representation ability. The schematic illustration of the pyramid phases extension is shown in Figure 4. To simplify the discussion, we only take into account the $M$ principal phases left by the previous state. First, we remain the $M/2$ phases with higher scores and set the rest to zero, then iterate until only two principal phases are left.

Finally, Each layer of the pyramid is called a component, and each component has a similar structure and the same dimension with Eq. 6. A total of $S$ components are generated after feature extension.

**B. Clustered Place Definition**

Tri-PF realizes the extension of histogram-like features, to realize the feature recombination and make the extended feature Tri-PF is more descriptive, individual images are clustered into places.

Suppose there are $P$ images in the training database. First, each image is treated as an independent cluster center and the cluster center is defined as the place, and the images within a certain distance $T$ from the place are grouped. The images contained in many places are duplicated through this clustering, then we remove the repetition and leave $Q$ final places. Figure 5 shows the main idea of the novel place definition. Then, the final recognized place is given by:

$$C^* = \arg \min_c \{I2P - Dist(F_q, F_c)\},$$

where $F_q$ and $F_c$ represent features of the query $q$ and the $c$ respectively. $I2P - Dist(\cdot)$ estimates the I2P distance between $q$ and $c$.

**C. Distance Measurement and Training Loss**

**I2P distance.** Suppose a place contains $N$ images and each image generates $S$ components by Tri-PF. In the process of recognition, first the minimum distance between the $s$-th component of the query and the place is calculated by following:

$$d_s(f_{c}, f_{j,s}) = \min_d d^p_d(f_{c}, f_{j,s})$$

where $j \in \{1, 2, ..., N\}$, $f_{c}$ and $f_{j,s}$ denote the $s$-th component of the query, and the $s$-th component of the $j$-th image in place $c$ respectively.

We add up the minimum distance of all components as the distance from the query image $f$ to the place $c$,

$$I2P - Dist(F_q, F_c) = \arg \min_{c} \sum_{s=1}^{S} \omega_s d_s(f_{q}, f_{c,s})$$

where $\omega_s$ is the indicator to evaluate the importance of the $s$-th component in the place $c$.

**Weakly supervised triplet loss.** From the training dataset, training dataset of tuples $q, p, n$ can be obtained. For each training query image $q$, we have a set of potential positives $p$, and a set of definite negatives $n$. We define a weakly supervised triplet loss for a trainable Tri-PF as:

$$loss = \sum_{s=1}^{S} \omega_s \min_{i} d^2_{d}(q, p_{k,s}) - d^2_{d}(q, n_{j,s}) + m$$
where \( l(x) = \max(x, 0) \), and \( m \) is the constant margin variable. \( n_{j,i} \) denotes the \( s \)-th component in Tri-PF of the \( j \)-th negative, \( q_{j,i} \) and \( p_{j,i} \) take similar concepts. The triplet loss on each extended feature are estimated and then all the loss are accumulated together as the final loss. \( \omega_i \) is the importance measurement of each component.

\[ \text{V. Experiments} \]

In this section, we introduce the benchmark dataset we used in our experiments and the implementation details for Tri-PF, and then we discuss the benefits of place clustering. Finally, we demonstrate the quantitative and qualitative results of Tri-PF compared with NetVLAD and state-of-the-art on each dataset.

\[ \text{A. Datasets and Implementation Details} \]

\textbf{Datasets.} We report our results on two open available datasets, Pitts250k-test[6] and Tokyo 24/7[5]. Pitts250k is a popular visual place recognition dataset and generated from Google Street View panoramas in Pittsburgh. Tokyo24/7 is another challenging dataset that captures queries during the day, sunset and night through different mobile cameras. Pitts250k-test contains 83k images in the database and 8k queries, and Tokyo 24/7 contains 75k images in the database and 315 queries, we fine-tune the pre-trained model using Pitts30k-train or TokyoTM-train according to the test set.

\textbf{Implementation Details.}

\textbf{a. General parameters setting.} The pre-trained VGG-16 network[50], cropped at the last convolutional layer before Relu, and the NetVLAD pooling layer are adopted as our base architecture. We reuse the parameters of the open-source NetVLAD, and cluster all database images to \( K=64 \) centers, set \( \text{margin}=0.1 \) and \( \text{batchsize}=8 \). During the training, SGD is used with the learning rate \( l=1e-4 \) for Pitts30k and 5e-4 for TokyoTM set, we stop training after 20 epochs because no significant performance improved after that.

\textbf{b. Place clustering.} Two core parameters need to be considered for place clustering: cluster center and a certain threshold to cluster places. Firstly every image in the database is treated as a cluster center, and other images close to the certain threshold are clustered to each center. There must be many centers that contain the same images and retain one from these classes as a new place. In practice, the effects of different thresholds are analyzed.

\textbf{c. Tri-PF generation.} We set \( \alpha = 0.95 \) as the balance factor to score each phase of NetVLAD and keep \( M=8 \) highest scored phases then halve the previous phase sequentially until only 2 phase left, and \( \omega_i \) is set to 1.0 and that is to say, each extended feature is considered equally important. In practice, the role of the principal phases features and pyramid extension are analyzed.

\[ \text{B. Results and discussion} \]

\textbf{Discussion of the clustered place definition.} The place in our method is defined as the abstraction of a region. Specifically, images around a geographic location and images near the location are clustered into a single place, in the traditional way, each image is treated as a place, even though their geographic location may be the same. Our clustered place definition upgrades traditional I2I retrieval to I2P retrieval. Through our experiments, we can summarize the two main benefits of the place clustering:

1. The new place definition makes sense because putting features together around the same geographic location avoids incorrect matches, and produces the best match with the query only at the specified perspective.

2. A higher recall rate gives the robot where it is currently, helping to improve the accuracy of subsequent modules, such as global path planning, autopilot, and robot navigation.

Figure 6(d) shows that the positive impact on visual place recognition only changes the evaluation to the I2P distance.

\textbf{Benefits of the Tri-PF.} In the environment we face every day, some features that are not easy to change, such as buildings, shopping malls, landmarks, etc., and some factors that change frequently, such as billboards, LED lights, etc. The features that remain unchanged are the most discriminating and those that change easily produce noise. The histogram-based features suppress the influence of the content of the change through statistical methods, the Tri-PF magnifies this effect. By extracting the principal phases feature, the content that is not the main feature but changes is directly suppressed. Then the effects of content that has changed and misleads the matching result are suppressed by the pyramid extension.

Table 1 shows a comparison results using different thresholds for place clustering and different parameters for the principal pyramid feature extension. Each column shows the effect of a different threshold for place clustering under the same pyramid level, and when the threshold goes larger, the better performance is gained. And each row shows that the different pyramid levels under the same place clustering threshold, and when the pyramid level Figure 7 demonstrates the recognized results of Tri-PF comparison with baselines.

\textbf{Comparison with the baseline.} NetVLAD uses neural networks to implement traditional VLAD features and has achieved great success in place recognition. Our approach is based on NetVLAD, so we first compare the performance between our method and NetVLAD. The results show that our method is more profitable than the baseline. Recall@1 of our method outperforms NetVLAD on Pittks250k-test and Tokyo24/7 4.01 % and 9.52 % respectively. Detailed results are shown in Table II.

\begin{table*}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
\textbf{Recall@1 in Tokyo24/7} & & & & &
\hline
\textbf{M =8} & & & & &
\hline
\textbf{T / PL} & 1 & 2 & 3 & base & -
\hline
12 & 62.86 & 64.13 & 67.62 & 60.00 & -
\hline
0 & 66.98 & 67.94 & 69.68 & 62.86 & -
\hline
9 & 68.25 & 68.25 & 69.21 & 64.13 & -
\hline
25 & 67.94 & 69.21 & 69.52 & 66.98 & -
\hline
\end{tabular}
\caption{Verification of different clustering threshold and pyramid levels. T and PL represent the threshold used while clustering places and pyramid level respectively.}
\end{table*}
analyzed the APANet and found that APANet mainly uses the attention mechanism to solve the place recognition problem, this will guide our future work to pre-process images with attention mechanisms before feature selection.

VI. CONCLUSION

In this paper, we proposed a novel feature mechanism based on place clustering in the visual place recognition field. We designed an Image-to-Place Distance to measure the similarity of extended features in the new defined place. Finally, we developed an end-to-end network to test and evaluate our method. The proposed method is proved to be robust to illumination and viewpoint change in the visual place recognition task. What’s more, our approach is general and can be extended to any other histogram-like technique. In future work, we will try the attention mechanism to improve performance.
**APPENDIX A**

**PROOF OF EQUATION**

In this section, we provide additional proof of the equations we used in our experiments.

### A. Phase Score Estimation

We analyze why we need to balance the two factors in Tri-PF generation in this part. As we know, a specified query image could only match a subset of visual words, and the remaining visual words have no contribution to the distance estimation. A rule used to estimate the phase score is generated naturally, the more features in a phase, the higher score is assigned, we write it in a mathematical way,

\[ r_k = \sum_{c_k} c_k, \]

where \( c_k \) represents the feature count fall into the \( k \)-th phase.

We look back to Eq. 1, VLAD cluster the accumulated residual errors as the final feature. In those phases that are not matched, the accumulated error will be zero, and the final feature distance will also be zero. For feature matching, zero feature distance is the best match, so we write it mathematically,

\[ r_k = \sum_{err_k} \frac{err_k}{k}, \]

where \( err_k \) represents the accumulated residual error of the \( k \)-th phase.

The particularity of the VLAD feature is that cumulative errors are used as features, taking into account the characteristics, we balance the two rules above, and we re-write Eq. 5 as bellow,

\[ r_k = a e^{-\frac{\text{error}}{k}} + (1 - a) e^{-\frac{\text{error}}{k}}, \]

where \( a \) is the coefficient to balance two factors, in practice, we set \( a = 0.95 \).

### B. Weakly Supervised Triplet Loss

We first review the original weakly supervised triplet loss function,

\[ \text{loss} = \sum_{i,j} \min_{q, p_j} d^2(q, p_j) - d^2(q, n_j) + m \]

where \( l(x) = \max(x, 0) \), and \( m \) is the constant margin variable. \( n_j \) denotes the \( j \)-th negative, \( q \) and \( p_j \) take the similar concepts. In the framework of Tri-PF, we need to estimate feature distance \( d^2 \) between each component, and we write a new loss function to fit our Tri-PF as Eq. 10.

### C. Feature Similarity Measurement

12I matching is used in traditional feature similarity measurement, it is expressed in a mathematical formula as,

\[ c_j = \arg \min_{c} \min_{i} d^2(f_{test}, f_{j}), \]

where \( j = 1, 2, ..., N_c \), and \( N_c \) is the count of training samples in class \( c \), \( f_{test} \) and \( f_{j} \) represent the feature of a test sample and the \( j \)-th sample in class \( c \).

While 12I distance is sensitivity to the single sample, our framework is designed to enhance the role of the collective and reduce the role of individual samples, we need to design the distance measurement \( \min_{c} d^2 f_{test}, f_{j} \) in Eq. 15, we write the 12P distance measurement as Eq. 9.

**APPENDIX B**

**EXAMPLES OF SUCCESS AND FAILURE**

In this section, we show the success and failure cases compared with the base network and make a brief analysis.

### A. Success Cases

Figure 8 shows some examples of success on Tokyo 24/7 dataset. Results show that our method is more robust to viewpoint change and illumination change than the baseline network. The positive results are due to the novel place definition, and the powerful feature extension strategy.

### B. Failure Cases

Figure 9 shows some examples of failures on Tokyo 24/7 dataset. Results show that our method can not handle well in very similar places, this may be caused by similar places generate similar principal phases, then non-main phases will have a great influence on the result but Tri-PF suppresses those phases, and these shortcomings will guide our future work.

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Fig. 8. Success cases compared to the base network NetVLAD. Each row represents the comparison of a specified query, the first column shows the queries, the second column is the result of the baseline and the third column is our result, the green rectangle shows the correct result and the red one is incorrect.

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