Compressive Self-localization Using Relative Attribute Embedding

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Abstract—The use of relative attribute (e.g., beautiful, safe, convenient) -based image embeddings in visual place recognition, as a domain-adaptive compact image descriptor that is orthogonal to the typical approach of absolute attribute (e.g., color, shape, texture) -based image embeddings, is explored in this paper.

I. INTRODUCTION

Most current state-of-the-art visual place recognition (VPR) algorithms employ absolute attribute (e.g., color, shape, texture) -based image embedding for image feature description [1]–[3] and image similarity search [4]. In this study, we are interested in relative attributes (e.g., beautiful, safe, convenient) [5]–[7]-based image embedding, as it provides a domain-adaptive ranking-based image description [8] and it is orthogonal to typical approach of absolute attributes-based embeddings. Specifically, we present two different solutions based on binary and real-valued relative attribute strength and experimentally evaluate them via cross-season VPR experiments [9].

II. APPROACH

VPR is formulated as a problem of similar image retrieval [10]–[12]. The objective is to search for the image most relevant to a given query image over an image database. The database is constructed as a collection of viewpoint-annotated view images from visual experiences in the training domain via structure-from-motion [13] or SLAM [14]. Specifically, the procedure for construction consists of two steps (Fig. 1): (1) extracting a feature descriptor from the image, and (2) evaluating the descriptor similarity between the query and each database images. Either step is detailed in the following.

A. Feature Descriptor

An input query/database image is described by measuring the relative attribute strength in \( \mathbb{R} \), with respect to a predefined prototype image [8]. If the strength value is negative, it means that the input image has stronger relative attribute than the prototype image, otherwise it means that it is weaker. (1) Specifically, the processing begins by evaluating the relative attribute strength \( p_i^\text{attr} \) of each \( i \)-th prototype image \( p_i \) with respect to the input image \( q \) for each \( j \)-th relative attribute model \( A_j \), which yields a length \( (N+1) \) list of relative attribute strength

\[
L = (q_j^\text{attr}, p_1^\text{attr}, \ldots, p_N^\text{attr})
\]  

(1)

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B. Descriptor Similarity

Next, descriptor similarity is evaluated between the input descriptor \( R \) and each database descriptor \( R' \), for which we have developed two different kinds of evaluation methods. The first method, called binary relative strength (BRS), treats the descriptor as a binary relative attribute (stronger or weaker), and evaluates the similarity by

\[
\text{BRS} = \sum_j |R_{ji} - R'_{ji}|.
\]  

(4)

The second method, called ranked relative strength (RRS), utilizes the real-valued strength from the descriptor, and evaluates the similarity by

\[
\text{RRS} = \sum_j \sum_i |R_{ji} - R'_{ji}|.
\]  

(5)

III. EXPERIMENTS

The experimental settings follow the procedure in [15]. The NCLT dataset used is a large scale, long-term autonomy dataset collected by a Segway robot in a university campus. Specifically, view images from the on-board front-facing camera (Ladybug camera) in the sessions 2012/03/31 and 2012/08/04 were used as training and test image sets, respectively. We considered a place classification task with a set of 8 place classes. Specifically, the entire workspace
of the range $[-740, 130] \times [-330, 120]$ was divided via grid-based place partitioning into a $10 \times 10$ grid of 100 place classes (Fig. 2), from which the 8 classes are randomly sampled. We simply sample $N = 8$ prototype images from each of the 8 place classes (Fig. 3). The relative attribute models were trained using the OSR dataset as in [16] (Fig. 4) on the $M = 6$ different attribute classes: natural, open, perspective, large-objects, diagonal-plane and close-depth. The training, testing and performance evaluation were iterated for 100 sets of randomly sampled 8 place classes. The mAP performance was $0.341 \pm 0.071$ and $0.364 \pm 0.079$ for the BRS and RRS methods, respectively. For comparison, absolute attribute counterparts of BRS and RRS were also developed using the 1-hot semantic histogram as the absolute attribute feature as in [15], and tested with results of $0.147 \pm 0.068$ and $0.310 \pm 0.079$, respectively. One can see that the RRS method outperforms the BRS method in the current experiments. Specifically, the real-valued relative attribute strength provided rich information, and the information loss was significant when it was binarized (i.e., the BRS method).

IV. CONCLUSIONS AND FUTURE WORKS

The use of relative attribute (e.g., beautiful, safe, convenient) -based image embeddings in visual place recognition, as a domain-adaptive compact image descriptor that is orthogonal to the typical approach of absolute attribute (e.g., color, shape, texture) -based image embeddings, is explored in this paper. In the future, we plan to integrate the proposed highly-efficient VPR method to train a visual navigation system as in [15]. During the training phase, the VPR module must be repeated a very large number of times. That is, the robot needs to experience a large number of (e.g., tens of thousands of) training episodes, and each training episode involves performing VPR at many (e.g., 10) viewpoints. Towards that goal, further acceleration of the VPR module while retraining the discriminative power is desired.

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