RELMOBNET: A ROBUST TWO-STAGE END-TO-END TRAINING APPROACH FOR MOBILENETV3 BASED RELATIVE CAMERA POSE ESTIMATION

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ABSTRACT

Relative camera pose estimation plays a pivotal role in dealing with 3D reconstruction and visual localization. To address this, we propose a Siamese network based on MobileNetV3-Large for an end-to-end relative camera pose regression independent of camera parameters. The proposed network uses pair of images taken at different locations in the same scene to estimate the 3D translation vector and rotation vector in unit quaternion. To increase the generality of the model, rather than training it for a single scene, data for four scenes are combined to train a single universal model to estimate the relative pose. Further for independency of hyperparameter weighing between translation and rotation loss is not used. Instead we use the novel two-stage training procedure to learn the balance implicitly with faster convergence. We compare the results obtained with the Cambridge Landmarks dataset, comprising of different scenes, with existing CNN-based regression methods as baselines, e.g., RPNet and RCPNet. The findings indicate that, when compared to RCPNet, proposed model improves the estimation of the translation vector by a percentage change of 16.11%, 28.88%, 52.27% on the Kings College, Old Hospital, St Mary’s Church scenes from Cambridge Landmarks dataset, respectively.

Index Terms—Relative Camera Pose estimation, RPNet, RCPNet, Cambridge Landmarks

1. INTRODUCTION

Classical methods involve extracting keypoints (SIFT/SURF/FAST) for making correspondence between two images to estimate the relative pose by exploiting 3D geometry properties [9, 27, 28, 12]. However, they can suffer from inconsistent feature correspondences due to the reasons such as insufficient or repetitive patterns, narrow overlap, large scale change or perspective change, illumination variation, noise, blur, etc. [7]. Among multiple feature-extractors, SIFT/SURF detectors are more resistant against scale differences but are relatively slow. Multiple approaches to improve the performance of a keypoint-based approach using non-maximal suppression are also proposed [25]. Nonetheless, these approaches use these keypoints to estimate a relative pose, focused on estimating a translation vector up to a scale factor, i.e. a proportional vector to a translation vector. Pose estimation quality greatly relies on corresponding features, which are traditionally extracted by different keypoint extractors, as each one has a specific resilience for speed, light condition, noise, etc. However, an ideal keypoint extractor must be invariant and robust to various lighting conditions and transformations at the same time.

Classical approaches have achieved admissible results in various tasks, including recharging sensor network [4], wireless power transfer [8], power grid operation [10], and robotic control [11]. Recently, to advance the classical approaches, several deep learning models are proposed based on the success of deep convolutional neural network (CNN) architectures. CNN is giving a superhuman performance on computer vision tasks such as image classification, object detection, semantic segmentation, place recognition, etc.

Firstly, PoseNet was proposed as a pose regressor CNN for the camera localization task [6]. Advancing that, various CNN-based approaches are proposed for the relative pose estimation. Generally, all of them handle this as a direct regression task such as in RPNet [2], cmnnSpp [5], RCPNet [3]. RPNet approach uses a manual hyperparameter of weighing between translation and rotation loss for each scene while RCPNet used a learnable parameter to balance the losses. Also, the aforementioned methods crop the images to a square of the same size as that of the pretrained CNN backbone on the ImageNet dataset. DirectionNet [7] uses a different parameterization technique to estimate a discrete distribution over camera pose. As identified by previous works, CNNs can
produce good and stable results where traditional methods might fail [6]. Deriving benefit from previous methods we propose yet another end-to-end approach to tackle the relative pose regression problem using a Siamese MobileNetV3-Large network for producing entire translation and rotation vectors.

In this paper, our key contributions can be outlined as follows:

1) We propose to exploit the full image by downsizing them with the same aspect ratio without cropping and leveraging the adaptive pooling layer before dense layers.

2) With the help of novel two stage training procedure, we eliminate the hyperparameter of weighing between rotation and translation loss for different scenes to account for generalization and still producing promising results for varied domains.

3) We exploit MobileNetV3-Large pretrained weights of SOTA performance on other computer vision tasks to compose a Siamese architecture for relative pose estimation.

The rest of the paper is structured as follows. Section 2 is for discussion of related work. Section 3 deals with the datasets and architecture in greater detail. The experiments and analysis are explained in Section 4. Section 5 concludes the paper.

2. RELATED WORK

2.1. Feature correspondence traditional methods

Methods based on SIFT, SURF, FAST, and ORB feature detectors are viable options for solving the relative pose. All of these take advantage of the epipolar geometry between two views, which is unaffected by the structure of the scene [1]. Conventionally, the global scene is retrieved using keypoint correspondence by calculating the essential matrix which uses RANSAC, an iterative model conditioning approach, to reject outliers [14, 15, 16]. Matching sparse keypoints between a pair of images using those descriptors can help unearth the relative orientation by the following pipeline of i) keypoint detection, ii) computation of the local descriptor, iii) matching local descriptors. Even so, the performance still depends on correct matches and speculation of the textures in the given images [13]. Inaccuracy in feature matching due to insufficient-or-repetitive nature or less overlap of a given image pair can have a significant impact on the performance.

Several deep learning-based methods are also proposed to tackle sub-issues in the pipeline such as fundamental matrix estimation [18] and feature matching [19, 20], and Differentiable RANSAC [16, 17]. [18] proposed a neural network with specific modules and layers to preserve mathematical properties to find the fundamental matrix in an end-to-end manner. D2-Net reported promising results leveraging a CNN for performing two functions of detection and description of the keypoints by deferring the detector stage to utilize a dense feature descriptor [19]. SuperGlue used a graph neural network to match sets of local features by finding correspondence and rejecting non-matchable points simultaneously [20]. DSAC enabled deep learning pipelines to use robust optimization algorithms by converting non-differentiable RANSAC into differentiable RANSAC [17]. LoFTR employs a cross attention layer of transformers to obtain feature descriptors conditioned on both images to obtain dense matches in low texture areas where traditional methods struggle to produce repeatable points [26].

2.2. End-to-End methods

PoseNet [6] is the first end-to-end pose regressor CNN that can estimate 6 DOF camera pose with an RGB image. It typically fits a model on a single landmark scene, consisting of different images, to estimate an absolute pose from an image. To some extent, it is resistant to low and high lighting and motion blur by learning the scene implicitly. This method however learns a specific scene at training, which makes it difficult to scale for other scenes. [22] utilizes a novel geometric loss function for improving the performance across datasets by leveraging properties of geometry and minimizing reprojection errors [22].

![Image](image_url)

Fig. 1. RelMobNet: a Siamese network architecture, built with a MobileNetV3-Large backbone with adaptive average pooling layers to handle variable input image sizes, combined with a pose regressor to estimate a translation and a rotation vector.

To solve the relative pose problem, firstly, [5] demonstrated estimation of relative pose by using image pairs as input to train a CNN. RPNet [2] proposed to recover the relative pose with a full translation vector in an end-to-end fashion. In RPNet image pairs are generated by selecting eight different images in the same sequence using the Cambridge Landmarks dataset [2]. RCPNet [3] is a similar approach to interpret relative camera pose with autonomous navigation of UAVs with a newly collected Tuebingen Buildings dataset. In [3] authors presented results for a model trained with multiple scenes in the Cambridge Landmarks dataset and also reported comparative results with PoseNet, RPNet. All of the aforementioned approaches used Euclidean distance loss with a hyperparameter to balance between translation and rotation loss. In contrast, we show that without a scene-dependent hyperparameter to balance between these two losses, it is possible to estimate translation vectors with higher accuracy.
3. METHOD

3.1. Dataset creation as image pairs

The Cambridge Landmarks dataset contain video frames with their ground truth as absolute pose for outdoor relocalisation as presented in [6]. The dataset is constructed with the help of structure from motion (SFM) methods. Pair creation for relative pose estimation is done in the same way as done in the RPNet [2]. For example, the images from the same sequence of video frames from a single scene are used to make a pair. The camera’s relative posture is expressed as a 3D value for translation \((x, y, z)\) and a 4D value for rotation \((a, b, c, d)\) in unit quaternion. For the unit quaternion \(q_1, q_2\) the equivalent rotations matrices are \(R_1, R_2\). Respective translations are represented with \(t_1, t_2\). Projection matrix is the composition of rotation matrix and translation vector used to project a point from global coordinate system to camera coordinate system. Relative translation and relative rotation (in matrix and quaternion form) are represented as \(T_{12}, R_{12}, q_{12}, q_t_{12}\) and \(T_{12}\) are calculated as

\[
q_{12} = q_2 \times q_1^* \\
T_{12} = R_2(-R_1^*t_1) + t_2
\]

where \(^*\) represent the conjugate operation on quaternion.

The ground truth labels are based on a unit normalized length quaternion which is used to train the deep learning model. When the deep learning model outputs values for rotation, they are normalized to unit length at test evaluation. As a novel training procedure, we perform the model training in two-stages, using two sets of ground truth. In the first set, both rotation and translation values are normalized. In the second set, only rotation values are normalized to unit length with translation values unnormalized.

3.2. Architecture Details

As shown in Fig. 1, to compute the features from two images, the Siamese model composed of two parallel MobileNetV3-Large branches with shared weight is utilized. MobileNetV3-Large architecture improves efficiency over CNN by redesigning expensive intermediate layers with Neural Architecture Search (NAS) technique [21]. In addition, we add adaptive average pooling layer of the PyTorch library is leveraged to handle the different input images. The layer before the adaptive pooling layer gives 960 channels of different image features. As a result, the 2d adaptive pooling layer will provide the single (1*960 Dimension) vector.

The outputs from the two parallel branches are then concatenated to make up a flattened feature vector. This feature vector is passed to the pose regressor block. The first layer in the pose regressor block consists of 1920 units of neurons to accommodate for the concatenated feature vector. Secondly, it has two parallel 128-unit dense layers to predict the relative translation \((x, y, z)\) and the rotation \((a, b, c, d)\), respectively. Lastly, Euclidean distance is set as the objective criterion for translation and rotation to train our network. We did not employ a hyperparameter to balance between the rotation and translation losses. Defining \(r_{pose}\) as the ground truth and \(r_{pose}\) as the prediction of the network, the goal to minimize the error is as follows

\[
L(r_{pose}, r_{pose}) = \sum_i (\|T_{i12} - T_{i12}\|_2 + \|q_{i12} - q_{i12}\|_2)
\]

where \(i\) denotes the number of samples in the current batch, \(T_{i12}\) is the predicted relative translation and \(q_{i12}\) is the normalized predicted relative rotation respectively.

4. EXPERIMENTS

For comparison, we use the findings of Yang et al [3]. With the proposed architecture, we trained a shared model combining multiple scenes into a single dataset and we trained individual models on individual scene datasets similarly to RCPNet [3]. We combine four scenes (Kings College, Old Hospital, Shop Façade, St Mary’s Church) of the Cambridge Landmarks dataset for training whereas RCPNet kept Shop Façade scene unseen at the training stage. We used the training and test splits as that of the RPNet [2].

To begin, we integrated all of the training splits from four landmarks datasets into a single training set to train the CNN. The training is performed in two stages. In the first stage, we used the unit quaternion and normalized version of the translation vector as the ground truth and trained it for 30 epochs. In the second stage, we trained it with the same training split for 20 epochs with unit quaternion and unnormalized translation vector as the ground truth. By performing model training in this way, the model was able to learn the balance between the rotation and translation vector implicitly and converges the model faster. Results are reported in Table 1.

Individually for each scene, models are trained for comparison with the baseline methods. The same two-stage training as explained above is used for individual training. The input image was downsized for computation efficiency with the height set to 270 pixels while maintaining the original aspect ratio. We show the histogram of errors in the test sets for individual models and the shared model in Fig. 2. The curves are depicting the ability of the model to achieve good estimation, i.e. low error, for translation and rotation without
the need of weighing between losses. We implemented our model in PyTorch. All models are trained on NVIDIA 1080Ti GPU with ADAM optimizer having 0.001 as the learning rate, 64 as the batch size.

5. CONCLUSION

The present study put light on the problem of finding relative pose for varied scene domains. The proposed MobileNetV3-Large backbone based Siamese network is lightweight as well as performing comparatively with computationally heavy architectures. The experiments show that features extracted simultaneously using multiple scene domains could help to have better learning and generalization of the network. Further, an end-to-end training using the full input image is adopted by adding adaptive pooling layers to the network. The two-stage training procedure, as proposed, not only comply the model to converge the model in the fewer number of epochs but also remove the need for a hyperparameter to weigh between translation and rotation losses. When compared with baseline methods, the proposed method improves translation estimation while achieving comparable rotation estimation.

Table 1. Performance comparison on four scenes of the Cambridge Landmarks dataset adopted from [3]. Bold numbers represent results of better performance.

| Scene          | Frames | Pairs | Spatial Extent(m) | RPNet   | RCPNet     | Ours       |
|---------------|--------|-------|------------------|---------|------------|------------|
| King’s C.     | 343    | 1220  | 2424             | 140x40  | 1.93m,3.12- | 1.85m,1.72- | 1.80m,1.72- | 1.45m,2.70- | 1.51m,2.93- | 16.11 %     |
| Old Hospital  | 182    | 895   | 1228             | 50x40   | 2.41m,4.81+ | 2.87m,2.41+ | 3.15m,3.09- | 2.51m,3.60- | 2.24m,3.63- | 28.88 %     |
| St Mary’s C.  | 530    | 1487  | 10736            | 80x60   | 2.29m,5.90+ | 3.43m,6.14+ | 4.84m,6.93+ | 2.14m,6.47+ | 2.31m,6.30+ | 52.27%      |
| Shop Facade   | 103    | 231   | 607              | 35x25   | 1.68m,7.07- | 1.63m,7.36+ | 1.38m,28.6+ | 2.63m,11.80+| Not applied |

Fig. 2. Cumulative histogram of test errors in rotation and translation for individual models and the shared model.
(a) Individual model translation (b) Individual model Rotation (c) Shared model Translation (d) Shared model Rotation

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