RGB-D CAMERA POSE ESTIMATION USING DEEP NEURAL NETWORK

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ABSTRACT

This paper presents a study for RGB-D camera pose estimation using deep learning techniques. The proposed network architecture is composed of two components: the convolution neural network (CNN) for exploiting the vision information, and the Long Short-Term Memory (LSTM) block for incorporating the temporal information. The CNN, more precisely a RGB-D variant of GoogLeNet, functionalizes as a feature-oriented camera pose estimator, while the LSTM works as a temporal filter to model the pose transition. A modified loss function is also proposed to help regulate the convergence of the pose parameters. Experimental results show that the combination of CNN and LSTM can achieve a higher pose estimation accuracy, while the pipeline structure defined in the network can also provide flexibility for handling different scenarios.

Index Terms— RGB-D camera pose estimation, CNN, LSTM

1. INTRODUCTION

As witnessed in recent years, the deep learning technique has successfully established itself as a well generalized foundation for solving a variety of computer intelligence problems, especially in the domains of object recognition, activity understanding and natural language processing. Although the purposes of these systems are different from each other, a common notion can be interpreted as that a complex high-level identification problem could be approximated using a deep neural network, which is mainly implemented by convolution neural networks (CNNs), and recurrent neural networks (RNNs) alike. In terms of CNN structure, one of the most accepted examples shall be accredited to the Inception module defined in [1], also known as the GoogLeNet. By constructing a cascaded module pipeline, the entire network could reach a fairly high performance in recognition rate. Earlier work could be traced back to [2], in which the AlexNet structure was defined, while recent study such as VGG network [3] and ResNet [4] also draw considerable amount of attention from the community. In fact, by investigating the interaction between the data and the network layers, one can come to an inference that the convolution layers and pooling layers are essentially acting as feature extractors, while the dense layers, a.k.a. fully connected layers, are more inclined to synthesizing the output of convolution layers into final decision. As such, typical applications of CNNs are mainly focused on static scene analysis, for example, still image analysis. On the contrary, the natural structure of RNNs defines the routing of information flow, which is more favorable to temporal processing systems. In the recent studies, a lot of efforts have been made to explore the possibility of introducing the RNN into time-sensitive processing systems. For example, Long Short-Term Memory (LSTM), a special kind of RNN, has been applied to address the problems of human action recognition [5] and [6]. Briefly speaking, the CNN excels at extensive feature perception, while the LSTM is favorable to sequential information analysis.

The objective of the RGB-D camera pose estimation algorithm is to determine the physical location and orientation of the camera. In theory, the visual clues can be derived from any suitable feature extraction methods, such as CNN, because the nature of image convolution coincides with the general concept of template window based image processing. Considering another fact that real-time image sequence usually implies consecutive pose transition, the entire image sequence could be segmented into a series of overlapped short sequences, and each short sequence is well compatible with the LSTM model in terms of pose information propagation. Motivated by such ideas, the major objective of this paper is to investigate the feasibility of using CNN and LSTM to handle the RGB-D camera pose estimation problem. In addition, possible amendment is also applied to the cost function in order to satisfy the constraint on pose quaternion.

2. RELATED WORK

One of the most related work is PoseNet [7], which implements a variant of GoogLeNet to solve the pose regression problem. In this section, we will briefly describe PoseNet and LSTM. Since this paper is mainly focused on deep learning based estimation methods, direct methods, such as the Simultaneous Localization and Mapping (SLAM) family, will not be covered though.
2.1. PoseNet

As stated earlier, the network structure of PoseNet strictly follows the GoogLeNet, which is composed of 9 cascaded inception modules with 3 extra convolution layers and 1 dense layer, disregarding the pooling. The major difference between PoseNet and GoogLeNet is the output. The outputs of GoogLeNet is class label index, while the outputs of PoseNet are camera pose parameters. The dimension of the output layer for PoseNet is fixed to 7, including a 3-dimension spatial coordinate and 4-dimension quaternion orientation. As for GoogLeNet, the outputs are determined by class label information. In summary, GoogLeNet is for classification, PoseNet is for regression.

Such difference also leads to the redefinition of loss function. GoogLeNet accepts standardized cost function such as cross entropy, yet PoseNet specifies its own loss function as

$$loss(I) = \|x - \hat{x}\|_2 + \beta \frac{\|q - \hat{q}\|}{\|q\|}_2,$$

in which $I$ stands for the input image, $(x, q)$ denotes the ground-truth translation and rotation (quaternion), and $(\hat{x}, \hat{q})$ are the predicted parameters. $\beta$ is a hyper parameter used to adjust the balance between translation error and orientation error, which provides some flexibility to cope with different scenarios. Another point worth to mention is that the loss function defined above does not guarantee the predicted $\hat{q}$ always resides on the unit sphere in quaternion space. The author argues that the predicted quaternion is close enough to the ground-truth, thus omitting the constraint.

2.2. LSTM

LSTM, as a RNN architecture, is well-known for its flexibility in processing sequential information. The vanilla LSTM block is defined by several gates, usually known as the input gate, the forget gate and the output gate, which are driven by corresponding weight matrices and bias matrices as to perform entry-wise information traffic control.

In our scenario, a common assumption is that, the camera motion is relative stable within a short time frame. If trained with a series of pose parameters, the motion pattern of the camera can be learnt by the LSTM model. Compared with PoseNet or traditional single-frame based methods, introducing the LSTM model can help exploit the temporal information embedded within the consecutive frames, thus expected to produce more accurate pose estimation result. The LSTM process can be interpreted as: defining the cell state propagation scheme using pre-trained weights; the estimated pose parameters for current frame are derived from the cell state, while the cell state is determined by the raw input and the information propagated from previous frames.

3. PROPOSED METHOD

The network structure of the proposed method is a concatenation of the PoseNet and LSTM model. However, there exists several necessities requiring adjustments or special attention.

3.1. Network Structure

The entire network structure is illustrated in Fig.1. The details for the inception module and LSTM can be found in the original papers [1][8], thus are not covered here. It's worth noticing that, the number of pipelines of the proposed network is adjustable. For relative stable camera movement, the total number of pipelines can be reduced, not only for simplicity, but also for avoiding over fitting. For complex movement, especially for overlapped path or trajectory with multiple intersections, increasing the pipeline usually leads to better estimation accuracy, provided that a sufficient amount of training data is available.

3.2. Specifications

3.2.1. PoseNet Input

Since PoseNet has proven CNN is capable of solving pose regression problem, our natural choice is to follow such conclusion and borrow its architecture as the baseline structure. However, in order to fit it into the RGB-D scenario, the foremost needed change is to accommodate 4D input sequences. Although such modification looks trivial, it does affect the dimension of all the successive layers, which actually implies that carrying over pre-trained weights from PoseNet might not be the option.
3.2.2. LSTM Input/Output

As discussed, our general design is to utilize the PoseNet as a baseline pose estimator, and the LSTM shall be working as a temporal filter to process the estimated pose sequence. Therefore, the input and output of LSTM are both 7D pose vectors. The output of LSTM model is actually the output for the entire network.

3.2.3. Loss Function

Defining the interface dimensions helps shape the network structure. However, it cannot guarantee the intermediate output, i.e. the output of the PoseNet, could also converge to the true pose vector. And if this is not the case, even the final output is close enough to the idea result, it lacks the support of meaningful physical interpretation, thus limiting its generalization ability. To regulate the training process, a new term reflecting the intermediate output has to be integrated into the loss function. Another consideration is about the unit quaternion constraint that PoseNet has omitted. Admittedly, a deep structured network is capable of bringing the predicted result extremely close to the real term. Yet, instead of completely disregarding the minor difference, a reasonable alternative is to add the unit quaternion constraint to the loss function.

The proposed loss function is defined as follows

$$\text{loss}(I) = \sum_{i} \left\| x^i_p - \hat{x}^i_p \right\|_2^2 + \beta \sum_{i} \frac{\left\| q^i_p - \hat{q}^i_p \right\|_2}{\left\| q^i_p \right\|_2} + \left\| x_L - \hat{x}_L \right\|_2 + \gamma \left\| q_L - \hat{q}_L \right\|_2 + \left\| q_L - 1 \right\|_2$$.

(2)

Compared with Eq.(1), the predicted pose vectors are separated into two groups \((x^i_p, q^i_p)\) and \((x_L, q_L)\), representing the outputs of PoseNet and LSTM respectively. Since the network may contain multiple pipelines, the superscript 1 specifies the indices of corresponding RGB-D frames. The last term is the simplified version for unit quaternion constraint. According to the result in PoseNet, \(q^i_p\) is close enough to be a unit quaternion, therefore the filtered output \(\hat{q}_L\) should better satisfy such condition, hence there’s no further need for normalization. To maintain the balance between translation error and rotation error, an extra hyper parameter \(\gamma\) is also added. The rest variables without hat stand for their ground-truth values as before. In summary, by keeping the error terms that are associated with PoseNet, the intermediate outputs would be redirected toward the ideal result during the training process. Such behavior ensures that the CNNs are trained to produce feature-based prediction results, from which the LSTMs can further exploit the embedded temporal evidence.

4. EXPERIMENTS

To verify the performance of the proposed network, a series of experiments have been conducted on the ICL-NUIM RGB-D dataset [9]. The dataset is provided with two scenes, one for living room and the other for office. Each scene is composed of 4 sets of RGB-D sequences, taken from different camera trajectories.

4.1. Experiment Configuration

Unfortunately, we couldn’t find published work using similar technique to solve the RGB-D pose estimation problem, so that the experiments are more focused on comparing with the main reference method, i.e. PoseNet. However, PoseNet is not designed to accept 4D image sequence. As a compromise solution, we decide to take out the RGB components from the dataset to form a new pool that is compatible with PoseNet.

Another concern is that the proposed network is supposed to take advantage of the temporal information, which raises the question of how to separate the dataset for training and testing. A commonly adopted method is to randomly shuffle the sequence, and then pick out a proportion as training sample, while leaving the rest for testing. Yet this procedure is not suitable for our network structure, because the random shuffling would break the coherence of consecutive frames, thus will nullify the effectiveness of LSTM. To avoid such dilemma, the RGB-D sequence is firstly divided into triples or quadruples, determined by how many pipelines are defined in the network. The shuffling process would then be applied to these segments to randomize the data, while maintaining the temporal information within the segment.

4.2. Training and Testing

For both networks, we take 75% from the data pool to construct the train samples, the rest is for testing. Theoretically, the training process for PoseNet can be simplified by transferring the weight from pre-trained networks, however the dataset used in the original paper is taken from outdoor scene, while our data is from indoors. Such difference may affect the evaluation, not to mention it’s fairly hard to unify the total training time on different hardware platforms. Also, there’s no reference for the proposed network that we can borrow weight from, so the training procedure for both networks is conducted from scratch. As for testing, the major criterion is the error between predicted pose and ground-truth. According to the output layer definition in PoseNet, the translation parameters and rotation parameters are treated separately, therefore the evaluation is also conducted accordingly. Table 1 summarizes the comparison results from all the experiments.
### Table 1. Average pose estimation error in multiple cases (the index specifies different sets of shuffled data)

<table>
<thead>
<tr>
<th>Scene</th>
<th>index</th>
<th>network</th>
<th>3-pipeline</th>
<th>4-pipeline</th>
<th>3-pipeline</th>
<th>4-pipeline</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>PoseNet</td>
<td>0.62m, 3.64°</td>
<td>0.58m, 3.40°</td>
<td>0.54m (-12.9%), 3.21° (-11.8%)</td>
<td>0.47m, 2.88°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4D PoseNet</td>
<td>0.57m, 3.45°</td>
<td>0.44m, 2.72°</td>
<td>0.42m, 2.62°</td>
<td>0.41m (-12.8%), 2.56° (-11.1%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>proposed</td>
<td>0.56m, 3.26°</td>
<td>0.47m, 2.88°</td>
<td>0.54m (-12.9%), 3.21° (-11.8%)</td>
<td>0.47m, 2.88°</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>PoseNet</td>
<td>0.57m, 4.15°</td>
<td>0.44m, 3.04°</td>
<td>0.52m (-8.8%), 3.81° (-8.2%)</td>
<td>0.41m, 2.81°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4D PoseNet</td>
<td>0.55m, 4.06°</td>
<td>0.43m, 2.93°</td>
<td>0.50m (-12.9%), 3.81° (-8.2%)</td>
<td>0.41m (-8.8%), 2.69° (-11.5%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>proposed</td>
<td>0.54m, 3.95°</td>
<td>0.44m, 3.04°</td>
<td>0.52m (-8.8%), 3.81° (-8.2%)</td>
<td>0.41m (-8.8%), 2.69° (-11.5%)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>PoseNet</td>
<td>0.61m, 3.94°</td>
<td>0.46m, 2.97°</td>
<td>0.55m (-10.9%), 3.65° (-12.1%)</td>
<td>0.43m, 2.67°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4D PoseNet</td>
<td>0.57m, 3.85°</td>
<td>0.44m, 2.72°</td>
<td>0.55m (-10.9%), 3.65° (-12.1%)</td>
<td>0.43m, 2.67°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>proposed</td>
<td>0.56m, 3.63°</td>
<td>0.45m, 2.88°</td>
<td>0.55m (-10.9%), 3.65° (-12.1%)</td>
<td>0.43m, 2.67°</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>PoseNet</td>
<td>0.59m, 4.01°</td>
<td>0.46m, 3.02°</td>
<td>0.54m (-8.5%), 3.58° (-10.7%)</td>
<td>0.41m, 2.62°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4D PoseNet</td>
<td>0.58m, 3.82°</td>
<td>0.45m, 2.88°</td>
<td>0.54m (-8.5%), 3.58° (-10.7%)</td>
<td>0.41m (-8.5%), 2.75° (-8.9%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>proposed</td>
<td>0.56m, 3.70°</td>
<td>0.45m, 2.88°</td>
<td>0.54m (-8.5%), 3.58° (-10.7%)</td>
<td>0.41m (-8.5%), 2.75° (-8.9%)</td>
</tr>
<tr>
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<td>4</td>
<td>PoseNet</td>
<td>0.62m, 3.89°</td>
<td>0.45m, 2.95°</td>
<td>0.55m (-12.9%), 3.51° (-9.8%)</td>
<td>0.41m, 2.73°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4D PoseNet</td>
<td>0.61m, 3.78°</td>
<td>0.44m, 2.82°</td>
<td>0.55m (-12.9%), 3.51° (-9.8%)</td>
<td>0.41m (-11.1%), 2.70° (-8.5%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>proposed</td>
<td>0.55m, 3.65°</td>
<td>0.44m, 2.82°</td>
<td>0.54m (-12.9%), 3.51° (-9.8%)</td>
<td>0.41m (-11.1%), 2.70° (-8.5%)</td>
</tr>
</tbody>
</table>

### 4.3. Result Analysis

As seen from Table 1, compared with PoseNet, the proposed network has improved the pose estimation accuracy by 8% to 12%. In order to better understand the reason for such enhancement, the comparison between the original PoseNet and the 4D PoseNet is also included. Since the 4D PoseNet is nothing more than a vanilla PoseNet with 4D input layer, the improvement on its performance shall be mainly accredited to the introduction of extra depth information. In fact, the depth map delivers the direct measurement of the scene surface geometry. Sometimes, it is more favorable to be utilized as evidence for finding pose information than high-level vision assessment, especially when the visual features are hardly discernible. Therefore it’s reasonable to see the estimation accuracy is increasing accordingly. Also, we can draw another conclusion that the LSTM models integrated in the proposed architecture are the major factor that helps further improves the accuracy. The reason is that both the input and output of the LSTMs are pose vectors, no extra information is directed into the system. The only possibility is that the training process manages to reach a proper approximation to model the coherence between consecutive frames, thus ruling out a certain amount of uncertainty brought by the feature oriented estimation pipelines.

Based on the comparison between the 3-pipeline and 4-pipeline results, another assumption can be verified that the total number of pipelines is related to the camera movement. Inspecting the original dataset, we can notice that the camera movement in the "Office" scene is more stable than the "Living Room" scene. Therefore, for the "Office" scene, the accuracy difference between the two structures is less than the "Living Room" scene. That is to say, adding a new pipeline won’t affect the performance too much, because 3 pipelines might be sufficient enough to model the camera motion in a given scenario; yet for wilder movement, the total number of pipelines is preferred to be increased in order to describe a more complex trajectory.

### 5. Conclusion

In this paper, a deep neural network composed of CNNs and LSTMs is presented for solving the camera pose estimation problem from RGB-D image sequences. A customized loss function is also proposed for better satisfying the intrinsic constraint of pose parameters. Experiment results show that the proposed method is capable of delivering a higher performance in terms of pose estimation accuracy. In addition, it demonstrates that the deep neural network can provide excellent flexibility for handling the information from various scenarios and modalities.

### 6. References


