Squeezed Deep 6DoF Object Detection using Knowledge Distillation

Heitor Felix ¹, Walber M. Rodrigues ², David Macêdo ³,⁴, Francisco Simões ¹,⁵, Adriano L. I. Oliveira ³, Veronica Teichrieb ¹, and Cleber Zanchettin ³,⁶

¹Voxar Labs, Centro de Informática, Universidade Federal de Pernambuco, Recife, Brasil
²RobôCIn, Centro de Informática, Universidade Federal de Pernambuco, Recife, Brasil
³Centro de Informática, Universidade Federal de Pernambuco, Recife, Brasil
⁴Montreal Institute for Learning Algorithms, University of Montreal, Quebec, Canada
⁵Instituto Federal de Pernambuco, Campus Belo Jardim, Belo Jardim, Brasil
⁶Department of Chemical and Biological Engineering, Northwestern University, Evanston, United States of America

Emails: {hc2, wmr, dlm, fpms, alio, vt, cz}@cin.ufpe.br

Abstract—The detection of objects considering a 6DoF pose is common requisite to build virtual and augmented reality applications. It is usually a complex task which requires real-time processing and high precision results for an adequate user experience. Recently, different deep learning techniques have been proposed to detect objects in 6DoF in RGB images but they rely on high complexity networks, requiring a computational power that prevents them to work on mobile devices. In this paper, we propose an approach to reduce the complexity of 6DoF detection networks while maintaining accuracy. We used Knowledge Distillation to teach portables Convolutional Neural Networks (CNN) to learn from a real-time 6DoF detection CNN. The proposed method allows real-time applications using only RGB images while decreasing the hardware requirements. We used the LINEMOD dataset to evaluate the proposed method and the experimental results show that the proposed method reduces the memory requirement almost 99% in comparison to the original architecture reducing half the accuracy in one of the metrics. Code is available at https://github.com/heitorcfelix/singleshot6Dpose.

Index Terms—6DoF, Knowledge Distillation, Object Detection, Squeezed Network

I. INTRODUCTION

A key functionality in augmented reality applications is the ability to recover the pose of an object considering the position and orientation of the camera. Such information allows the creation of the interaction between the real and virtual environments. In robotics, this information allows the robots to interact, avoid collisions and manipulate objects.

The object detection with two degrees of freedom retrieves the coordinates of the object relative to the image plane. In object detection with three degrees of freedom, the method recovers the position or translation of a real-world object corresponding to the camera. These points have the information about the depth, but not the rotation. In object detection with six degrees of freedom (6DoF), there are three degrees for object translation and three degrees for object rotation considering the position of the camera. Hence, with the 6DoF approach, it is possible to make robots to pick an object precisely [1] or to create augmented reality applications with more interaction between real and virtual objects [2]. Approaches to this problem often use complicated and expensive array of sensors instead of an RGB camera [2]. Our 6DoF object detection method was summarized in Figure 1.

Fig. 1: Flowchart of our method of 6DoF object detection and its possible application in augmented reality. The squeezed network receives an input image, estimates the bounding box of the object to be detected. Then, its 6DoF pose is estimated using a PnP algorithm. With the pose, it is possible to create augmented reality applications by rendering the 3D model over the image.

There are many efficient methods for detecting objects in 6DoF. However, these methods [3] suffer from challenges as weakly textured or untextured objects, and low-resolution images. Among the relevant works for 6DoF object detection, Tekin et al. [4] presents results for pose estimation using only RGB images as input and achieved real-time detection for untextured objects using a YOLOv2-based architecture [5]. Many works have already improved the architecture of YOLOv2 [6–8] and one of these improvements can be efficient for Tekin et al. architecture. The evaluation of the method consider the object reprojection and pose errors from the object model points in camera coordinates analized in the LINEMOD dataset. The inference time and network size is
also metrics compared to the related works. These evaluation metrics are also used in [9]–[12].

The Tekin et al. [4] approach achieves a reasonable pose estimate in real-time but requires high-end hardware. This limitation makes embedding the method on mobile devices and robots a challenging task, which makes this approach less accessible for augmented reality and robotics applications.

There are different approaches to optimize deep learning networks [13]–[16]. An approach that has been used recently is the Knowledge Distillation [14]. This technique has different variations and the main idea is uses a larger and complex network with high quality prediction results as a target model (teacher). Consequently, the small network (student) is trained with the help of the teacher. The idea is to train the student network targeting on the teacher’s network knowledge instead of use only the original problem labels, which are in general more complex and difficult to learn in relation to the teacher assistance.

In Mehta and Ozturk work [7], the authors used Knowledge Distillation for object detection. The student network is the Tiny-YOLO network, and the YOLOv2 network is the teacher network. Mehta and Ozturk achieved better accuracy with the same network using Knowledge Distillation training in relation to Tiny-YOLO without Knowledge Distillation. Since the network used for Mehta and Ozturk is a direct reduction of the network used as a basis by Tekin et al., the results of Mehta and Ozturk show the potential performance gain of using Knowledge Distillation to detect 6DoF objects.

In this paper, we use a variation of Knowledge Distillation that replaces only target labels of student training to optimize adapted Tekin et al. architecture for Deep 6DoF Object Detection. This variation replaces the label during the training of the student network with the prediction of the teacher network. This distillation makes the student network learns from a network that already has its activation regions defined and makes learning easier. The process diagram is shown in Figure 2. We performed experiments with LINEMOD dataset and compared it with the original model.

This paper is organized as follows. In Section II, we revise works related to complexity reduction in Convolution Neural Networks (CNNs). In Section III, we describe our methodology using Knowledge Distillation for CNNs. In Section IV, we define our experimental protocol, including Dataset, Evaluation Metrics, and the Knowledge Distillation for pose estimation. Section V shows the obtained results and, finally, Section VI gives some concluding remarks.

II. RELATED WORKS

Several techniques have been proposed to reduce the complexity of deep networks, including Parameter Pruning and Sharing, Low-rank Factorization, Transferred or Compact Convolution Filters, and Knowledge Distillation [13].

Pruning weights was one of the primary methods for reducing complexity [17]. When first proposed, parameter pruning removed meaningless neurons connections. Although this method can drastically reduce the complexity of fully-connected architectures, in CNN networks, this approach is overwhelmed by the number of weights in complex networks. This problem was solved by He et al. [16], which introduced a channel-pruning to remove a filter altogether.

Low-rank Factorization uses the intrinsic CNN characteristic of matrix multiplication to create filters that can be separated into two matrices multiplications. This method intends to reduce the number of multiplications needed to apply a filter and can achieve up to 2 times speed-up on complex networks such as VGG-16 [13].

Compact Convolution Filters is another popular and powerful method. Based on changing complex 7x7 and 5x5 filters by 3x3 or 1x1 filters to reduce the number of operations, it is gaining attention in the field. Works such as [6] and [7] broadly uses that method to reduce complexity without losing too much accuracy.

Another method of optimization classified by [13] is Knowledge Distillation. This method proposes that a complex and powerful network teaches a smaller network, which is trained using the output of the bigger network by trying to mimic it. This method makes the smaller network achieve better results by learning from the teacher network than trained with the original data [7]. It proved to be efficient, and some variations were proposed for the most diverse problems [18].

Our work aims to create a faster and lighter version of an object detection model based on Tekin et al. [4] to estimate the pose of an object. Also, use the original architecture to train our squeezed architecture using Knowledge Distillation. Thus, improve the inference time and memory consumption with little accuracy reductions in relation to training without Knowledge Distillation.
III. KNOWLEDGE DISTILLED SQUEEZED MODELS

In 6DoF detection problems, Knowledge Distillation approaches can be particularly useful due to the fact that the larger network learned a decision region that is smoother than what can be learned directly from the dataset. So the smaller network, called student network, does not have to learn hard instances during training, because the larger network, called teacher network, has already dealt with these cases, creating a specific activation region for the problem. As expected, in Knowledge Distillation, the student network does not achieve the accuracy of the teacher network, since the teacher network is more complex, has more parameters, thus requiring more computational power than the student network.

In this seminal work, Tekin et al. [4] propose an architecture using YOLOv2 [5] as its base and by changing its last layer and adding a second shorter network path. The filters of the shorter path have a size different from the first path forcing the network to learn a completely different set of filters. Problems with a multidimensional activation region, such as inpainting [19], use this path addition.

In our work, we use a modified architecture of Tekin et al. made to reduce network complexity. With this new architecture, we use a variation of Knowledge Distillation represented in Figure 2. In this variation, to student network, we substitute the basis of the original work that is the YOLOv2 architecture by a architecture based on the Tiny-YOLO [5] and the YOLO-LITE [6] architectures.

The YOLO-LITE work was used for its focus on small architectures for computers without GPU. With the good performance obtained by these networks, they are good options for the basis of the 6DoF object detection architecture.

In YOLO-LITE several architectures were proposed. These architectures are called Trials and range from 1 to 13. We chose the best Trial based on the trade-off between complexity and mAP. According to Huang et al. [6], Trial 3 without batch normalization (BN) got the best result. Since the input image size in Trial 3 is 224x224 pixels and the architecture used as teacher and base to student uses images with 416x416 pixels, we will use Trial 10 as a basis for squeezed network, using with and without batch normalization.

Our model is trained by modifying the label of the associated image. Instead of using the dataset label, we employ the output of the teacher architecture, in this case, is the original Tekin et al. [4] architecture, associated with the image of the dataset used. All other training steps of the original network were maintained.

The baseline model has a complex architecture composed of 23 layers with filters 1x1 and 3x3 filter sizes. Although having small filter sizes, it uses up to 1024 filters per layer, highly increasing the network size.

IV. EXPERIMENTS

All experiments were performed using the Ubuntu 18.04 operating system and developed with Python 3.7 using the Deep Learning API PyTorch 1.2. We used a computer with an Intel Xeon 1.7GHz x 16 processor, 16GB RAM, and GeForce RTX 2080Ti GPU.

Initially, in Subsection [IV-A] the dataset used is explained. In Subsection [IV-B] the metrics used are detailed. The details of the experiments performed are in Section [V].

A. Dataset

The dataset used is the LINEMOD [20], which is also used in other works [4, 9–11] for a reliable comparison. Also, LINEMOD is one of the main datasets used for object detection, having several challenges such as occlusion, polluted background, blurring, and lighting change. Figure 3 (a) is one of the images contained in the LINEMOD Dataset.
Fig. 4: Qualitative Results on object Ape. On the left, detection performed with the original Tekin et al. network. On the right, detection using YOLO-LITE Trial 10 without BN.
| Object    | Distilled Models | Not-distilled Models |
|-----------|------------------|----------------------|
|           | YOLO-LITE Trial 10 | YOLO-LITE Trial 10 w/ BN | YOLO-LITE Trial 10 | YOLO-LITE Trial 10 w/ BN |
| Ape       | 51.428           | 46.761               | 44.095           | 45.809 |
| Benchvise | 45.736           | 45.445               | 46.608           | 40.406 |
| Cam       | 36.176           | 27.156               | 36.566           | 26.666 |
| Can       | 52.854           | 51.181               | 53.444           | 48.425 |
| Cat       | 43.712           | 40.718               | 38.722           | 46.906 |
| Driller   | 23.984           | 20.317               | 31.714           | 16.253 |
| Duck      | 30.140           | 24.600               | 32.394           | 29.577 |
| Eggbox    | 38.591           | 37.652               | 38.967           | 42.065 |
| Glue      | 50.965           | 46.718               | 50.482           | 45.173 |
| Holepuncher | 36.822          | 25.784               | 34.443           | 45.173 |
| Iron      | 25.638           | 24.821               | 21.161           | 68.800 |
| Lamp      | 29.654           | 24.856               | 30.134           | 28.598 |

**TABLE I:** Results of 2D Projection for Distilled and Not-distilled YOLO-LITE Trial 10, YOLO-LITE Trial 10 with Batch Normalization (BN) and the teacher network by Tekin et al. In bold the best result for the Tiny models per object.

| Object    | Distilled Models | Not-distilled Models |
|-----------|------------------|----------------------|
|           | YOLO-LITE Trial 10 | YOLO-LITE Trial 10 w/ BN | YOLO-LITE Trial 10 | YOLO-LITE Trial 10 w/ BN |
| Ape       | 4.095            | 4.380                | 2.571            | 5.619 |
| Benchvise | 30.620           | 30.803               | 30.523           | 29.360 |
| Cam       | 12.156           | 10.294               | 14.705           | 10.392 |
| Can       | 22.637           | 18.503               | 23.228           | 21.161 |
| Cat       | 7.185            | 9.880                | 7.185            | 10.479 |
| Driller   | 21.110           | 19.127               | 25.173           | 13.974 |
| Duck      | 3.192            | 10.294               | 3.380            | 2.723 |
| Eggbox    | 10.328           | 9.295                | 12.582           | 7.897 |
| Glue      | 11.389           | 10.135               | 9.485            | 11.583 |
| Holepuncher | 9.419            | 7.326                | 8.087            | 7.326 |
| Iron      | 25.331           | 27.885               | 28.804           | 27.374 |
| Lamp      | 25.815           | 21.305               | 24.088           | 23.416 |

**TABLE II:** Results of 3D Transformation for Distilled and Not-distilled YOLO-LITE Trial 10, YOLO-LITE Trial 10 with Batch Normalization (BN) and the teacher network by Tekin et al. In bold the best result for the Tiny models per object.

LINEMOD is made up of thirteen objects, where each object has about twelve hundred color images in 640x480 JPEG format and a 3D model. Also, for each image, the binary mask for the image objects and the rotation and translation vector values of the 6DoF pose of the object are informed.

Training images went through a process of synthetic data augmentation as used by Tekin et al. During synthetic data augmentation, new images are created for each image for the object being trained. The object is segmented using its binary mask, available in LINEMOD, and added to a random background from the dataset VOC2012, besides that, the object in the image is rotated and translated aiming to avoid overfitting and to increase the number of images available for training. Figure 3 (b) was obtained from the Ape object data augmentation.

**B. Evaluation Metrics**

For performance evaluation, we used two evaluation metrics for 6DoF pose estimation and the pose inference time. These metrics were also used in related works as [4], [9]–[12] and evaluate the prediction of the pose of objects in different ways. The metrics used are the 2D Projection [22] and 3D Transformation [22].

The 2D Projection metric is defined as the average of 2D reprojected object hit on the image from the test set images. The reprojection hit is calculated using (1) when the projection distance is lower or equal than five pixels, and it is considered to be a hit [22].

$$\Delta_{2D}(x_1, x_2) = \begin{cases} 1, & \text{if } |x_1 - x_2| \leq 5 \text{ pixels} \\ 0, & \text{otherwise} \end{cases}$$ (1)

The 3D Transformation metric is defined as the average of object model transformation hit on the image from the test set images. Projection hit is calculated using the 3D model points of the object, its ground truth matrix of extrinsic parameters, and its estimated matrix of extrinsic parameters. For each point of the transformed 3D model using the matrices, the pose error is calculated from a distance between the transformed point using the ground truth matrix and the transformed point using the estimated matrix. The pose error is calculated using (2), where n is the total number of points in the 3D model of the object. Object model transformation hit is considered if m is lower or equal than 10% of object model diameter [22]. The 3D Transformation metric consist this hit average in the test images.
In bold, the best values per method.

TABLE IV: Evaluation with 2D Projection in the Ape object. In bold, the best values per method.

| Model                | 2D Projection |
|----------------------|---------------|
|                      | Not Distilled | Distilled    |
| Baseline             | 92.10%        | 44.09%       |
| Tiny-YOLO            | 37.05%        | 35.43%       |
| YOLO-LITE Trial 10 w/ BN | 45.80%    | 46.76%       |
| YOLO-LITE Trial 10   | 44.09%        | 51.42%       |

TABLE III: Evaluation with 3D Transformation in the Ape object. In bold, the best values per method.

| Model                | 3D Transformation |
|----------------------|-------------------|
|                      | Not Distilled     | Distilled     |
| Baseline             | 21.62%            | 2.29%         |
| Tiny-YOLO            | 5.61%             | 4.38%         |
| YOLO-LITE Trial 10 w/ BN | 2.57%        | 4.09%         |
| YOLO-LITE Trial 10   | 2.57%             | 4.09%         |

TABLE V: Evaluation of inference time in the Ape object. In bold, the best values per method.

| Model                | Inference Time (ms) |
|----------------------|---------------------|
|                      |                     |
| Baseline             | 6.5                 |
| Tiny-YOLO            | 2.5                 |
| YOLO-LITE Trial 10 w/ BN | 2.0              |
| YOLO-LITE Trial 10   | 2.0                 |

TABLE VI: Sizes in MB for each evaluated model. In bold, the smallest models.

| Model                | Weights (MB) |
|----------------------|---------------|
|                      |               |
| Baseline             | 202.3         |
| Tiny-Yolo            | 44.1          |
| Yolo-Lite 10 w/ BN   | 2.2           |
| Yolo-Lite 10         | 2.2           |

\[
m = \frac{1}{n} \sum_{i=1}^{n} \left\| (r_{gt}x_i + t_{gt}) - (r_{pr}x_i + t_{pr}) \right\| \]  

(2)

V. RESULTS AND DISCUSSION

According to the mentioned models, for each metric, the values shown in Tables II, III, V and VI were obtained. The use of the 3D Transformation metric produces the results shown in Table II. Here we can see that for all architectures, the non distilled models outperform the distilling ones. For the 2D Reprojection technique, however, as shown in Table II, the results are balanced between distilled and non distilled models. A detailed result for each object in the dataset is shown at Table II and Table III.

As an explanation, the results show that distilling can improve the performance in this application. 3D Transformation is a hard task to be performed, as the baseline model only achieves 21.62%. This tells us that the quality of the target in which the student model learns plays a major role in its performance. On the other side, as 2D projection is a simpler task, distilling and non distilled models have performance equally distributed.

The negative performance on distilled models is explained by Saputra et al. [23]. In their work, it is proved that if the teacher is not reliable enough the Knowledge Distillation will not improve accuracy as it will add noise to the training. For the inference time, shown in Table VI it can be observed the significant gain compared to the teacher network because it is much more complex, requiring longer processing time, resulting in an inference time more than 3x faster.

To analyze the weights differences between network architectures, the network weight file sizes are compared. The sizes of networks in MB are shown in Table VI. In Tables V and VI, Trial 10 with batch normalization and without batch normalization have the same values because of its shares the same architecture. The large difference between the network weight sizes, which directly impacts the memory space to use the networks and the number of parameters in them. The table shows that the architecture based on YOLO-LITE is almost 99% smaller than the original reference architecture and almost 95% smaller than the Tiny-YOLO.

From a visual qualitative point of view, Figure 4 shows that our Distilled YOLO-LITE Trial 10 without batch normalization proposal produces similar results when compared with the baseline approach. It also achieves a massive gain in time and processing power. Our results open new possibilities of using the remaining processing time to increase its precision by integrating a refinement technique as the DeepIM [24].

VI. CONCLUSIONS AND FUTURE WORKS

This work showed the benefits and consequences of exchanging the basis network for the 6DoF object detection technique proposed by Tekin et al. [4]. In this way, it is possible to analyze and compare which basis network of 2D object detection to use for 6DoF object detection. The comparison can be made by looking at the network weights or the inference time. Thus choose the right architecture for the target hardware, which can be a smartphone or a robot. Also, Knowledge Distillation [14] was used to train simpler networks as tiny basis, Tiny-YOLO [5] and YOLO-LITE [6], to improve their accuracy. The main goal of this work was to show how it is possible to reduce the 6DoF object detection network proposed by Tekin et al. by more than 90x (weights in MB), reducing the hit rate by a smaller factor, but still achieving comparable results in the qualitative evaluation.

The methodology proposed by this work can also be used in future works where new state-of-the-art 6DoF object detection techniques like DPOD [12] can be used as a new teacher network. This assumption is supported by Saputra et al. which claims that Knowledge Distillation achieves greater can be used as a new teacher network and thus improve the efficiency of the use of Knowledge Distillation that according to Saputra et al. [23] achieves greater efficiency with detectors that generate less noise.
REFERENCES

[1] C. Hernandez, M. Bharatheesha, W. Ko, H. Gaiser, J. Tan, K. van Deurzen, M. de Vries, B. Van Mil, J. van Egmond, R. Burger et al., “Team delft’s robot winner of the amazon picking challenge 2016,” in Robot  World Cup. Springer, 2016, pp. 613–624.

[2] D. J. Tan, N. Navab, and F. Tombari, “6d object pose estimation with depth images: A seamless approach for robotic interaction and augmented reality,” arXiv preprint arXiv:1709.01459, 2017.

[3] H. Tjaden, U. Schwanecke, and E. Schomer, “Real-time monocular pose estimation of 3d objects using temporally consistent local color histograms,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 124–132.

[4] B. Tekin, S. N. Sinha, and P. Fua, “Real-time seamless single shot 6d object pose prediction,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 292–301.

[5] J. Redmon and A. Farhadi, “Yolo9000: better, faster, stronger,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 7263–7271.

[6] R. Huang, J. Pedrecorn, and C. Chen, “Yolo-lite: a real-time object detection algorithm optimized for non-gpu computers,” in 2018 IEEE International Conference on Big Data (Big Data). IEEE, 2018, pp. 2503–2510.

[7] R. Mehta and C. Ozturk, “Object detection at 200 frames per second,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 0–0.

[8] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” arXiv preprint arXiv:1804.02767, 2018.

[9] M. Rad and V. Lepetit, “Bb8: A scalable, accurate, robust to partial occlusion method for predicting the 3d poses of challenging objects without using depth,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 3828–3836.

[10] E. Brachmann, F. Michel, A. Krull, M. Ying Yang, S. Gumhold et al., “Uncertainty-driven 6d pose estimation of objects and scenes from a single rgb image,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3364–3372.

[11] W. Kehl, F. Manhardt, F. Tombari, S. Ilic, and N. Navab, “Ssd-6d: Making rgb-based 3d detection and 6d pose estimation great again,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 1521–1529.

[12] S. Zakharov, I. Shugurov, and S. Ilic, “Dpod: 6d pose object detector and refiner,” in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 1941–1950.

[13] Y. Cheng, D. Wang, P. Zhou, and T. Zhang, “A survey of model compression and acceleration for deep neural networks,” arXiv preprint arXiv:1710.09282, 2017.

[14] G. Hinton, O. Vinyals, and J. Dean, “Distilling the knowledge in a neural network,” arXiv preprint arXiv:1503.02531, 2015.

[15] S. Han, J. Pool, J. Tran, and W. Dally, “Learning both weights and connections for efficient neural networks,” in Advances in neural information processing systems, 2015, pp. 1135–1143.

[16] Y. He, X. Zhang, and J. Sun, “Channel pruning for accelerating very deep neural networks,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 1389–1397.

[17] Y. LeCun, J. S. Denker, and S. A. Solla, “Optimal brain damage,” in Advances in neural information processing systems, 1990, pp. 598–605.

[18] R. Tang, Y. Lu, L. Liu, L. Mou, O. Vechtomova, and J. Lin, “Distilling task-specific knowledge from bert into simple neural networks,” arXiv preprint arXiv:1903.12136, 2019.

[19] Y. Wang, X. Tao, X. Qi, X. Shen, and J. Jia, “Image inpainting via generative multi-column convolutional neural networks,” in Advances in Neural Information Processing Systems, 2018, pp. 331–340.

[20] S. Hinterstoisser, V. Lepetit, S. Ilic, S. Holzer, G. Bradski, K. Konolige, and N. Navab, “Model based training, detection and pose estimation of texture-less 3d objects in heavily cluttered scenes,” in Asian conference on computer vision. Springer, 2012, pp. 548–562.

[21] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (voc) challenge,” International journal of computer vision, vol. 88, no. 2, pp. 303–338, 2010.

[22] E. Brachmann, F. Michel, A. Krull, M. Ying Yang, S. Gumhold et al., “Uncertainty-driven 6d pose estimation of objects and scenes from a single rgb image,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3364–3372.

[23] M. R. U. Saputra, P. P. de Gusmao, Y. Almalioglu, A. Markham, and N. Trigoni, “Distilling knowledge from a deep pose regressor network,” in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 263–272.

[24] Y. Li, G. Wang, X. Ji, Y. Xiang, and D. Fox, “Deepim: Deep iterative matching for 6d pose estimation,” International Journal of Computer Vision, Nov 2019. [Online]. Available: http://dx.doi.org/10.1007/s11263-019-01250-9