ZippyPoint: Fast Interest Point Detection, Description, and Matching through Mixed Precision Discretization

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Abstract

Efficient detection and description of geometric regions in images is a prerequisite in visual systems for localization and mapping. Such systems still rely on traditional hand-crafted methods for efficient generation of lightweight descriptors, a common limitation of the more powerful neural network models that come with high compute and specific hardware requirements. In this paper, we focus on the adaptations required by detection and description neural networks to enable their use in computationally limited platforms such as robots, mobile, and augmented reality devices. To that end, we investigate and adapt network quantization techniques to accelerate inference and enable its use on compute limited platforms. In addition, we revisit common practices in descriptor quantization and propose the use of a binary descriptor normalization layer, enabling the generation of distinctive binary descriptors with a constant number of ones. ZippyPoint, our efficient quantized network with binary descriptors, improves the network runtime speed, the descriptor matching speed, and the 3D model size, by at least an order of magnitude when compared to full-precision counterparts. These improvements come at a minor performance degradation as evaluated on the tasks of homography estimation, visual localization, and map-free visual relocalization. Code and models are available at https://github.com/menelaoskanakis/ZippyPoint.

1. Introduction

The detection and description of geometric regions in images, such as salient points or lines, is one of the fundamental components in visual localization and mapping pipelines – essential prerequisites for Augmented Reality (AR) and robotic applications. Achieving such detection and description efficiently with handcrafted algorithms [29,48] has produced successful robot localization methods [15,17,30,37,38]. On the other hand, Deep Neural Networks (DNNs) have significantly advanced the representational capability of descriptors by learning on large scale natural images [13], using deeper networks [14], or introducing new modules to learn feature matching [50]. However, these advances often come at the cost of more expensive models with slow run times and large memory requirements for representation storage, making them unsuitable for computationally limited platforms. While the de-
mand for real-time applications such as robotics and AR is increasing, efficient DNN methods that can operate in real-time on computationally limited platforms have received surprisingly little attention.

A key component for the successful deployment of mobile robots in large-scale applications is the real-time extraction of binary descriptors. This not only enables efficient storage of the detected representation, e.g. the map in Simultaneous Localization and Mapping (SLAM) or Structure-from-Motion (SfM) pipelines, but also accelerated descriptor matching. In particular, matching computations in localization scale non-linearly with the number of images or map size. Therefore, improved two-view matching speed can translate to very high gains in real applications. Fast and light weight descriptor methods include BRISK [29], BRIEF [8] and ORB [48], however, their matching capability is often inferior to standard hand-crafted features such as SIFT [35] and SURF [5], as presented by Heinly J. et al. [22]. In challenging scenarios, however, hand-crafted feature extractors are outperformed significantly by learned representations [51]. While the performance gains of learned methods are highly desired, embedded platforms are limited in storage, memory, providing limited or no support for Floating-Point (FP) arithmetic, thus limiting the use of learned methods.

Motivated by the desire for improving the performance of feature points on low-compute platforms, we explore DNN quantization to enable the real-time generation of learned descriptors under such challenging constraints. However, the quantization of a DNN is not as straightforward as selecting the discretization level of convolutional layers. Quantized DNNs often require different levels of discretized precision for different layers [34, 46]. Operations such as max-pooling favour saturation regimes [46], while average pooling is affected by the required rounding and truncation operations. Moreover, prior works often focus on image-level classification tasks, with findings that do not necessarily transfer to new tasks [6]. To render the search for a Quantized Neural Network (QNN) tractable, we propose a layer partitioning and traversal strategy, significantly reducing the architecture search complexity. While most research considers homogeneous quantization precision across all layers [40], we find Mixed-Precision (MP) quantization yields superior performance. In addition, we find that replacing standard pooling operations with learned alternatives can further improve QNN performance.

Besides the need for real-time inference, DNNs need to additionally generate binary local descriptors for storage efficiency and fast feature matching. This adds further challenges as the discretization of the output layer draws less precise boundaries in the feature domain [28], making the network optimization more challenging. Furthermore, prior works focus on global feature description and present findings that do not trivially transfer to our task [27, 55]. To this extent, we introduce a Binary Normalization (Bin.Norm) layer that constrains the representation to a constant pre-defined number of ones. Bin.Norm is therefore analogous to the $L_2$ normalization, a staple and key component in FP metric learning [39].

In summary, our contributions are:

- We propose the use of a normalization layer for the end-to-end optimization of binary descriptors. Incorporating the Bin.Norm layer yields consistent improvements when compared to the common practices for descriptor binarization.

- We provide a detailed analysis of ZippyPoint, our proposed QNN with binary descriptors, on the task of homography estimation. We further demonstrate the generality of ZippyPoint on the challenging applications of Visual Localization (VisLoc) and Map-Free Visual Relocalization. ZippyPoint consistently outperforms all real-time alternatives and yields comparable performance to a full precision counterpart while addressing its known limitations, illustrated in Fig. 1.

2. Related Work

**Hand-crafted feature extractors.** The design of hand-crafted sparse feature extractors such as SIFT [35] and SURF [5] has been undoubtedly very successful in practice, still widely used in applications such as SfM [53]. However, the time needed for detection and descriptor extraction, coupled with their FP representation, limits them from being used on compute-limited platforms, such as lightweight unmanned aerial vehicles. Motivated by this limitation, methods like BRISK [29], BRIEF [8], and ORB [48], aimed to provide compact features targeted for real-time applications [30, 37, 38]. While fast and lightweight, they lack the representational strength to perform well under a wide variety of viewing conditions such as large viewpoint changes [22, 53] or times of day and year [51].

**Learned feature extractors.** Advances in DNNs have enabled the learning of robust, (pseudo-)invariant, and highly descriptive image features, pushing the boundaries of what was previously possible through hand-crafted methods.
While hand-crafted local features [5, 8, 29, 35, 48, 59] have not evolved much, systematic incremental progress can be seen in the learned local features [9, 13, 14, 16, 45, 47, 58]. Improvements have been achieved using contrastive learning [9], self-supervised learning [13], improved architectures [47, 58] and outlier rejection [58], to name a few approaches. Nevertheless, time and memory inefficiency remain major drawbacks of the learned methods.

In the same vein, large scale descriptor matching calls for light-weight representations. Binary descriptors enable efficient matching with moderate performance drops while significantly decreasing the storage requirements. Yet, the existing literature on binary representations focuses on image retrieval [27, 31, 54, 55], neglecting the detection and description of local features. For descriptor binarization, [31, 54, 55] use multistage optimization procedures. More similar to our work, [42] defines a differentiable objective for the hamming distance, [27] uses sigmoids to soften the optimization objective, while [57] rely on a hard sign function and gradient approximations. In the same spirit, we also optimize the network in a single optimization step. However, we argue that the lack of normalization layer in these methods, a staple in metric learning [39], greatly hinders the descriptor performance. To address this limitation, we propose a normalization layer for binary descriptors. Bin.Norm provides a more stable operation [43, 44, 62], and hardware-aware optimizations [46].

Efficient Neural Networks. Several solutions have been proposed to deploy neural networks in constrained scenarios. These solutions can be partitioned in topological optimizations, aiming at increasing accuracy-per-operation or accuracy-per-parameter [7, 21, 23], software optimizations such as tensor decomposition and parameter pruning [43, 44, 62], and hardware-aware optimizations [46].

Amongst hardware-aware optimizations, quantization plays a central role [34, 46]. By replacing FP with Integer (Int) operands, a QNN can reduce its storage and memory requirements with respect to an equivalent DNN. In addition, complex FP arithmetics can be replaced by simpler Int arithmetics. Due to these properties, QNNs can be executed at higher throughput (number of operations per cycle) and arithmetic intensity (number of arithmetic operations per memory transaction) [24]. When operand precision is extremely low, e.g. Binary (Bin), standard instruction set architectures can be exploited to increase these metrics even further [46]. Unlike mainframes and workstations, embedded platforms have limited storage and memory, limited or no support for FP arithmetics, and are optimized to execute SIMD (Single Instruction, Multiple Data) Int arithmetics. These considerations make QNNs an ideal fit for embedded applications, such as robots and mobile devices.

However, QNNs have limited representational capacity compared to their FP counterparts. Specifically, linear operations using discretized weights draw less precise boundaries in their input domains. In addition, discretized activation functions lose injectivity with respect to their FP counterparts, making quantization a lossy process [28]. To strike a balance between throughput and performance, practitioners require to identify a single Int precision [40], or alternative linear layers [34], that achieve the desired performance. These design choices are applied homogeneously across the entire network. We instead hypothesize that a single set of hyperparameters across the entire network can be suboptimal. We, therefore, investigate the use of heterogeneous layers throughout the network, e.g. different Int precision at different depths of the network, made possible through the proposed layer partitioning and traversal strategy.

3. Mixed Precision Discretization

Efficiently identifying salient points in images and encoding them with lightweight descriptors is key to enabling real-time applications such as robot localization. In this paper we explore the efficacy of learning-based descriptor methods under two constraints: minimizing run-time la-
tency and using binary descriptors for accelerating keypoint matching and efficient storage. In Sec. 3.1 we introduce the baseline architecture we initiate our investigation from. In Sec. 3.2 we propose a strategy to explore structural changes to the network’s topology. In Sec. 3.3 we introduce a standard formulation of metric learning, which we use to then define our Bin.Norm descriptor layer.

3.1. Baseline Architecture

We initiate our investigation from the state-of-the-art KP2D [58] network, which exploits outlier filtering to improve detections. The KP2D model maps an input image $I \in \mathbb{R}^{H \times W \times 3}$ to keypoints $p \in \mathbb{R}^{N \times 2}$, descriptors $x \in \mathbb{R}^{N \times M}$, and keypoint scores $s \in \mathbb{R}^{N}$, where $N$ represents the total number of keypoints extracted and $M$ the descriptor size. The model is comprised of an encoder with 4 VGG-style blocks [56], followed by a three-headed decoder for keypoints, keypoint scores, and descriptors. The encoder is comprised of 8 convolutional operations, the keypoint and keypoint score branches of 2, and the descriptor branch of 4. All convolutional operations, except for the final layers, are followed by batch normalization and leaky ReLUs [36]. The model is optimized through self-supervision by enforcing consistency in predictions between a source image $I_s$ and a target image $I_t = H(I_s)$, related through a known homography transformation $H$ and its warping function $H$.

We chose KP2D as the starting point for our investigation due to its standard architecture design choices: a VGG style encoder [10, 13, 14, 47], encoder-decoder structure [10, 13], and the detection and description paradigm [10, 13, 14, 47]. Therefore, we expect that the investigated quantization strategy can transfer to other similar models, such as the ones listed above.

3.2. Network Quantization

For the quantization of a convolutional layer, several design choices are required. These include weight precision, feature precision, and whether to use a high precision residual. When considering independently each layer of a DNN, it leads to a combinatorially large search grid, rendering an exhaustive search of the ideal quantization policy prohibitive.

To simplify the search space, we propose the layer partitioning and traversal strategy, depicted in Fig. 2. First, we partition the operations of our target architecture into macro-blocks. For each macro-block, we define a collection of candidate quantized configurations. We then traverse through the macro-blocks and identify the optimal configuration for each, one at a time. This heuristic algorithm terminates once we have reached the most downstream network layer, the prediction heads. Note that, while we maintain the macro-block configurations the same once selected, the architecture is always optimized end-to-end. This strategy reduces the search complexity from combinatorial (the product of the number of configurations for each macro-block) to linear (the sum of the number of configurations for each macro-block). In addition, it ensures that when a macro-block is optimized on features with given representation capabilities, it will not degrade due to optimization of a different macro-block upstream. We detail our choice of macro-blocks and their configurations in the experiments section.

3.3. Binary Learned Descriptors

Preliminaries. When describing an image or a local region, the learned mapping aims to project a set of data points to an embedding space, where similar data are close together and dissimilar data are far apart. A fundamental component to the success of learned descriptors is the advancement of contrastive losses [12, 20, 61]. To ensure stable optimization and avoiding mode collapse, descriptors are often normalized [39]. A common selection is $L_2$ normalization, defined as

$$y = \frac{1}{||x||_2}x.$$  \hspace{1cm} (1)

While the solution, and hence gradients, can be expressed in closed-form, it assumes FP representation spaces $x$ and $y$. However, Bin descriptors can only take discrete values $\{0,1\}$. In search for a normalization layer applicable for Bin descriptors, we instead view and rewrite Eq. (1) as the generalized optimization objective

$$y = \arg\min_{z \in \mathbb{R}^M} d(z; x)$$

subject to $\text{constr}(z)$, \hspace{1cm} (2)

where we search for the vector $z$ that minimizes a distance function to $x$ under a normalization constraint $\text{constr}(z)$. Eq. (2) is therefore equivalent to Eq. (1) when $d(z; x) = \frac{1}{2}||z - x||_2^2$ and $\text{constr}(z) = ||z||_2 = 1$. This enables the definition of optimization objectives that can be utilized where $L_2$ normalization does not provide the required behaviour. While constrained optimization problems are not differentiable, their use in DNNs is made possible through advances in deep declarative networks [19].

Normalization for Binary Descriptors. We hypothesize that normalization for binary descriptors is equivalent to having a constant number of ones in each descriptor. To this end, we take inspiration from multi-class classification problems and view the Bin.Norm as a projection of the descriptors living in an $M$-dimensional hypercube on a $k$-dimensional polytope [3]. In other words, an $M$-dimensional descriptor has entries that sum to $k$. This trivially yields the constraint from Eq. (2) to $\text{constr}(z) = 1^\top z = k$, where $1$ is a vector of 1s of the same dimension as $z$. 

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We define the new optimization objective as
\[
    y = \arg \min_{x \in [0,1]^M} -x^\top z - H(z)
\]
subject to \(1^\top z = k\)
\[ (3) \]

where \(H(z)\) is the binary entropy function applied on the vector \(z\) for entropy based regularization.

To optimize the objective, we introduce a dual variable \(\nu \in \mathbb{R}\) for the constraint of Eq. (3). The Lagrangian then becomes
\[
- x^\top z - H(z) + \nu (k - 1^\top z).
\] Differentiating with respect to \(z\), and solving for first-order optimality gives
\[
- x + \log \frac{z^\star}{1 - z^\star} - \nu^\star = 0,
\] that yields
\[
y \approx z^\star = \sigma(x + \nu^\star),
\] where \(\sigma\) denotes the logistic function. We identify the optimal \(\nu^\star\) by using the bracketing method of [3], efficiently implemented for use on GPUs, and backpropagate using [2].

The selection of the optimization objective in Eq. (3) is two-fold. The entropy regularizer helps prevent sparsity in the gradients of the projection. In addition, the forward pass in Eq. (6) can be seen as an adaptive sigmoid that ensures the descriptor entries sum up to a specific value. This enables the direct comparison with the common practice of approximating binary entries using the sigmoid function.

At inference, the descriptor optimization strategy in Eq. 3 is replaced by a thresholding function that sets the top-64 to ones, however, we found that both smaller and larger numbers yield a comparable performance.

4. Experiments

We present the implementation details in Sec. 4.1. In Sec. 4.2 we investigate the effect of network quantization using the layer partitioning and traversal strategy, as well as evaluate the proposed Bin.Norm layer for descriptor binarization. We then combine the two contributions into ZippyPoint and evaluate its performance on the task of homography estimation. We evaluate the generalization capabilities of ZippyPoint on fundamental tasks in robotic and AR pipelines, namely VisLoc in Sec. 4.3, and Map-Free Visual Relocalization in the supplementary material. We envision our work can both spark further research in the design of binary descriptors and quantized networks, as well as promote the incorporation of ZippyPoint in robotic systems.

4.1. Implementation Details

We implement our models in TensorFlow [1], and use the Larq [18] library for quantization. Our models are trained on the COCO 2017 dataset [32], comprised of 118k training images, following [10, 13, 58]. The models are optimized using ADAM [25] for 50 epochs with a batch size of 8, starting with an initial learning rate of \(10^{-3}\) while halving it every 10 epochs. To ensure robustness in our results, we optimize each model configuration three times and report the mean and standard deviation.

To enable self-supervised training, spatial and non-spatial augmentations for the homography transformation are required. For spatial transformations, we utilize crop, translation, scale, rotation, and symmetric perspective. Non-spatial transformations applied are per-pixel Gaussian noise, Gaussian blur, color augmentation in brightness, contrast, saturation, and hue. Finally, we randomly shuffle the color channels and convert images to gray scale. Please refer to [38] for more details.

4.2. Designing ZippyPoint

We conduct our DNN quantization investigation on the task of homography estimation, a commonly used task for the evaluation of self-supervised learned models [10, 13, 58]. Homographic transformations largely eliminates domain shifts due to missing 3D, providing a good benchmark for ablation studies.

We evaluate our method on image sequences from the HPatches dataset [4]. HPatches contains 116 scenes, separated in 57 illumination and 59 viewpoint sequences. Each sequence is comprised of 6 images, with the first image used as a reference. The remaining images are used to form pairs for evaluation. As is common practice, we report Repeatability (Repeat.), Localization Error (Loc), Matching Score (M.Score), and Homography Accuracy with thresholds of 1, 3 and 5 pixels (Cor-1, Cor-3, Cor-5). We additionally benchmark and report the CPU speeds in Frames Per Seconds (FPS) on an Apple M1 ARM processor.

Baseline. We initiate our investigation in Table 1 from a re-implementation of KP2D with minor modifications to enable a structured search with minimal macro-block interference. Specifically, KP2D uses a shortcut connection between the encoder and decoder macro-blocks. We remove this skip-connection to constrain the interaction between two macro-blocks to a single point. Furthermore, we replace the leaky ReLUs with hard-swish [23], a comparable but faster alternative. The functional performance of Baseline is comparable to KP2D while slightly improving the throughput.

We then partition our baseline architecture into macro-blocks. These include the first encoder convolution, the remaining encoder convolutions, spatial reduction layers,
tion improves throughput by as much as otherwise. Specifically, we find that using an Int8 convolution reduces additional degradation of functional performance, our findings suggest though [34, 46] suggest that keeping the first convolution in block I, we considered two configurations: FP and Int8. Although high-precision Int8 residuals improve performance significantly. This again advocates for the redundancy of FP representation in the encoder, as the encoder is now bottlenecked by Int8 precision.

Macrow-Block II: Encoder Convolutions. For the encoder convolutions, we considered three configurations: Int8, Bin, and Binary with a high-precision Residual (Bin-R). While using Bin convolutions in the encoder significantly improves application throughput, functional performance is severely hindered, as measured by the halving of the correctness metrics. This drop is consistent with findings in the literature for semantic segmentation [63] while conflicting with image-level classification experiments [46]. This further supports our arguments for the importance of task-specific investigations.

To alleviate such drastic performance drops, we introduce high precision Int8 representations in the form of a residual operation. For convolutional operations with a mismatch in the number of input and output channels, we introduce additional Int8 1 × 1 convolutions on the residual path. This ensures the high-precision paths maintain their Int8 precision, while matching the channel dimensions. The additional high-precision Int8 residuals improve performance significantly. This again advocates for the redundancy of FP representation in the encoder, as the encoder is now bottlenecked by Int8 precision.

Macrow-Block III: Spatial Reduction. For the spatial reduction layers, we considered four configurations: max-pooling (Max), average-pooling (Aver.), sub-sampling (Sub.S.) and a learned projection (Learn). As is common in DNNs, our baseline utilizes max-pooling. However, max-pooling has been found to favour saturated regimes and therefore eliminates information when applied on low-precision features like those found in QNNs [46]. Average pooling further degrades the performance, attributed to the errors introduced due to the roundings and truncations which are essential for integerized arrays. To further highlight this error, a simple Sub.S. that only uses information from a quarter of the kernel window yields comparable performance to Aver.
and general-purpose features can be extracted using low-optimal results. This observation suggests that good quality Bin-R or Int8 convolutional operations would yield sub-MP QNNs. In other words, a network comprised of only addition, enhanced performance can be achieved through having an insignificant effect on functional performance.

Network Quantization Findings. Network latency can significantly improving the throughput. Meanwhile, the descriptor branch can be optimized with Int8, significantly leading to a more stable optimization process. To test this assumption, we append an normalization layer after the element-wise sigmoid operation. This constrains the activations and dramatically improves performance. Furthermore, it suggests that the dense task predictor heads benefit from higher Int8 precision to accurately reconstruct the target information from the encoded features. Finally, we observe that the prediction heads for regression tasks (score and location) cannot be quantized and should be left in FP, while the descriptor head can be quantized to Int8. This further drives the importance of the structured investigation, like the layer partitioning and traversal strategy.

Binarizing descriptors. We initiate the descriptor exploration from the common practice of utilizing sigmoid as a soft approximation for every bit [27, 33], and the hamming triplet loss proposed by [27]. While some works use a hard sign function [57], we found it unable to optimize the network to a meaningful degree. Table 2 demonstrates a significant performance drop and large variance compared to the baseline, especially in the correctness metrics. We conjecture that this spans from the lack of a normalization layer, causing the sigmoid to saturate, and yielding uninformative gradients. To test this assumption, we append an $||L_2||$ normalization layer after the element-wise sigmoid operation. This constrains the activations and dramatically improves performance and reduces the variance, as seen experimentally, leading to a more stable optimization process.

In this paper we hypothesize that, analogous to $||L_2||$ normalization, we can optimize the network using a Bin normalization layer by constraining the descriptor to a constant number of ones. Using the proposed Bin.Norm layer, the functional performance gap is significantly decreased when compared to the FP descriptors.

Comparison to state-of-the-art. We compare ZippyPoint with state-of-the-art methods in Table 3. For a fair com-

| Norm       | Repeat † | Loc. † | Cor-1 † | Cor-3 † | Cor-5 † | M.Score † |
|------------|----------|--------|---------|---------|---------|-----------|
| Full Precision | $L_2$    | 0.644 ± 0.003 | 0.788 ± 0.005 | 0.580 ± 0.007 | 0.886 ± 0.008 | 0.933 ± 0.010 | 0.569 ± 0.003 |
| Sigmoid    | $L_2$    | 0.640 ± 0.005 | 0.809 ± 0.049 | 0.173 ± 0.300 | 0.285 ± 0.493 | 0.305 ± 0.528 | 0.187 ± 0.318 |
| Sigmoid + Bin.Norm (Ours) | $L_2$    | 0.650 ± 0.001 | 0.803 ± 0.010 | 0.491 ± 0.015 | 0.822 ± 0.009 | 0.888 ± 0.003 | 0.513 ± 0.003 |

| Repeat. † | Loc. † | Cor-1 † | Cor-3 † | Cor-5 † | M.Score † |
|-----------|--------|---------|---------|---------|-----------|
| SuperPoint [13] | 0.631 | 1.109 | 0.491 | 0.833 | 0.893 | 0.318 |
| SIFT [55]  | 0.451 | 0.855 | 0.622 | 0.845 | 0.878 | 0.304 |
| SURF [3]   | 0.491 | 1.150 | 0.397 | 0.702 | 0.762 | 0.255 |
| KP2D [55]  | 0.686 | 0.890 | 0.591 | 0.867 | 0.912 | 0.544 |
| ZippyPoint (Ours) | 0.652 ± 0.005 | 0.926 ± 0.022 | 0.506 ± 0.025 | 0.853 ± 0.007 | 0.917 ± 0.003 | 0.571 ± 0.003 |

| Repeat. † | Loc. † | Cor-1 † | Cor-3 † | Cor-5 † | M.Score † |
|-----------|--------|---------|---------|---------|-----------|
| BRISK [29] | 0.566 | 1.077 | 0.414 | 0.767 | 0.826 | 0.258 |
| ORB [48]   | 0.532 | 1.429 | 0.131 | 0.422 | 0.540 | 0.218 |
| ZippyPoint (Ours) | 0.652 ± 0.005 | 0.926 ± 0.022 | 0.433 ± 0.007 | 0.820 ± 0.007 | 0.887 ± 0.006 | 0.571 ± 0.003 |

FP convolutional layers this would cause a 4× speedup for each convolution, in quantized convolutions the gain is even greater [18].
Camera localization is one of the key components in several robotic and mapping applications. Both relative [41] and absolute [26] camera localization require good local feature point descriptors to match, and are key building blocks in seminal pipelines [11, 15, 17, 30, 37, 38]. To further demonstrate the potential of ZippyPoint, we assess its generalization capability on the task of absolute camera localization, where the pose of a query image is estimated with respect to a 3D map.

We utilize the hloc framework [49], similar to prior works [47, 50], and evaluate the performance on the challenging real-life AachenV1.1 Day-Night datasets from the VisLoc benchmark [51, 52]. More precisely, we reconstruct the 3D map using ZippyPoint features instead of SIFT [35]. For each query image, we perform a coarse search of the map and retrieve the 30 closest database images based on their global descriptors, representing candidate locations.

The query image is then localized within the 3D map by utilizing the candidate locations. Please refer to [49] for more details.

The results are presented in Fig. 3 with respect to the FPS speed for matching two images. In Fig. 1 we additionally depict the average performance score for both day and night query sets with respect to 3D model size, query localization time, and model inference speed. While ZippyPoint performs comparably to SuperPoint during day time, we decrease the 3D model size, query localization time, and model inference speed by at least an order of magnitude. This is attributed to the lightweight binary descriptors, the more efficient similarity comparison between the descriptors, and the network quantization. Localization with ZippyPoint at night is slightly inferior to SuperPoint, however, we expect optimization of the image transformations during training can close this gap further.

On the binary descriptor front, ZippyPoint consistently outperforms ORB by a significant margin at a comparable matching speed. BRISK on the other hand is competitive to ours on the day dataset, with the slower run-time of BRISK attributed partly to the larger descriptor size, twice that of ZippyPoint, and the increased number of detected keypoints. However, the more challenging night dataset paints a different picture, with ZippyPoint outperforming BRISK by 42.9% and ORB failing to localize. This further attests to the need for efficient learned detection and description networks, in particular for more challenging and adverse conditions.

5. Conclusion

In this paper, we investigated efficient detection and description of learned local image points through mixed-precision quantization of network components and binarization of descriptors. To that end, we followed a structured investigation, we refer to as layer partitioning and traversal for the quantization of the network. In addition, we proposed the use of a binary normalization layer to generate binary descriptors with a constant number of ones.

We obtained an order of magnitude throughput improvement with minor degradation of performance. In addition, we find that the binary normalization layer allows the network to operate on par with full-precision networks, while consistently outperforming hand-crafted binary descriptor methods. The results show the suitability of our approach on visual localization and map-free visual relocalization, challenging downstream tasks and essential prerequisites for robotic applications, while significantly decreasing the 3D model size, matching, and localization speed. We believe ZippyPoint can spark further research towards bringing learned binary descriptor methods to mobile platforms, as well as promote its incorporation in both new and established robotic pipelines.
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