Highly-Efficient Binary Neural Networks for Visual Place Recognition

Bruno Ferrarini\textsuperscript{1}, Michael Milford\textsuperscript{2}, Klaus D. McDonald-Maier\textsuperscript{1} and Shoaib Ehsan\textsuperscript{1}

Abstract—VPR is a fundamental task for autonomous navigation as it enables a robot to localize itself in the workspace when a known location is detected. Although accuracy is an essential requirement for a VPR technique, computational and energy efficiency are not less important for real-world applications. CNN-based techniques archive state-of-the-art VPR performance but are computationally intensive and energy demanding. Binary neural networks (BNN) have been recently proposed to address VPR efficiently. Although a typical BNN is an order of magnitude more efficient than a CNN, its processing time and energy usage can be further improved. In a typical BNN, the first convolution is not completely binarized for the sake of accuracy. Consequently, the first layer is the slowest network stage, requiring a large share of the entire computational effort. This paper presents a class of BNNs for VPR that combines depthwise separable factorization and binarization to replace the first convolutional layer to improve computational and energy efficiency. Our best model achieves higher VPR performance while spending considerably less time and energy to process an image than a BNN using a non-binary convolution as a first stage.

I. INTRODUCTION

Mobile robots need to track their position within the workspace to operate autonomously. As part of the navigation system, place recognition is fundamental in the localization process. It enables a robot to localize itself in the environment when a previously visited place on the map is detected. The rapid improvements in vision sensing capabilities made cameras the primary source of information for many robotics platforms motivating the interest in addressing place recognition with visual information\textsuperscript{[1], [2]}. Visual Place Recognition (VPR) primarily consists of matching the current camera view with an internal representation of the environment (a map) to determine the current robot’s location. The changes occurring in an environment such as illumination, weather variations, and the different angles from which the camera captures a place render VPR an arduous endeavor. Convolutional Neural Networks (CNNs) are successfully employed in VPR applications achieving state-of-the-art performance under intense appearance changes\textsuperscript{[3]}. However, CNNs have high runtime requirements unaffordable for many small robots\textsuperscript{[4], [5]}. Binary neural networks (BNN)\textsuperscript{[6]} are a more efficient yet effective alternative to CNNs for enabling VPR in resource-constraint contexts\textsuperscript{[7]}. BNNs use a single bit to encode weights and activations, allowing compact model sizes and bitwise operations to achieve high computational efficiency\textsuperscript{[8]}. Although a BNN can be one order of magnitude faster than a CNN, there is a substantial margin for improvement. For better classification and VPR accuracy, the first layer of BNNs takes high precision inputs\textsuperscript{[8], [7]}. Hence, the first convolution is incompatible with bitwise operations resulting in the most inefficient stage of a BNN, as exemplified in Fig. 1. Such a bottleneck problem is particularly relevant for VPR as many techniques use a relatively small number of convolutions\textsuperscript{[7], [9], [10], [11], [12]}. Therefore, the first layer computes a significant part of the total operations to process an image that cannot be binarized without impacting the VPR performance.

This paper addresses the first layer bottleneck in BNNs by proposing the \textit{Half-Binary Depthwise Separable} (HB-DS) module. HB-DS combines depthwise separable factorization\textsuperscript{[13], [14]} with binarization to enhance the computational efficiency of a BNN without affecting the VPR performance. The HB-DS module is then used to design a BNN that can be tuned to train models with several levels of efficiency to meet different application requirements. Our best model\textsuperscript{1} achieves higher performance requiring considerably lower resources than several VPR techniques regarded as highly efficient. For example, our network requires 50\% of the time and energy spent by FloppyNet\textsuperscript{[7]}, a BNN for VPR, and it is four times faster than CALC\textsuperscript{[9]}, a small-factor CNN proposed to address loop closure detection efficiently.

The rest of this paper is organized as follows. Section II presents the related work. Section III describes the HB-DS

\textsuperscript{1}https://github.com/bferrarini/Half-Binary-Depthwise-Separable-Module
module and the proposed network. The experimental setup and evaluation criteria are detailed in Section IV. Section V presents and discusses the experimental results. Conclusions are drawn in Section VI.

II. RELATED WORK

A. Visual Place Recognition

Solving the VPR problem is the key to enable a robot to operate autonomously in a workspace. Despite the attention received and the significant advances in recent years, VPR remains challenging due to the viewpoint and appearance changes a robot encounters in real-world applications. Among the most effective VPR techniques are those using CNNs, which achieve the highest performance in dynamic environments [3], [15], [16]. The features computed by a CNN can be used as an image descriptor to match place images. A pre-trained AlexNet model [17] on Imagenet [18] is used for loop-closure detection [19], [10] and for enhancing the viewpoint tolerance of SeqSLAM [20], [21]. AMOSNet and HybridNet [22] are CNN trained on Specific Place Dataset (SPED) [22] with the aim to compute specific descriptors for place images. Zhou et al. followed the same idea proposing Place365 [23], a large place dataset used to train several CNNs, including VGG-16 [24], to solve the VPR problem in changing environments. CNN features can be post-processed to compute a robust and compact image descriptor. R-MAC [12] applies a max pooling schema to the last convolutional layer of a pre-trained CNN and aggregates the resulting features into a vectorized image descriptor. Cross-Region-Bow [11] and Regional-VLAD [25] identify regions-of-interest (ROIs) in a pre-trained CNN’s feature map and aggregate the underlying features using Bag-of-Visual-Words (BoW) [26] and VLAD [27], respectively. Unlike the others two-stage techniques, NetVLAD [28] trains the CNN and subsequent modules end-to-end to obtain a VLAD-like descriptor highly tolerant to viewpoint variations.

Although effective for VPR, CNNs are computationally intensive. CALC [9] is an attempt to reduce the runtime requirement for VPR. It consists of a lightweight CNN trained using an autoencoder to recreate a HOG [29] descriptor from geometrically distorted place images. CoHOG [30] is a trainingless methods proposed as a computationally efficient alternative to CNNs. It detects regions of interest using image-entropy [31] that are subsequently assigned with a HOG descriptor to form an image representation. Neurological-inspired techniques are considered as well to address VPR efficiently. FloppyNet+CANN [32] uses a compact pattern recognition stage followed by a time filter to match image sequences. DrososNets [33] consists of an ensemble of compact bio-inspired place classifiers connected to a voting systems to determine the correct match with the camera’s view. Binary neural networks (BNNs) [6] use 1-bit parameters and bitwise arithmetic to speed-up convolution and reduce dramatically the memory usage. FloppyNet [7] is a recently proposed BNNs for VPR applications. Its three-layer structure, along with bitwise arithmetic, makes FloppyNet a compact and computationally efficient image feature extractor. In this paper we propose a BNN with the same VPR accuracy as FloppyNet but substantially higher computational and energy efficiency.

B. Binary Neural Networks

CNNs successfully address the VPR problem but requires a heavy computational effort to build an image representation [5], [4]. Improving CNNs efficiency is a challenging task that received significant attention in the last decade. The earliest approaches reduce the computational complexity by pruning redundant connections and weights in trained models [34], [35], [36]. Post-training quantization is another method to reduce the computational requirements of a CNN. While post-quantization works reasonably well with eight or more bits in practical cases [37], post-binarization affects the performance of a model dramatically [38]. Binary-aware training is necessary to enable BNNs with good classification accuracy [39]. Training a binary model was attempted decades ago [40]. However, only after introducing the Straight-Trough-Estimator (STE) method [41], binary-aware training becomes easy to implement with gradient-based techniques. STE has become a standard in BNNs training. It is supported by an increasing number of machine-learning frameworks, including Larq [42] and Brevitas [43].

Since the first BNN trained with STE [6], several additions to the field were made. XNOR-Net [44] places max-pooling layers before the quantization function to prevent pooling from binarized features that would result in a non-informative map overpopulated by ones. Tang et al. [45] learn a positive gain to apply to negative values to prevent frequent binary weight oscillations to ensure a shorter training and better performance. In [46] the binarization threshold is a learnable parameter for better classification accuracy. The application of BNN to VPR is investigated in [7]. Training a model using
a fully connected stage including only full-precision neurons improves a model’s performance when convolutional features are used for VPR.

An open problem in BNNs concerns the first convolutional layer, which is not binarized in most state-of-the-art BNNs to avoid performance loss [39], [47]. Consequently, the first convolution is incompatible with bit-wise operations resulting in the slowest stage of a binary network (Section V-C). Hardware-driven techniques have been proposed to improve a BNN’s first layer efficiency. [48] presents a stochastic-based BNN employing logical gates to approximate the operations in the first convolutional layer. FBNA [49] is an in-place replacement for the first convolution in BNNs. FBNA decomposes a convolution in multiple binary channels computed in parallel in the FPGA implementation proposed by the authors. Similarly to [50], [51], we propose an in-place replacement of the first convolution based on depthwise factorization. Our HB-DS module enables performance tuning of a BNN to obtain different trade-offs between VPR accuracy and computational efficiency to meet an application’s requirements.

III. SOLVING THE FIRST LAYER BOTTLENECK PROBLEM

The first convolutional layer is crucial for a BNN’s performance. A common practice in BNN design is using high-precision inputs because binarization negatively affects performance [8]. Consequently, the first convolutional layer is incompatible with bit-wise operations resulting in the slowest stage of a BNN. For example, this is the case of FloppyNet [7], a recently proposed BNN optimized for VPR applications consisting of three convolutions and three max-pool layers. The first FloppyNet’s convolution takes approximately 83% of the total processing time, as detailed in Section V-C.

This section presents the Half-Binary Depthwise Separable module (HB-DS), to solve the first layer bottleneck problem. Then we use it to design a highly efficient and tunable binary network. The HB-DS module and the proposed BNN are detailed below.

A. Depthwise Separable Convolutions

Our approach uses depthwise separable factorization to split a convolution into two separate layers: a depthwise convolution and a pointwise convolution [13], [14]. Depthwise convolution convolves the input channels individually. The input is convolved without changing the depth. Hence, the resulting feature map has the same channels as the input. The pointwise layer consists of a $1 \times 1$ convolution that builds a new map from the depthwise layer’s features. Fig. 2 shows the idea underlying depthwise separable decomposition.

The term complexity is used here as a synonym for the number of multiply-accumulate operations (MACs) computed by a convolution. Hence, lower computational complexity means fewer MACs. Let us assume a convolutional layer takes an input tensor $T_{in} = h_i \times w_i \times c_i$ and uses a kernel, $k \times k$, to output a feature map $T_{out} = h_o \times w_o \times c_o$. The computational cost is:

$$C_{conv} = (k^2 \cdot c_i) \cdot h_o \cdot w_o \cdot c_o ,$$  \hspace{1cm} (1)

where $(k^2 \cdot c_i)$ is the cost for a single element in $T_{out}$.

A depthwise convolution convolves the input channels individually, creating a feature map having the same depth, $c_i$, as the input tensor. Fig. 2b shows an example of a depthwise convolution processing a three-channel tensor (e.g. a color image). The computational cost of a depthwise convolution is as follows:

$$C_{depth} = k^2 \cdot c_i \cdot h_o \cdot w_o .$$  \hspace{1cm} (2)

The subsequent pointwise stage is a standard convolution with $k = 1$:

$$C_{point} = c_i \cdot h_o \cdot w_o \cdot c_o ,$$  \hspace{1cm} (3)

The total computational cost of a depthwise separable convolution is:

$$C_{sep} = C_{depth} + C_{point} = c_i \cdot h_o \cdot w_o \cdot (k^2 + c_o) .$$  \hspace{1cm} (4)

Compared to a standard convolution, the depthwise separable factorization reduces the complexity by:

$$\frac{C_{conv}}{C_{sep}} = \frac{k^2 c_o}{c_o + k^2} .$$  \hspace{1cm} (5)

The larger the kernel, more effective is the depthwise separable factorization.

B. Half-Binary Depthwise Separable Convolutions

We proposed a half-binary variant of depthwise separable factorization where only the second layer resulting from the decomposition is binarized (Fig. 2c). Hence, the depthwise layer takes full precision inputs while the subsequent
pointwise convolution is binary for higher computational efficiency. The share of binary MACs is:

$$C_{\text{point}} \over C_{\text{sep}} = {c_o \over k^2 + c_o}.$$  \hspace{1cm} (6)

Conversely, the full precision MAC are those in the depthwise convolution:

$$C_{\text{depth}} \over C_{\text{sep}} = {k^2 \over k^2 + c_o}. \hspace{1cm} (7)$$

If $c_o > k^2$ the effect of binarization is dominant on factorization. Conversely, the complexity reduction is primarily due to factorization.

The implementation of the HB-DS module is illustrated in Fig. 3. A batch normalization layer [52] is placed before the binary convolution to improve a model’s accuracy and training speed [47].

Depthwise convolution can apply multiple kernels to an input channel creating a thicker feature map. Let $d$ denotes the depth multiplier. The resulting feature map has $d \cdot c_i$ channels, as exemplified in Fig. 4 for $d = 2$. The application of a depth multiplier increases the computational complexity of HB-DS by $d$ times. Therefore, Eq. 5 is rewritten as follows:

$$C_{\text{conv}} \over C_{\text{sep}} = {k^2 c_o \over d(c_o + k^2)}. \hspace{1cm} (8)$$

On the other hand, the VPR performance of a BNN improves as $d$ increases. Section V-C demonstrates the use of $d$ as a tuning parameter to adapt a model to different hardware capabilities while keeping HB-DS faster than an ordinary convolutional layer.

C. Network Architecture

The proposed network shown in Fig. 5 is inspired by FloppyNet. The HB-DS module uses a $11 \times 11$ kernel, stride of 4 and has 96 output channels. The rest of the network includes two pairs of binary convolution-max pooling blocks. The binary convolutions do not use bias but are preceded by batch normalization. The output features are from the last pooling layer.

Fig. 5. The proposed BNN uses HB-DS as a first stage. $d$ denotes the depth multiplier.

IV. EXPERIMENTAL SETUP

The proposed network is trained with several depth multipliers, $d$. The resulting models are assessed on VPR under various environmental changes. A model’s efficiency is evaluated using processing time and energy usage as criteria.

A. Training Data

All the binary models are trained from scratch using Place365 [23] within the Larq framework [42]. Places365 is a place-themed dataset consisting of 1,803,460 images divided into 365 classes, including between 3068 and 5000 samples. The validation set includes 100 images per category.

B. Test Data

VPR assessment is carried out under different image variations that a robot encounters over extended runs. The test data is divided into five datasets, each containing one or more image changes. They include: GardenPoints [53], 200 places randomly sampled from SPED [22], the Cross-Season sequence from RobotCar [54], Nordlands [55] and Old City [1]. Table I summarizes the characteristics and the ground truth criteria for each dataset. All of them include a reference set representing the knowledge of the environment and a query set representing the current view of a robot’s camera. Fig. 6 shows some examples of matching pairs.

We included a sixth dataset, Combined, to simulate a large complex environment. The reference set is the union of the other five datasets; the query set includes 200 randomly sampled images for a total of 1000 queries. The Combined dataset is intended to provide more realistic global performance measures than averaging the results from the five datasets tested individually.

| Dataset   | Condition                | Reference Images | Query Images | Ground Truth |
|-----------|--------------------------|------------------|--------------|--------------|
| GardenPoints | Lateral Shift; Night-Day. | 201              | 201          | 2 frames     |
| SPED      | Weather; Night-Day.      | 1000             | 200          | 5 frames     |
| RobotCar  | Lateral Shift; Illumination; Dynamic Elements. | 203              | 180          | 5 frames     |
| Nordlands | Seasons (summer-winter). | 1622             | 1622         | 5 frames     |
| Old City  | Strong 6-DOF            | 5408             | 5643         | by authors   |
| Combined  | All above                | 8434             | 1000         | Mixed        |

Fig. 6. A matching pair from every test dataset.
C. Evaluation Criteria

1) VPR Performance: VPR is cast as a loop closure detection problem. A query image representing the current robot’s camera view is compared to the reference images showing the previously visited locations. The image descriptor for our model is obtained from the vectorized output of a convolutional or pooling layer by L2-normalization:

$$D = \frac{\|\hat{X}_l\|_2}{\|X_l\|_2},$$

where $\hat{X}_l$ is the output of the $l^{th}$ layer. The similarity between the images is determined using cosine:

$$\cos(\psi) = \frac{D_1 \cdot D_2}{\|D_1\| \cdot \|D_2\|}.$$  

The reference image scoring the highest similarity with the query image is regarded as the current location. VPR performance is measured on a dataset using several criteria including the percentage of true positive matches (TP%) and two metrics computed from Precision-Recall curves: Extended Precision (EP) [56] and Area Under the Curve (AUC). EP extends the recall at 100% precision ($R_{P100}$) [21] to the lower spectrum by incorporating the precision at the minimum recall ($P_{R0}$):

$$EP = \frac{P_{R0} + R_{P100}}{2}.$$  

EP is in $[0, 1]$: higher the value, better the VPR performance.

2) Processing Time and Energy Usage [7]: The processing time, $T_i$, and power usage, $P_w$, are acquired from deployed models and techniques running on a test hardware platform. $T_i$ is the time required to elaborate an input image. The image loading and preprocessing (e.g. reshaping) are excluded so that $T_i$ reflects the actual computational complexity of a VPR technique.

The energy per image processed, $E_i$, indicates the energy spent to compute a single image representation. It is determined from the power usage as follows:

$$E_i = P_w \cdot T_i,$$  

where $P_w$ is the power absorbed during image processing.

V. RESULTS DISCUSSION

This section presents the results for the proposed BNN discussing both the VPR performance and efficiency. The experiments include several implementations of our BNN using different depth multipliers, $d$ (Section III-B). By convention, HBX-FN denotes a binary model using HB-DS with $d = X$. The computational time and energy usage are measured from deployed models. We used Late-Compute-Engine (LCE) [57] to run binary models on a Raspberry Pi4 (RP4) [58].

In the first part of this section, we compare HB12-FN to other VPR techniques. We selected HB12-FN as we consider it the best-balanced model between computation and performance. The second part of this section presents the experiments for various $d$ values and discusses the use of depth multiplier as a tuning parameter.

A. Comparative Analysis

The VPR networks and methods included in the comparison are FloppyNet [7], VGG-16 [24], CALC [9], CoHOG [30] and HOG [29]. To the best of our knowledge, FloppyNet is the only BNN proposed for VPR. Thus, we consider it as a baseline comparison for HB12-FN. VGG-16 is a large CNN used in several state-of-the-art VPR applications [28], [11], [12]. It includes 13 convolutions and computes

| VPR       | Type  | $T_i$ [ms] | $E_i$ [mJ] | VPR (combined) |
|-----------|-------|-----------|-----------|----------------|
| VGG-16    | CNN   | 995.7     | 2608.7    | 0.676 0.679 | 80.5 |
| CALC      | CNN   | 45.8      | 120       | 0.306 0.323 | 37.1 |
| CoHOG     | Trainless | 87.4  | 210.6     | 0.349 0.37 | 42.5 |
| HOG       | Trainless | 20.4  | 20.6      | 0.318 0.335 | 38.6 |
| FloppyNet | BNN   | 18.2      | 46.2      | 0.554 0.568 | 67.3 |
| HB12-FN   | BNN   | 9.1       | 23.1      | 0.553 0.566 | 67.2 |
| HB12-FN-1T | BNN  | 27.4      | 27.7      | 0.553 0.566 | 67.2 |

TABLE II

VPR METRICS ARE GIVEN FOR THE COMBINED DATASET. $T_i$ AND $E_i$ ARE MEASURED ON A RASPBERRY PI4.
TABLE III
PERFORMANCE AND EFFICIENCY FOR SEVERAL IMPLEMENTATION OF THE PROPOSED BNN. $T_i$ AND $E_i$ ARE MEASURED ON A RASPBERRY PI 4.

| BNN          | Structure   | First Stage | $T_i$ [ms] | $E_i$ [mJ] | VPR (Combined Dataset) |
|--------------|-------------|-------------|------------|------------|-------------------------|
|              | $(k_s,s_c,o_d)$ | $d$ | 32 bit | 1 bit | 32bit | 1bit | First | Total | $E$ | AUC | TP (%) |
| HB1-FN       | HD-BS(11,4,96,1) | 4 | 366 | 288 | 1.1 | 0.87 | 2.4 | 5.6 | 14.2 | 0.442 | 0.458 | 53.2 |
| HB4-FN       | HD-BS(11,4,96,4) | 8 | 2928 | 2304 | 8.8 | 7.0 | 4.3 | 7.7 | 19.6 | 0.554 | 0.566 | 67.8 |
| HB8-FN       | HD-BS(11,4,96,8) | 12 | 4392 | 3456 | 13.2 | 10.5 | 5.7 | 9.1 | 23.1 | 0.553 | 0.566 | 67.2 |
| HB12-FN      | HD-BS(11,4,96,12) | 24 | 8784 | 6912 | 26.4 | 20.9 | 7.7 | 10.9 | 27.7 | 0.569 | 0.587 | 68.1 |
| HB24-FN      | HD-BS(11,4,96,24) | 48 | 17568 | 13824 | 52.7 | 41.8 | 11.4 | 15.2 | 38.6 | 0.575 | 0.591 | 69.0 |
| HB48-FN      | HD-BS(11,4,96,48) | N/A | 34848 | 0 | 105.4 | 0 | 15.1 | 18.2 | 46.2 | 0.554 | 0.568 | 67.3 |
| FloppyNet    | C(11,4,96) | N/A | 34848 | 0 | 105.4 | 0 | 15.1 | 18.2 | 46.2 | 0.554 | 0.568 | 67.3 |

Fig. 7 shows the EP score for all the considered methods. HB12-FN and FloppyNet performs equally well on the Combined dataset while on GardenPoints and Nordalnd the latter achieves slightly higher EP. Our network outperforms by a substantial margin the other lightweight techniques: HOG, CALC, and CoHOG. VGG-16 captures the highest EP score in every environmental condition and on the Combined dataset. These results are not surprising considering the VGG-16’s large size and depth. However, VGG-16 requires around 1s to compute an image descriptor, resulting in two orders of magnitude slower than any considered BNN. The complete set of $T_i$ is reported in Table II while Fig. 8A compares a selection of the most efficient techniques: the BNNs, CALC, and HOG. HB12-FN is the fastest one taking 9.1 ms to process an image, 50% of FloppyNet’s inference time. Considering these two BNNs have similar VPR performance, our network represents a significant improvement over FloppyNet. The HOG implementation used for the experiments (OpenCV 4.5.0) can run only on a single thread. For a fair comparison, we reported the processing time of the proposed model for 1-thread (1T) execution using gray bars in Fig. 8A. HOG takes about 7 ms less than HB12-FN-1T to compute a descriptor. However, their VPR performance is very different. While HOG scores $E = 0.318$, HB12-FN achieves 0.553. Such a EP gap corresponds to 28.6% fewer place correctly recognized in the Combined dataset (TP% column in Table II). We believe this gap is too wide to consider HOG as a good alternative to the proposed BNN.

B. Energy Usage

The energy usage, $E_i$, is reported in Table II and Fig. 8B. $E_i$ is determined using Eq. 12 from the average power usage measured directly from a RPI4 board on 100 consecutive runs. RPI4 has an approximately constant power usage during runtime. Thus, $E_i$ is mainly influenced by the interference time and the number of active CPU cores. To this end, the processing time reduction due to HB-DS contributes to energy saving, which is essential for battery-supplied robotic platforms. The positive effect of HB-DS is well depicted by the difference in energy usage between FloppyNet and HB12-FN as they differ only in the first stage. HOG is the most energy-efficient technique. However, as motivated above, HOG has too low VPR performance to replace our best model.
C. Depth Multiplier as a Tuning Parameter

The HB-DS design enables the performance tuning of a BNN by acting only on the depth multiplier, \( d \), without changing any other network parameter. Fig. 9 plots the EP score on the Combined dataset versus the processing time for several depth multipliers. The circles’ diameter represents the energy usage in \( \text{mJ} \) per processed image. HB12-FN, the model we selected for the comparison presented above, reaches the same VPR performance as FloppyNet, spending one-half of the processing time and energy. Nevertheless, the VPR performance can be further improved by increasing \( d \). For example, HB24-FN and HB48-FN outperform HB12-FN by a small margin at the cost of longer processing time and energy usage. If the target application has enough resources, HB24-FN and HB48-FN might be good options. On the opposite side, lower \( d \) values can find application in reducing a BNN’s complexity to fit for extremely resource constraint hardware or saving energy to extend battery life. For example, the EP loss from HB12-FN to HB1-FN is 0.11, which corresponds to \(-14\%\) correctly matched places in the Combined dataset (TP\% in Table III). While HB12-FN is possibly the best option in many scenarios, HB1-FN might be preferred when energy saving is a strict requirement as it spends less energy than HB12-FN to process an image: 14.2 \( \text{mJ} \) against 23.1 \( \text{mJ} \). It is worth mentioning that HB1-FN, which holds the worst VPR performance among our models, outperforms HOG, CALC and CoHOG while achieving higher computational efficiency (Tables II and III). Finally, Fig. 10 shows \( T_{i} \) for several depth multipliers. The blue bars represents the time spent on the first layer, which depends on \( d \). The gray bars are for the rest of the layers. FloppyNet uses a regular non-binary convolution as a first stage. The time spent on the first convolution is 83\% of the entire processing time. The networks using HB-DS have a more fair distribution of the latency between the first and the other layers proving that our approach mitigates the bottleneck problem of BNNs.

VI. CONCLUSIONS

BNNs are an efficient class of deep neural networks using binary arithmetic to speed up convolutions. The slowest stage in a BNN is the first convolutional layer, non-binary for higher accuracy. This paper proposed a binary neural network achieving state-of-the-art VPR performance among BNNs jointly with high computation and energy efficiency. Our network uses HB-DS, a module introduced in this paper, to address the latency bottleneck in the first stage of a BNN. HB-DS enables the performance tuning of a BNN by acting only on a single parameter to train models suitable for different deploy scenarios. An extension of this work is investigating HB-DS for different network architectures (e.g. ResNet) and different tasks than image matching, such as object detection and image segmentation.

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