Bayesian Learning for Disparity Map Refinement for Semi-Dense Active Stereo Vision
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Abstract—A major focus of recent developments in stereo vision has been on how to obtain accurate dense disparity maps in passive stereo vision. Active vision systems enable more accurate estimations of dense disparity compared to passive stereo. However, subpixel-accurate disparity estimation remains an open problem that has received little attention. In this paper, we propose a new learning strategy to train neural networks to estimate high-quality subpixel disparity maps for semi-dense active stereo vision. The key insight is that neural networks can double their accuracy if they are able to jointly learn how to refine the disparity map while invalidating the pixels where there is insufficient information to correct the disparity estimate. Our approach is based on Bayesian modeling where validated and invalidated pixels are defined by their stochastic properties, allowing the model to learn how to choose by itself which pixels are worth its attention. Using active stereo datasets such as Active-Passive SimStereo, we demonstrate that the proposed method outperforms the current state-of-the-art active stereo models. We also demonstrate that the proposed approach compares favorably with state-of-the-art passive stereo models on the Middlebury dataset.

Index Terms—Stereo Vision, Disparity Estimation, Bayesian Neural Network, Bayesian Modelling, Multitask Learning, Self-Supervised Learning.

I. INTRODUCTION

THE past few years have seen a surge in the use of deep learning networks for disparity estimation in stereo vision [1], [2]. State-of-the-art methods use an end-to-end approach where a network is trained for all the steps of the stereo matching pipeline, including feature extraction, cost volume construction and regularization, as well as disparity map refinement. Most of these methods, which use deep neural networks with large and multiscale receptive fields, have been designed to address challenges faced by passive stereo systems such as how to estimate accurate disparities up to the pixel level in textureless regions and in regions with repetitive patterns and self-similarities. Compared to passive stereo, active stereo-based techniques use projected patterns to facilitate the matching, and thus the disparity computation, by removing textureless areas and regions with similar patterns from the image [3].

Motivated by the success of end-to-end models, several papers applied to active stereo technics that have been originally developed for passive stereo [4], [5]. While these borrowed architectures were optimized to guarantee a dense reconstruction of the disparity maps, which is a major problem in passive stereo, they are not meant to address challenges such as accurate subpixel disparity refinement. This makes such models redundant in the case of active stereo where simpler methods will correctly match a large proportion of pixels without requiring large and expensive modules. However, subpixel accuracy is still an open issue. We argue in this paper that active stereo vision should be tackled with a different approach, centered around subpixel refinement. The proposed model should be lightweight to enable its use for embedded platforms [6], [7] such as smartphones, virtual and augmented reality headsets, and consumer-grade stereo cameras [3].

Since active stereo vision ensures a high proportion of pixels correctly matched even with low-end matching algorithms, it makes semi-dense stereo matching an interesting approach. Semi-dense stereo matching [8], which is the process of producing a disparity map where some pixels, considered as outliers, are discarded and not used in the subsequent steps of the process. This is especially relevant for applications such as Augmented Reality (AR) [9] where the visual quality of the depth map is important, but some pixels can be discarded without impacting the performances of downstream tasks. This is critical for lightweight models, which cannot hold as much information as larger scale ones [10], [11]. This derives

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Fig. 1: The proposed disparity refinement approach uses the model confidence, learned in an unsupervised manner, to adjust the learning behavior (via a confidence-dependent loss) and help the network learn which image areas are worth focusing on in order to increase its precision.

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naturally from the Data processing inequality [12]. We discuss these issues in more detail in the supplementary material, where we provide theoretical guarantees on our semi-dense model benefits.

In this paper, we propose a novel method that is optimized for semi-dense active stereo. The method jointly learns both aspects of semi-dense stereo matching, i.e., identifying outliers and refining raw disparity maps at the sub-pixel accuracy level. We first propose to characterize the outliers via a Bayesian probabilistic model where the only meta-parameter to set is the desired reconstruction accuracy. The benefit of using a Bayesian model is that it allows us to account not only for aleatoric uncertainty (i.e., the baseline uncertainty present in the data) but also for epistemic uncertainty (i.e., the uncertainty due to the lack of information when training the model) [13]. We then propose a novel deep neural network architecture (Fig. 1) composed of an outlier detection branch, trained in an unsupervised manner, and a refinement branch trained in a supervised manner. The role of the outlier detection branch is to invalidate, during training, the pixels that are outliers so that the refinement network focuses on the inliers hereinafter referred to as validated pixels, which are easier to reconstruct. The outlier detection branch can be seen as a form of meta learning that influences the loss derived from a Bayesian Probabilistic Graphical Model (PGM) and used to train the refinement branch. At test time, the outlier detection branch can still be used to clean up the disparities predicted by the model.

We demonstrate, in the context of semi-dense active stereo vision, that the proposed lightweight Bayesian Neural Network (BNN) based on this principle is able to double the accuracy of the disparity refinement at the validated pixels compared to a similar refinement network trained without the detection and invalidation of the outliers. Despite its small size, the proposed architecture achieves state-of-the-art performance, with errors of the order of 0.2 pixel in the validated areas. We also show that the proposed BNN trained on active stereo is able to generalize to passive stereo, albeit at the cost of a drastically reduced proportion of inliers. This demonstrates that the proposed architecture allows the network to be aware of when it can safely make a prediction, a very desirable property of BNNs. Finally, the proposed architecture is significantly faster than the state-of-the-art both at training and test time.

The remainder of the paper is organized as follows; Section II reviews the related work. Section III details the proposed model and training approach. Section IV evaluates the performance of the proposed model and discusses its generalization ability under domain shift. Section V concludes the paper.

II. RELATED WORK

Stereo matching algorithms usually address one or more of the following three challenges: (1) disparity map densification, i.e., how to increase the number of patches that are correctly matched across a pair of images. Usually, a match is considered correct if the matching error is within two or three pixels. (2) Outliers removal, which is the problem of detecting and removing incorrectly matched pixels from the estimated disparity map. (3) Disparity map refinement, which aims to improve the resolution and accuracy of the disparity, and thus depth, maps. This paper focuses on the second and third problems. The first one has been extensively explored; see the surveys of Han et al. [14], Laga et al. [1], and Poggi et al. [2] for more details.

A. Real time stereo models

A major issue of the state-of-the-art stereo models is their computational cost [15]. Powerful and expensive GPUs are often required to achieve an interactive frame rate. Different mitigation strategies have been proposed: For example, Wang et al. proposed AnyNet [16], a hierarchical model where successive levels of disparities are refined in succession from low to high resolution. CascadeStereo [17] was proposed to leverage a coarse to fine approach making end-to-end matching networks more memory efficient and thus better suited to handle high-resolution images. RealTimeStereo [15] introduced an attention-aware feature aggregation module to reduce the dimension of the feature space while using a hierarchical approach similar to AnyNet. MobileStereoNet [18], on the other hand, leverage the optimized activation functions of MobileNet [19] for stereo matching. To reduce the computation time, Yee and Chakrabarti [20] proposed to remove the initial feature computation module and instead compute the cost volume using traditional methods. Their method uses a Neural network only to infer the disparity from the cost volume. Rahim et al. [21] also proposed to use separable convolutions to speed up the processing of the cost volume.

All the aforementioned methods trade accuracy to gain speed. In contrast, because our approach is based on semi-dense stereo, it sacrifices the density of the depth map instead of accuracy.
B. Outliers detection and semi-dense stereo matching

The aim of outlier detection is to ensure that a subsequent process is not adversarially affected by a small number of out-of-distribution samples [22]. This is very important for applications such as augmented reality and digital art, which require accurate 3D reconstruction. Most outlier detection methods in stereo matching use cues in the cost volume [23], but some methods also use the estimated raw disparities as a source of information [8].

When used for invalidation [4], [24] (i.e., for discarding pixels whose error is high), the outlier detection task operates jointly with another task. The latter is referred to as the main task. Since outliers are defined by their impact on the main task, one efficient learning strategy is to jointly learn how to detect them and perform the main task [25]. Bevandić et al. [26] showed that outlier detection in a multi-task setting can share features with semantic segmentation without degrading the performance of the main or outlier detection tasks. Xu et al. [27] showed that detecting and invalidating outliers during training can improve training performances. However, because their approach solely attaches a confidence variable to each training sample, it cannot detect outliers at runtime. In contrast, our proposed approach improves the training performance while being able to detect outliers at runtime.

The process of invalidating outliers in stereo vision is called semi-dense stereo vision. This has been extensively investigated using traditional methods [28] and more recently using deep learning techniques [29]. Whether a pixel is an outlier depends on the technique used to generate the disparity. This implies that no labeled data can be prepared before the training is actually conducted so that a network can learn how to detect its own outliers. Consequently, the training of an outlier detection network has to be performed in an unsupervised or a self-supervised manner by using auxiliary supervisory signals such as left-right or multi-view consistency [30], [4], [31]. Outliers can also be defined using the regression module’s prediction errors [32], [33], [8]. In our case, a Bayesian model is used to define outliers based on their expected stochastic properties. This provides multiple advantages over the aforementioned methods. The most important one is that our model accounts for not only aleatoric uncertainty but also epistemic uncertainty. As a result, our model is less likely to fail to recognize error cases it did not see at training time.

C. Disparity refinement

Various traditional methods have been proposed to deal with noise in stereo matching. Examples include smoothing either the estimated raw disparities or the cost volumes using low-pass filters [34], morphological operators, simple regularizers [35], or adaptive filtering [36], [37] guided either by an RGB frame, if available, or by the raw depth map itself [38], [39]. Other methods rely on interpolation [40] either in the input image space [41], [42] or in the cost volume space [43]. Interpolation in the cost volume is computationally cheaper but does not have a closed-form solution that is both optimal and universal since the optimal interpolation function depends on the cost function used for matching [44]. In the latest end-to-end deep learning approaches for stereo matching, the cost volume is generally interpolated on the fly via the use of the softargmax or softargmin operators [1], which offers the benefits of giving a smooth estimate of the disparity from the cost volume in a differentiable fashion. The use of the softargmax or softargmin operators is a key feature for end-to-end models but offer poor performances in term of subpixel accuracy. Our approach is based on cost-volume interpolation, which significantly reduces the memory and computation footprint required. Since we are using a learning based method, the lack of a universal interpolation formula [44] is not an issue, since the proposed network learns an optimal solution for the matching cost at hand directly from the data.

D. Active stereo vision

In contrast to passive stereo, active vision has received little attention from the deep learning community. One major issue which hampered the development of active stereo method was the lack of good quality datasets. Yet, a few self-supervised models have been proposed such as ActiveStereoNet [4] and TSFE-Net [5]. ActiveStereoNet [4] is based on the architecture of StereoNet [45], an end-to-end deep learning model, with an edge-aware upsampling module, originally developed for passive stereo setups. The main contribution of ActiveStereoNet is not the model itself but its self-supervised training method, which was developed to overcome the lack of active stereo datasets suitable for training. Another end-to-end architecture was employed by TSFE-Net [5]. Utilizing a local contrast normalization module, the authors demonstrate how the network can exploit the relationship between the speckle intensity and the distance from the active pattern projector. Unlike these models, which mimic the architectures used for passive stereo, our approach focuses on the refinement step in the stereo pipeline. Using our active stereo model design, one can achieve better subpixel accuracy at a fraction of the computational cost of conventional approaches (Sec. IV-B).

III. PROPOSED APPROACH

The focus of this paper is on the refinement steps of the stereo matching pipeline. Hence, to build the initial disparity estimate and cost volume, we use a standard coarse to fine hierarchical algorithm [46] based on the Zero-Mean Normalized correlation (ZNCC) matching cost [47]. The ZNCC function was initially proposed to match images with different bias and gain factors. We choose this function as it ensures the cost is normalized with respect to the input image, which should increase the robustness of our refinement model to variations in the input images intensities. This coarse to fine
Hierarchical algorithm is significantly faster than the current state-of-the-art deep learning-based cost volume construction and regularization, making it ideal for lightweight systems. The implementation we are using, which runs on the CPU, requires around 60ms per frame with 160 disparity levels. This is negligible when compared to more than 2 seconds for ActiveStereoNet running on the CPU, or 500ms for our refinement (see Table I).

To perform the refinement and outlier pixels invalidation, we propose two modules that work collaboratively: a supervised disparity refinement module and an unsupervised outlier pixel invalidation module (Fig. 1). In contrast to previous studies, we identify the outliers corrupting a disparity map based on their stochastic properties, which we model using a Probabilistic Graphics Model (PGM), hereinafter referred to as the stochastic model (Section III-A), rather than an error threshold [8] or a left-right consistency criterion [4].

Let \( d_{\text{raw}} = S(I_L, I_R) \) be a raw disparity map estimated using a stereo matching algorithm \( S \) from a pair of left \( I_L \) and right \( I_R \) images. We define the refinement process as a function of the raw disparity \( d_{\text{raw}} \) and the matching cost volume \( V \). To minimize the amount of data the model has to process, thus decreasing its memory and computational footprint, we only consider a version of the cost volume that is truncated along the disparity dimension, hereinafter denoted by \( V^i \), which is defined at pixel \( k = (i, j) \) as:

\[
V^i(k) = \begin{cases} V(d_{\text{raw}} + k) & \text{if } d_{\text{raw}} + k \in [0, d_{\text{max}}], \\ 0 & \text{otherwise}. \end{cases}
\]

Let also \( \chi \) be a tensor defined at pixel \( (i, j) \) as:

\[
\chi(k) = \begin{cases} 1 & \text{if } d_{\text{raw}} + k \in [0, d_{\text{max}}], \\ 0 & \text{otherwise}. \end{cases}
\]

Here, \( d_{\text{max}} \) is the maximum disparity under consideration. We designate a tuple of inputs \( (d_{\text{raw}}, V^i, \chi) \) as \( x \).

Let \( \delta \) be the error in the initial disparity map \( d_{\text{raw}} \). Our goal is to learn an estimator \( \delta(x) \) defined as a function of \( d_{\text{raw}}, V^i \), and \( \chi \). In other words, the true disparity \( d \) can be written as:

\[
d = d_{\text{raw}} + \delta(x) + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2).\]

We assume that the error between \( \delta \) and \( \delta \), denoted by \( \varepsilon \), follows a normal distribution with mean 0 and standard deviation \( \sigma_\varepsilon \).

To learn \( \delta(x) \), we use a BNN whose architecture, or functional model, is composed of a feature extraction, a disparity refinement, and an outlier detection module (Fig. 3); see Section III-B for more details.

Training a BNN involves finding the probability distribution \( p(\theta|D) \) of its parameters \( \theta \) knowing the training set \( D \). This is difficult to achieve in practice. Instead, we use variational inference and Monte-Carlo dropout as an approximation [48]. To simplify the predictions at runtime, we also limit the number of Bayesian layers that we position at the end of the network [49], [50]. Variational inference is the process of learning the parameters \( \phi \) of a distribution \( q_\phi(\theta) \) that closely approximates \( p(\theta|D) \). Monte-Carlo dropout is the process of using dropout layers at runtime as a form of variational inference [48]. The loss for learning \( \phi \) is derived from the stochastic model (Fig. 4). Since the training process is stochastic, epistemic uncertainty, i.e., the uncertainty on the model itself rather than the uncertainty due to noise in the data, is properly accounted for. This is an important benefit of using a BNN.

At runtime, the prediction of a BNN and its uncertainty are usually obtained via Monte-Carlo sampling, i.e., by running the network multiple times with different sets of weights sampled from the posterior. However, this is not practical for real-time applications. Since we are using Monte-Carlo dropout and variational layers positioned at the end of the network, an estimate of the mean prediction can be obtained in a single pass by flattening the dropout layers and using the mean weights for the variational layers. Using a stochastic neural network only for training seems redundant, but doing so allows the outlier detection module to be properly calibrated based on the uncertainty of the network during training. At runtime, while the marginal distribution of the refined disparity can still be estimated by running multiple passes, the uncertainty is mostly given by the outlier detection branch of the network. This preserves most of the advantages of BNNs, especially their robustness to outliers, while significantly reducing the computation time required to estimate the uncertainty. We detail each of these modules in the following subsections.

### A. Stochastic model

We use a PGM (Fig. 4) to describe the stochastic properties of the considered model. This means that we have to specify \( p(d|o, x, \theta), p(o|x, \theta), \) and \( p(\theta) \), where \( o \) is a binary stochastic variable indicating whether the pixel under consideration is an outlier or not. Here, \( p(\theta) \) is simple to define as the BNN parameters do not depend on any other variables. We chose a Gaussian prior with a standard deviation \( \sigma_\theta = 1 \). The choice of \( \sigma_\theta \) sets the amount of \( \ell_2 \) regularization for the network weights \( \theta \) [48]. It has been chosen based on the expected range of corrections to apply, which should be around one pixel on average.
The conditional probability \( p(o|x, \theta) \) is a Bernoulli distribution. We do not set its probability to a constant value in the prior. Instead, we assume it is a function of \( x \) and \( \theta \), which is given by the functional model; see Section III-B. As long as the prior \( p(\theta) \) ensures that all values between 0 and 1 are equiprobable for the probability of a given pixel being an outlier, our model makes no assumptions about the proportion of outliers in the training data. Instead, it learns the appearance of an outlier directly from the data. This can be understood as being a type of hierarchical Bayes, a formulation used to perform Bayesian meta-learning [51]. In the final model, we marginalize the variable \( o \) since learning to predict the probability \( p_{out} \) that a given pixel is an outlier is already informative enough in itself:

\[
p(d|x, \theta) = \int p(d|o, x, \theta)p(o|x, \theta)do. \tag{4}
\]

According to Equation (3) the conditional probability \( p(d|o, x, \theta) \) is set as a Normal distribution with mean \( d_{raw} + \hat{\delta}(x) \) and standard deviation \( \sigma_z \). We assume \( \sigma_z \) is equal to \( \sigma_{z\in}^{in} \) for inliers and \( \sigma_{z\in}^{out} \) for outliers. Since \( o \) is marginalized, we can approximate the solution to Equation (4) by a normal distribution of mean \( d_{raw} + \hat{\delta}(x) \) and whose standard deviation can be approximated by combining \( \sigma_{z\in}^{in} \) and \( \sigma_{z\in}^{out} \):

\[
p(d|x, \theta) \sim N(d_{raw} + \hat{\delta}(x), (\sigma_{z\in}^{in} + (\sigma_{z\in}^{out} - \sigma_{z\in}^{in})p_{out})^2). \tag{5}
\]

The posterior given the training set \( D \), up to a scaling constant, is then:

\[
p(\theta|x, D) \propto \left( \prod_{d \in D} p(d|x, \theta) \right) p(\theta). \tag{6}
\]

This formulation can be seen as the dual of learning while dealing with noisy labels, a problem related to ours that has been explored in the literature [53]. This includes meta learning approaches where a stochastic model is learned to adjust the loss to account for the noise in the training set [54], [55]. The proposed stochastic model deals with the uncertainty of the BNN, instead of dealing with the noise in the training set.

### B. Functional model

We use a single Bayesian CNN as an estimator for both the refined disparity \( \hat{d} \) and the probability map \( p_{out} \):

\[
(d, p_{out}) = \Phi(d_{raw}, V^t, \chi). \tag{7}
\]

Using a single network allows the two tasks to share the first layers. This results in a more compact architecture, which is easier to deploy on embedded devices without sacrificing the network performance [26].

The final network architecture (Fig. 5) is composed of a context aggregation module, a regression module in charge of predicting the disparity residuals, and an outlier detection module. Monte-Carlo dropout layers are positioned in the intermediate layers of the network, while the variational inference layers are positioned at the end of the network.

1) Context aggregation module: Aggregating non-local information is key to the performance of fully-convolutional networks. An hourglass model is typically used for this where the inner layers are pooled to reduce the resolution while the number of channels is increased to retain the information. This is prohibitively expensive for ultra-light networks. In mitigation, the inner levels are bypassed and each tensor is transferred to the levels on the other side of the hourglass. Thus, the required number of channels in the inner layers can be drastically reduced while maintaining high-resolution information. We extend this concept and propose a fast context aggregation layer to extract contextual information with a minimum number of convolutions (Fig. 6). Three types of pooling algorithms are used at each level in this architecture: max pooling, average pooling, and min pooling. These enable the network to estimate a rough distribution of the features within each pooled window. A single convolution layer is then applied at each level before the images are directly upsampled and concatenated together. Although this approach may seem restrictive, it produces good results in the case of active stereo. This is because, unlike passive stereo, the surrounding of a match contains a lot of information, and hence it reduces the amount of global information that the model requires.

A single fast context aggregation layer is used in the context aggregation module. Its role is to aggregate context for
### Parameters

| Model | w/o pout | w/ pout | ActiveStereoNet [4] | MobileStereoNet [18] | ACVNet [52] | CascadeStereo [17] |
|-------|----------|---------|---------------------|----------------------|-------------|-------------------|
| Base network | 19,180 | 12,824 | 447,492 | 2,352,706 | 7,173,488 | 10,943,776 |
| Additional Variational | 5,081 | 941 | 0 | 0 | 0 | 0 |
| **Total** | **24,261** | **13,765** | **447,492** | **2,352,706** | **7,173,488** | **10,943,776** |

### Memory footprint [MB] for images of size 640 × 480

| Model | Tensors (w/o gradient) | Tensors (w/ gradient) | GPU (GeForce RTX 2080 Ti) | CPU (20 x i9-10900X @ 3.70GHz) |
|-------|------------------------|-----------------------|-----------------------------|--------------------------------|
| Model | 0.097 | 0.055 | 1.790 | 9.411 | 28.694 | 43.775 |
| Tensors (w/ gradient) | 756.361 | 462.274 | 2,106.368 | 20,436.285 | 13,230.648 | 13,802.343 |
| Tensors (w/o gradient) | 11.148 | 9.915 | 421.904 | 4,229.265 | 4,216.855 | 4,225.285 |
| One pass time [ms] for images of size 640 × 480 | 471 | 7.17 | 112 to 119 | 331 | 234 | 8,017 |

1. Our model also requires an additional 45 to 83 ms on cpu for the initial matching, but compared to the cpu time of either our model or ActiveStereoNet, this is negligible.
2. The computation time varies depending on the maximum disparity. Here, computed for the range 20 to 160 ps.
3. Disparity range has to be non-zero for the set of real numbers, minus singleton points. Although f serves the same purpose as the Leaky-ReLu activation but is based on the Hardswish function, it has a quadratic region that can be exploited to smooth the output disparity. The final layer is a 1 × 1 convolution layer without an activation function. Its purpose is to aggregate all the channels from the previous layer into the final estimate for $\delta$. Following Equation (3), the final disparity estimate is obtained by taking the sum of $d_{\text{raw}}$ and $\delta$.

3) **Outliers detection module.** The outlier detection module is based on the same principles as the disparity regression module, with a series of 1 × 1 convolution layers acting on the previously aggregated context. The Leaky-ReLu activation function is used again, but with a smaller slope of 0.1 for negative activations instead of 0.3. The rationale behind this decision is to provide stronger non-linearities for the module used to perform classification instead of regression.

Our experiments have also shown that the outlier classification module tends to be over-optimistic and might, during training, start to classify all pixels as outliers if only a few cannot be differentiated from inliers. Those problematic pixels are usually located close to the boundaries between inliers and outliers. To reduce the chances of this happening, the final convolution layer in the module has a receptive field of 5 × 5 instead of 1 × 1. To keep the number of parameters low, the filter has been implemented as a separable convolution [21], with the first layer aggregating the 25 inputs channels, then one layer applying a 1 × 5 filter on the resulting channel, followed by a similar layer of shape 5 × 1. It means 35 parameters are required instead of 625. The final output is then passed through a sigmoid activation function to get $p_{\text{out}}$.

Our final architecture is very minimalistic, making it more suitable for embedded systems with limited memory and computational power than the state-of-the-art models (see Table I).

### IV. Experiments

We trained the proposed model using the active stereo frames from the Active-Passive SimStereo dataset [57], a simulated dataset containing raw active stereo frames annotated with high-quality ground truth suitable for subpixel accurate models. We then evaluated our model on both the Active-Passive SimStereo dataset and images from the Shapes dataset. The Shapes dataset is a dataset of real active stereo images we acquired with an Intel RealSense camera. It contains images of polystyrene 3D blocks cut from Computer-Aided Design (CAD) models with known dimensions. The CAD models can then be realigned on the images to obtain a highly accurate
Fig. 7: The Active-Passive SimStereo dataset is composed of different scenes with (a) RGB frames, (b) NIR frames with pseudo-random pattern and (c) ground truth disparity used to supervise the regression module. An initial algorithm, NCC, extracts the raw disparity (d) which will serve as inputs of the BNN, (e) the truncated cost volume and (f) the support indicator function.

Fig. 8: Left (a) and right (b) frames of an Image pair from the Shapes dataset with the outlined CAD models aligned onto the real scene.

ground truth disparity map over the shapes. More details on this dataset are given in the Supplementary Material. In Section IV-A we discuss the effect of our Bayesian training strategy by comparing our model trained with or without the outlier identification module. In Section IV-B, we compare our method with (1) a selection of state-of-the-art active and passive stereo models, (2) real-time optimized models, and (3) baseline methods. We also tested the performances of our model on the images from the Middlebury 2014 test set [58] to check if the model is able to generalize to passive stereo. The details of that experiment are discussed in the Supplementary Material.

A. Ablation study

The most important benefit of our approach is the fact that the refinement module co-evolves with the outlier detection module. It enables the networks to focus, during training, on the pixels which it decides should be validated in the final semi-dense disparity map. As a result, the information the network is storing during the training phase is used more efficiently thus the performances on validated pixels should increase compared to a similar network which is not trained jointly with the outlier detection module. To measure this contribution, we trained a second version of the module without the outlier detection branch. We refer to this as the baseline module. We used a standard deviation of 1px for all pixels, with all other parameters such as the number of training epochs and the learning rate remaining the same. We then compared the baseline module with the full module (with outlier detection). As shown in Figure 9a, the Bayesian model leads to significant improvements. As shown in Table II, on average, the accuracy of the model with the outlier module is three times higher than the accuracy of the baseline model. This demonstrates that the proposed joint learning approach allows our network to greatly improve its performance on validated pixels by not wasting information on the pixels that have been invalidated by the outlier detection module. This is possible only because outliers are discarded. As shown in Figure 10, the proportion of inliers varies significantly depending on the images. Some images can have less than 10% inliers pixels, while others will reach around 90%, with an average of 52% of inliers for the Active-Passive SimStereo test set; see Figure 10. As shown in Table III, our model with the outlier module is, relatively to the same model without the outlier module, four times as accurate, when evaluated on the Shapes dataset. This is globally coherent with the relative improvements with the results for the Active-Passive SimStereo dataset.

B. Comparison with state-of-the-art

We compare the proposed model to the state-of-the-art active stereo model ActiveStereoNet [4], using the pretrained weights provided by the authors [59]. However, since ActiveStereoNet was trained in a self-supervised fashion, we also finetuned it on the training dataset to obtain a more accurate and fair comparison. To this end, we used the training method described for StereoNet [45]. The Adaptive Robust Loss of [60] was used with the same meta-parameters as the original StereoNet [45]. We also finetuned a collection of real-time and state-of-the-art passive stereo methods to offer a larger and more recent base of comparison. We selected methods that have their codes and pretrained models publicly available. We used ACVNet [52], CascadeStereo [17], AnyNet [16], MobileStereoNet [18] and RealTimeStereo [15]. ACVNet [52] was the top performing method on Kitti with both code

| Method | MAE
|---|---|
| Cost Interpolation [40] | 1.40px | 7.64px |
| Image Interpolation [40] | 1.39px | 7.64px |
| Active Stereo models: | | |
| ActiveStereoNet [4] | 1.30px | 2.32px |
| ActiveStereoNet [4] (finetuned) | 0.90px | 1.82px |
| State-of-the-art large scale models: | | |
| CascadeStereo [17] (finetuned) | 0.18px | 0.66px |
| ACVNet [52] (finetuned) | 0.22px | 0.66px |
| Real time models: | | |
| AnyNet [16] (finetuned) | 0.53px | 2.06px |
| RealTimeStereo [15] (finetuned) | 0.74px | 1.64px |
| MobileStereoNet [18] (finetuned) | 0.29px | 0.80px |
| Ours (w/o outlier module) | 0.36px | 1.97px |
| Ours (w/ outlier module) | 0.12px | 2.04px |

TABLE II: Sub-pixel accuracy comparison in terms of MAE on the Active-Passive SimStereo [57] test set.
This paper proposes a lightweight yet high-performance deep learning model for disparity map refinement for active stereo. The model is designed to be lightweight and high-performance, making it suitable for real-time applications.

The proposed model is evaluated against existing methods and dense models. It achieves an accuracy of 0.12px and 0.32px for validated pixels, which is comparable to state-of-the-art methods like CascadeStereo and ACVNet. Finetuning ActiveStereoNet improves the accuracy of pixels with large errors by 0.5px (22%) while pixels with the potential to be subpixel accurate were only improved by 0.4px (31%), despite being trained with a robust loss. This shows that much of the training efforts of dense models like ActiveStereoNet are focused on high error pixels for which the model is unlikely to predict a highly accurate disparity in the first place. Most of the information stored by the network during training is not relevant in the case of semi-dense stereo. This is despite the fact that ActiveStereoNet was finetuned with a robust loss, which in itself should already help the network focus more on inliers. This highlights the benefits of our proposed Bayesian learning strategy for semi-dense models. It can achieve an accuracy of 0.12px and 0.32px for validated pixels; see Tables II and III compared to 0.9px and 0.81px for ActiveStereoNet.

Note that the accuracy of our method on the Shapes dataset is not as good as its performance on the Active-Passive SimStereo dataset. One possible explanation is that it is caused by small errors during the ground truth acquisition process for the Shapes dataset (see the Supplementary Material for more information). At the level of accuracy reached by our method, those small errors would become visible in the error metric. Figure 12 illustrates the key difference between how our semi-dense approach treats the disparities and how large-scale end-to-end models do. Our estimated depth map has visible artifacts (Fig.12d) because it cannot be precise enough in those regions (Fig.12e). On the other hand, ActiveStereoNet depth maps do not have artifacts (Fig.12c) but are over smoothed which degrades the subpixel accuracy of the model, even when restricted to our inliers, which should have been easier to match.

V. Conclusion

This paper proposes a lightweight yet high-performance deep learning model for disparity map refinement for active stereo.
Fig. 11: Our method allows to obtain visible improvements in disparity, and thus depth, reconstruction when training the neural network by focusing in priority on inliers.

Fig. 12: Results on a frame from the shapes dataset with (a) the ground truth, (b) original self-supervised ActiveStereoNet, (c) ActiveStereoNet finetuned on Active-Passive SimStereo, (d) ours with the outlier prediction module, (e) ours without the outlier prediction module, and (f) the confidence map estimated by our module (validated pixels are those with a score equal or above 95%).
stereo matching. We demonstrated how a Bayesian model can be used to jointly improve the accuracy of depth predictions while efficiently detecting and invalidating outliers. The proposed architecture produces very accurate disparities on validated pixels, well above the state-of-the-art methods. Despite ignoring discarded pixels, our model performances are still competitive with the state-of-the-art dense methods on those pixels. This shows that state-of-the-art methods require significantly higher computational resources to deal with only a few outliers. Additionally, this work demonstrates the benefits of architectures tailored specifically to refine active stereo vision. Currently available end-to-end architectures require large amounts of computation and many of their functions are redundant with traditional matching algorithms in active stereo vision. Our model is also able to generalize to passive stereo, reaching an accuracy on par with the state-of-the-art semi-dense passive stereo models, albeit at the cost of a drastic reduction in validated pixels density.

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Bayesian Learning for Disparity Map Refinement for Semi-Dense Active Stereo Vision – Supplementary material

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I. THEORETICAL GUARANTEE ON MODEL PERFORMANCE

Let \( f : I \rightarrow O \) be a function where:

- \( I \) is a given input space, in our case a patch of pixels in a raw disparity map, along with a slice of the corresponding cost volume and support indicator function, and
- \( O \) is an output space, in our case all possible refined disparities.

Let also \( A : I \rightarrow O \) be a set of functions with the same input and output space, in our case all functions encoded by the considered neural network architecture.

The aim of the learning process is to find \( a \in A \) such that for a given distance \( d_f : (I, O) \rightarrow \mathbb{R}^+ \) to the function \( f \) is such that
\[
\int_I d_f(x, a(x))dx \leq \int_I d_f(x, a'(x))dx \forall a' \in A.
\]

(1)

Now, given a set of functions \( \Lambda : I \rightarrow \{0, 1\} \) with \( \lambda(I) = 1 \in \Lambda \), which represents possible classifications of the inputs as outliers, and a scale factor \( \alpha \in (0, 1) \), the aim of learning to approximate \( f \) for a given outlier classification \( \lambda \) is to find \( s \in A \) such that
\[
d(s, \lambda) \leq d(a', \lambda) \forall a' \in A,
\]

(2)

with
\[
d(a, \lambda) = \int_I (1 + (\alpha - 1)\lambda(x))d_f(x, a(x))dx.
\]

(3)

The key observation here is that \( s \) is always as close or closer to \( f \) as \( a \) when the proximity is measured only on inliers. To demonstrate this, let’s proceed by contradiction and assume that we have
\[
\int_I (1 - \lambda(x)) \cdot (d_f(x, a(x)) - d_f(x, s(x)))dx < 0.
\]

(4)

To keep the definition of \( s \) valid it means we have:
\[
\int_I \alpha \lambda(x) \cdot (d_f(x, a(x)) - d_f(x, s(x)))dx > 0
\]

\[
\int_I (1 - \lambda(x)) \cdot (d_f(x, s(x)) - d_f(x, a(x)))dx.
\]

(5)

But this implies, by linearity of the integral, that:

\[
\int_I \lambda(x) \cdot (d_f(x, a(x)) - d_f(x, s(x)))dx > \int_I (1 - \lambda(x)) \cdot (d_f(x, s(x)) - d_f(x, a(x)))dx,
\]

which is in contradiction with the definition of \( a \). Thus, \( s \) performs at least as good as \( a \) for the inliers. This demonstration generalizes for stochastic models where \( \lambda \) is not a binary value but a probability for a given point to be an outlier.

II. ADAPTIVE TRAINING STRATEGY

The challenge with the proposed approach is that even if the optimum of the loss function has very good properties, i.e., it encourages the network to distinguish between inliers and outliers based solely on the expected accuracy and requires no other hypothesis, finding such optimum is hard. Gradient descent algorithms tend to promote outliers predictions during their early steps, limiting the ability of the regression module and the outlier classification module to co-evolve. Worse, this will also slow the convergence towards a good set of parameters, leaving the loss to plateau in a region where the network classifies all points as outliers. For active stereo datasets with a high proportion of inliers, like Active-Passive SimStereo, this is a moderate problem; see Fig. 1a. However, for certain starting configurations, especially if the dataset is more challenging like, e.g., the Middlebury passive stereo dataset [1], the optimization can get stuck in a local optima and always predict all pixels as outliers; see Figure 1b.

To address this issue, we experimented with a training scheme, hereinafter referred to as adaptive scheme, where the stochastic model is adaptive. More specifically, we propose to set the standard error for inliers and outliers to a value \( \sigma_0 \) at the start of the training. This will have the effect of training the regression module while the classification module is kept idle. We keep those standard error constants for an initial burn-in number of epochs before continuing with a transition period, where the parameters of the stochastic model smoothly transition toward their values, and finally a certain number of epochs where the standard error in the stochastic model keep their final values. In more details, the probabilities of inliers or outliers are computed at a given epoch \( e \) as:

\[
\sigma(e) = \sigma_0 + \left( e > e_t \min\left(e_f, e\right) - e_t \right) \frac{\sigma_f - \sigma_0}{e_f - e_t},
\]

(7)

where \( e_t \) is the first epoch of the transition phase, \( e_f \) is the first epoch after the transition phase, and \( \sigma_f \) is the true (or final)
(a) Successful training on Active-Passive SimStereo without adaptive training

(b) Failed training on the Middleburry dataset without adaptive training.

(c) Successful training on Active-Passive SimStereo with adaptive training.

(d) Successful training on Middlebury with adaptive training.

Fig. 1: Evolution of the loss and average proportion of inliers without and with using an adaptive training scheme. The proportion of inliers is estimated by taking the average over all pixels of $(1 - p_{\text{out}})$.

standard error in the stochastic model for either the inliers or outliers.

Additionally, we add a penalty to the loss to encourage more pixels to be classified as inliers. The formulation is a reward for inliers, which converge towards 0 as training progresses:

$$\left[ e > e_t \right] \min(e_f, e) - e_t \right] \times \lambda \times \bar{p}_{\text{out}},$$

where $\lambda$ is a constant set by the operator, and $\bar{p}_{\text{out}}$ is the mean probability of any given pixel in the current minibatch being an outlier.

The results (Fig. 1) show that, during the initial training phase, the proportion of inliers is much larger, allowing for more co-evolution between the outliers detection module and the disparity regression module. When compared to a successful training without the adaptive scheme (Fig. 1a), the proposed training method leads to marginal improvements in terms of the proportion of validated pixels.

Note that, while the proposed adaptive training strategy breaks a few assumptions of our model during training, especially by having the model validate more pixels instead of figuring out by itself what the actual proportion of inliers in the data is, the final training epochs still use only the Bayesian model described in Section 3.1 of the main paper. A corollary is that as long as the model has converged to a, possibly local, minima of the objective function without the adaptive training scheme. This result means that, overall, our adaptive training scheme does not break our model hypothesis. It just makes it more likely for the model to converge to a configuration with more inliers. This is achieved by forcing the training algorithm to traverse regions of the parameters space where the network predicts a high proportion of inliers.

III. THE "SHAPES" DATASET

The Shapes dataset is a dataset of active stereo images pairs acquired with a D435i RealSense camera. To get a highly accurate 3D ground truth, we first used a computer-aided design (CAD) software to design a series of 3D objects with a variety of shapes and angles (Fig. 2). Each 3D object exhibits a series of corners that can be easily identified in the images. We then mandated a specialized workshop to cut these shapes into sheets of 200mm thick high-grade foamed polystyrene to produce volumetric shapes with known dimensions, up to mm precision; see Fig. 2.

The shapes were then arranged to form static scenes, which we captured from multiple directions using a D435i RealSense camera. We used the maximum resolution of the camera, i.e., $1280 \times 800$ px, and a bit depth of 16 bits per channel. This gives the maximum information available to any method benchmarked on the data.

The corners of the different shapes were then manually labelled using a photogrammetry toolbox implemented using
To ensure the reconstruction is as accurate as possible, angle and length constraints were entered into the model, measured from the CAD models of the shapes. After the bundle adjustment and the rectification of the stereo images, the CAD models were aligned onto the images to generate the ground truth disparities.

Based on the estimated a-posteriori accuracy of our fitting model, we found that the positions of the shapes are known with a precision of around 1mm. With the additional uncertainty due to the maximum precision of the cutting process, a standard deviation of at least $\sqrt{2}$mm is to be expected. This translates to a disparity error of 0.5 pixels when 300mm away from the camera and 0.2 pixels when 500mm away from the camera. Hence, while highly precise, the ground truth provided with the data has a small systematic error, which can affect the measurement performance for methods with subpixel accuracy well below 1px (like ours).

We downscaled and cropped the images to $640 \times 480$px in order to reduce the impact of those artifacts and to remove the blackened-out image regions which resulted from the rectification process. The scale factor used is $5/8$, which reduces the error in the disparity estimate by a similar factor, down to 0.31 pixels when 300mm away from the camera and 0.13 pixels when 500mm away from the camera.

The final dataset is made of 12 images from 3 different scenes, with disparities between roughly 20px and 100px.

\section{A. Generalization abilities}

In addition to our experiments on active stereo, we have tested the proposed model on the Middleburry 2014 stereo dataset [1]. The evaluation benchmark [10] provided with the dataset contains a semi-dense stereo vision section where each method provides a validated set of pixels, in addition to the disparity estimation. The final scores displayed on the website were calculated only from validated pixels. In our evaluation, we did not fine-tune our model using the training set from Middleburry 2014. In Table I, we compare the MAE accuracy of our method against the top 10 semi-dense matching methods on the "train sparse" and "avgerr" set category of the benchmark, which lists the MAE of semi-dense methods. Even without any fine-tuning, our method achieves performance comparable to the state-of-the-art, providing the
TABLE I: Sub-pixel accuracy (MAE) of our method, trained on our simulated dataset only, compared to the top-ten semi-dense stereo methods in the Middlebury challenge. All scores are from the semi-dense Middlebury Stereo Evaluation Benchmark - Version 3 [10] and represent the mean absolute error of each method on its specific set of inliers. All errors are scaled to correspond to the full resolution dataset, even if each method is free to use either the full half or quarter resolution dataset.

As can be seen in Figure 3b), the proportion of pixels classified as inliers with our method is relatively low. However, this is to be expected since matching patches in passive stereo is more ambiguous than in active stereo. This means that a smaller proportion of pixels will be inliers. However, our model is not designed for passive stereo. Therefore, the fact that the proposed method is still able to reliably detect pixels when presented with data from a completely different domain shows its robustness.

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