Fast Shadow Detection from a Single Image Using a Patched Convolutional Neural Network*

Sepideh Hosseinizadeh1, Moein Shakeri2, Hong Zhang3

Abstract—In recent years, various shadow detection methods from a single image have been proposed and used in vision systems; however, most of them are not appropriate for the robotic applications due to the expensive time complexity. This paper introduces a fast shadow detection method using a deep learning framework, with a time cost that is appropriate for robotic applications. In our solution, we first obtain a shadow prior map with the help of multi-class support vector machine using statistical features. Then, we use a semantic-aware patch level Convolutional Neural Network architecture that efficiently trains on patch level shadow examples by combining the original image and the shadow prior map. Experiments on benchmark datasets demonstrate the proposed method significantly decreases the time complexity of shadow detection without losing accuracy.

I. INTRODUCTION

Dealing with shadows is one of the most fundamental issues in image processing, computer vision and robotics. Shadows are omnipresent in outdoor applications and must be taken into account in the solutions to standard computer vision problems such as image segmentation, object recognition, place recognition, visual robot localization and navigation. Unfortunately in most of these cases images are strongly influenced by shadow at different times of a day so as to cause difficulty or mistake in scene interpretation. Although some of specific applications rely on robust features with impressive results, these features often do not provide sufficient invariance to shadow.

The problem of detecting shadow is a well-studied research topic and many methods have been proposed [1], [3], [4], [5], [6], [11], [12]. Existing methods can be categorized into two major groups. First group of the methods alleviate or remove the effect of shadows by providing an invariant representation of the image [1], [2], [3], [5], [6]. Most of these methods model the process of image formation and build the shadow-free images. Although these methods work to some extent, all of them have the limitation in terms of dealing with non-Plankian source of light, narrow-band color camera and environment calibration assumptions. They also tend to lose the original information in the shadow-free representation that can be important for scene understanding.

The other group of methods rely on learning frameworks on color and intensity of an image [9], [10], [11], [12]. These methods specifically focus on shadow detection while keeping the original color and intensity of images. However, these methods still have some difficulties to apply in robotics applications that we will elaborate in the next section.

State-of-the-art shadow detection methods come from the second group above and are based on convolutional neural networks (CNN). In this paper we present a novel and fast method, also based on CNN. Our method detects shadows of an image without any assumptions about the quality of images or camera sensors, which is appropriate for the real-time outdoor robotics applications. In our method, we first segment an image. Subsequently, we extract color and texture features from each super-pixel and, with the help of a trained SVM, compute a shadow prior in terms of the probability of the superpixel being shadow. Then, we use the combination of the original image and the obtained shadow prior as the input of a patch-level CNN to compute the improved shadow probability map of the image. This edge pixels between the super-pixels are further refined by running the same patch-level CNN the second, to produce the final shadow detection. We will show that the proposed method can provide comparable results with existing deep shadow detection methods due to the use of the combination of texture features and deep neural networks, but works much faster in both training and detection phases than existing CNN based methods, as the result of using super-pixels. This method enables us to detect shadows in robotic applications, a task that was not possible before due to the expensive time complexity.

The remainder of this paper is organized as follows. In Sections II we discuss related works in shadow detection. In Section III we introduce our novel method to this problem, focusing on improving the efficiency of an exiting deep neural network based solution. Comparative experimental results based on existing benchmark datasets are described in Section IV and finally Section V summarizes our method and concludes the paper.

II. RELATED WORKS

The importance of detecting shadows from a single image has been well appreciated for a long time in computer vision and robotics community. One common approach in robotics community computes “intrinsic images” [7] by decomposing an image into its reflectance and illumination constituents [3], [5]. As discussed in the previous section, these methods have restrictive assumptions. To relax these
assumptions, data-driven approaches have been proposed. Those methods work on original representation of images based on a learning framework to learn shadows in different situations from training images [8], [9], [10], [11]. Zhu et al. [11] proposed a method that classifies regions based on statistics of intensity, gradient, and texture, computed over local neighborhoods, and refines shadow labels by exploiting spatial continuity within a conditional random field (CRF) framework [18]. Lalonde et al. [8] find shadow boundaries by comparing the color and texture of neighboring regions and employing a CRF to encourage boundary continuity. To benefit from global information, Guo et al. [9] proposed a region based method, which can model long-range interaction between pairs of regions of the same material, with two types of pairwise classifiers, under similar/different illumination conditions. Then, they incorporated the pairwise classifier and a shadow region classifier into a conditional random field (CRF) via graph-cut optimization [19]. Vicente et al. [10] proposed a multi-kernel model to train a shadow support vector machine (SVM). Their multi-kernel model is a summation of base kernels, one for each type of local features. The main limitation of this model is the assumption of equal importance for all features. The weights and the scaling factors of base kernels are not learned. Furthermore, their approach is computationally expensive. Although these methods provide good accuracy in some cases, they are not applicable to robotics due to their time complexity.

Recently, some end to end deep learning frameworks have been proposed to learn the most relevant features for shadow detection. They outperform the state-of-the-art methods that use hand crafted features. The first method in this category is proposed by Khan et al. [12]. They train two convolutional neural networks (CNN), one for detecting shadow regions and the other for shadow boundaries. They also train a unary classifier by combining both CNNs, and the per-pixel predictions are then fed to a CRF for enforcing local consistency. [13] proposed a structured deep edge detection for shadows and showed that using structured label information, local consistency over pixel labels can be improved. More recently, Vincente et al. [17] proposed a method by combining an image level fully connected network (FCN) and a patch-based CNN. They train the FCN for semantically aware shadow prediction and use the output of the FCN as shadow prior with the corresponding input RGB image to train the patched-CNN from a random initialization. Although all of these methods provide satisfactory results, they are not applicable in robotic applications due to their extreme time complexities.

In this paper, we propose a novel method based on deep learning with a shadow prior, and our method can detect shadows from a single image, much faster than all existing methods based on deep learning. The key insight of our method is that it performs shadow detection on a per super-pixel basis. Naive implementation of such a detection method would however produce boundary effects between super-pixels. We overcome such artifacts with a post-processing step using edge refinement.

### III. PROPOSED METHOD

In this section we describe our proposed method to detect shadows from a single image. Our method first uses two steps to learn shadow from training images. First we obtain a prior map that we call shadow prior using a trained SVM on color and texture features, and then we train a patched-CNN using the original images and their shadow priors obtained from the first step. These two steps will be detailed in Section [III-A] and [III-B] respectively. For the detection of shadows in a given image, we compute its shadow prior first.
with the SVM and use the prior and the image as input to the trained patched-CNN, using the center pixel of each super-pixel as the representative in order to significantly reduce the computational time. In doing so, however, the super-pixels near object and shadow boundaries tend to produce unreliable “edge effects”. To overcome these problems, we refine prediction labels for the edge pixels along super-pixel boundaries. Therefore, detection of shadow algorithm makes use of patched-CNN twice. Output of the second patched-CNN shows the detected shadow areas. Edge refinement part will be discussed in Section II-C.

A. Computing Shadow Prior

Shadow prior production pipeline is illustrated in the first row of Fig. 1. To build the shadow prior, we first segment the image using mean shift algorithm [14] to obtain superpixels. Then, using a trained classifier on texture and color features, we estimate the shadow probability of each region. Segmentation enables us to estimate the shadow probability for each region instead of each pixel and therefore, the computation time significantly decreases.

In general, a shadowed region is darker and less textured than a non-shadow region [11]. Therefore, the color and texture of a region can help to predict whether it is in shadow. We exploit this observation and represent color with a histogram in L*a*b space, with 21 bins per channel, as was successfully applied in [9]. We represent texture with the texton histogram provided by [15]. We train our SVM classifier with the color and texture features with a \( \chi^2 \) kernel and slack parameter \( C = 1 \) [16]. We define the shadow prior of each super-pixel, as the log likelihood output of this trained classifier. In the subsequent step, we use this shadow prior as a critical input to our patched-CNN.

B. Training Patched-CNN with the Shadow Prior

In the next step of our shadow detection pipeline, we employ a patch-wise CNN to predict shadow. Current research in [17] showed that using patches of an image with a specific size has two benefits in the case of shadow recognition. First, these patches include enough local pattern of the image and more global information in a large-range of neighborhood pixels rather than pixel-based methods. Secondly, using patches we are able to provide more training samples with different patterns from a limited number of labeled images. As discussed, one of the challenging problems in the case of shadow detection is the number of training samples, which can significantly affect the accuracy of a deep neural network. Unfortunately, available shadow benchmark datasets are small due to the high cost of shadow annotation. This patch-wise structure enables us to provide a huge number of patches of shadow and non-shadow areas for training that can increase the overall accuracy of the network.

We utilized a similar network architecture used in [17]. The deep network has six convolutional layers, two pooling layers, and one fully connected layer. The input of this network is a 32\( \times \)32 RGBP patches selected from combining RGB image and shadow prior image \( P \). The output is the shadow probability map of the patch. We select equal number of patches for training in three ways as follows.

- **Shadow patches**: Since we are going to learn shadow areas, we first select patches from shadow regions.
- **Non-shadow patches**: We select patches from non-shadow image locations randomly to include patches of various textures and colors. Also, these selected patches prevent overfitting.
- **Shadow-Edge patches**: We also select patches on edges between shadow and non-shadow regions, to learn the shadow boundaries. Since the ground-truth is binary, locations of all shadow edges can be extracted accurately.

Using this strategy, we are able to provide millions of patches from thousands of images. The loss function of the network is the average negative log-likelihood of the prediction of every pixel.

C. Edge Refinement of Super-Pixel Labels

Predictions made by the patched-CNN are local, and the prediction results near shadow boundaries are poor. To improve the accuracy of our detection algorithm, higher level interaction between the regions is needed. Therefore, in this final step we process the edge pixels between the regions by patched-CNN once again, shown in the bottom row of Fig. 1.

We only process those pixels that are on edges between the segments, and includes in \( R(S) \) which is defined as:

\[
R(S) = \{ s_i \in S | s_i \geq \alpha \max_{1 \leq i \leq m} (s_i) \}
\]  

\( R(S) \) contains those segments with the higher probability than a threshold of maximum shadow probability in \( P1 \). \( \alpha = 0.2 \) is a constant threshold and \( m \) is the number of superpixels or regions in the image or \( P1 \). Absolute non-shadow regions always provide a very low shadow probability in the shadow prior map, and \( R(S) \) only filter out those regions. This thresholding step will reduce the time complexity significantly.

For each boundary pixel \((x,y)\) between segments that includes in \( R(S) \), a window patch with size 32\( \times \)32 surrounding the pixel \((x,y)\) from its shadow prior and corresponding original image are given to the patched-CNN to predict the shadow probability for that patch. Then we set the edge pixel \((x,y)\) and its 8 neighbor pixels’ values to be average value of these 9 pixels. This step can integrate the segmented probability maps obtained in previous step and the final shadow probability map becomes smooth.

IV. EXPERIMENTAL RESULTS

In this section we perform a set of experiments to evaluate our proposed method and compare it with other state-of-the-art methods. We first use three challenging available datasets “UCF” [11], “UIUC” [9], and “SBU” [17] for shadow detection to evaluate quantitatively the proposed method with the following details.
• **UCF Dataset**: This dataset contains 355 images with manually labeled region-based ground truth.

• **UIUC Dataset**: This dataset contains 108 images (32 train images and 76 test images) with region-based ground truth.

• **SBU Dataset**: This new dataset contains 4,727 images (4,089 train images and 638 test images) with region-based ground truth.

• **Combined Dataset**: Both UCF and UIUC datasets include an insufficient number of images, and to evaluate the propose method we need to select a portion of these datasets as training samples. Since our proposed method works on patches, it is able to provide many patches for training phase. However, to be fair in comparison with other methods, we combine UCF, UIUC, and SBU datasets to train for all methods. The combined dataset includes 5,078 images. We randomly selected 25% of the images for testing, and the rest for training.

In addition, we use two other datasets “UACampus” and “St. Lucia” [20] to obtain qualitative results of detecting shadows on the roads, one of the common problems in robotic applications.

### A. Evaluation Metrics

To evaluate the proposed method against other competitive methods in terms of detection accuracy, we use three evaluation metrics as follows.

\[
\text{ShadowAccuracy} = \frac{TP}{\text{all shadow pixels}} \tag{2}
\]

\[
\text{Non-shadowAccuracy} = \frac{TN}{\text{all non-shadow pixels}} \tag{3}
\]

\[
\text{TotalAccuracy} = \frac{TP + TN}{\text{all pixels}} \tag{4}
\]

For comparison in terms of computational efficiency, we simply use the execution time of shadow detection in a single image as the performance metric. Therefore, a total of four performance metrics, three for accuracy and one for efficiency, are considered in our experimental evaluation.

### B. Results on Benchmark Datasets

In this section we evaluate our proposed method and compare it with Stacked-CNN [17] and Unary-Pairwise [9] methods. We select the stacked-CNN method as a recent shadow detection method based on deep learning framework that uses a shadow prior map. We choose the unary-pairwise method since it is one of the best statistical methods to detect shadows from a single image. Fig. 2 shows example results of these methods and ours. In the third row, although the unary-pairwise method provides acceptable results in some cases, it completely fails in the first, third, fifth, and sixth columns. The forth row of Fig. 2 shows the results of stacked-CNN and in the most cases is comparable with our proposed method (the fifth row). The last row shows the binary shadow mask of the proposed method by a constant threshold.

Table I shows the quantitative results on SBU dataset. The values shown are the average of the performance metrics on all test images. Although the total accuracy of the proposed method is not the best, shadow accuracy outperforms the other methods. The goal of the proposed method is providing a fast shadow detection method without losing the accuracy. Therefore, in Table II we show the execution time of training and testing phases of the proposed method. Results in both Tables I and II illustrate that the proposed method works an order of magnitude faster than the statistical methods and two orders of magnitude faster than the deep learning competing method with the comparable accuracy. This is almost an entirely a result of predicting shadow/non-shadow labels on super-pixels rather than pixels, even with the additional cost to pay for refining the boundary pixels.

We also evaluate the proposed method and compare it with the other methods on the combined dataset to investigate the effect of increasing the number of images for training and testing. Table III shows that our method is still comparable with other methods in terms of accuracy, and Table IV shows that the execution time of our method is significantly less than the other two methods, as was the case on individual datasets.
C. Shadow Detection in Road Detection Application

To illustrate the utility of our method in a real application, we consider the problem of detecting shadow on roads in this section. Cast shadows on roads can cause difficulty or mistakes in the scene interpretation or segmentation for this application. To determine the performance of our method in this application, we apply the proposed method on St. Lucia and UACampus datasets to show the potential of the method in detecting shadows on roads. Figs. 3 and 4 show the results of our method in terms of shadow probability maps of sample images. It is clear from these examples that our method is able to generate a probability map of high accuracy in these cases, and can serve as a useful building block for road detection in, for example, autonomous driving.

TABLE IV

| Method         | Testing (hours) | Testing (sec/image) | Training (hours) |
|----------------|-----------------|---------------------|------------------|
| Stacked-CNN    | 39.38           | 111.62              | 5.4+1FCN         |
| Unary-Pairwise | 20.77           | 58.87               | -                |
| Our method     | **1.45**        | **4.11**            | **2.18**         |

Fig. 2. Comparison of our qualitative results with the results of other methods. Rows from top to bottom: input images, ground truths, results of unary-pairwise method, results of stacked-CNN, obtained probability map of our method, binary mask of shadows based on the probability map of our method.

Fig. 3. Qualitative results of the proposed method on sample images of the St.Lucia dataset.

Fig. 4. Qualitative results of the proposed method on sample images of the UACampus dataset.

Fig. 5. Qualitative results of the proposed method on aerial images. Last row shows the binary mask of the shadow probability map.

We also apply the proposed method on aerial images to detect shadows, a common problem for many application that rely on the aerial images. Fig. 5 shows the qualitative results of the proposed method to detect shadows of the aerial images. Once again, the results are highly accurate, and our method can directly contribute to solutions in aerial imaging applications.

V. CONCLUSION

In this paper, we have presented a method for accurately detecting shadow in a single image. Our method combines traditional color and texture features and deep learning in a
novel way, and achieves start-of-the-art performance in terms of detection accuracy and out-performance state-of-the-art in terms of computational efficiency. Our method uses color and texture features to compute a shadow prior map by training an SVM. The prior map and the original input image are then used as input to a patched-CNN to compute shadow probability map, one for each super-pixel, to achieve the desired computational efficiency. In the final step, we refine the prediction result of the patched-CNN by re-estimating the class labels of boundary pixels between super-pixels with the same patched-CNN. Extensive experimental results demonstrate that the proposed method works significantly faster than the existing deep or statistical methods without losing the accuracy.

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