Classic versus deep learning approaches to address computer vision challenges

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Abstract—Computer vision and image processing address many challenging applications. While the last decade has seen deep neural network architectures revolutionizing those fields, early methods relied on ‘classic’, i.e., non-learned approaches. In this study, we explore the differences between classic and deep learning (DL) algorithms to gain new insight regarding which is more suitable for a given application. The focus is on two challenging ill-posed problems, namely faint edge detection and multispectral image registration, studying recent state-of-the-art DL and classic solutions. While those DL algorithms outperform classic methods in terms of accuracy and development time, they tend to have higher resource requirements and are unable to perform outside their training space. Moreover, classic algorithms are more transparent, which facilitates their adoption for real-life applications. As both classes of approaches have unique strengths and limitations, the choice of a solution is clearly application dependent.

I. INTRODUCTION

Computer vision and image processing address many challenging applications. While the last decade has seen deep neural network architectures revolutionizing those fields, early methods relied on ‘classic’ approaches. Here, ‘classic’ refers to techniques that do not rely on machine learning, such as engineered feature descriptors, theoretic-based algorithms, search methods, and usage of theoretically proven characteristics. In this study, we explore the differences between classic and deep learning (DL) approaches and their associated constraints in order to gain new insight regarding which is more suitable for a given application. While DL is only a subset of machine learning, this manuscript does not cover other machine learning algorithms as they have become less popular. Indeed, currently, around 25% of all papers presented at computer vision and image processing conferences take advantage of DL. Moreover, a session dedicated to it has become the norm on the program of many scientific venues.

In order to conduct that investigation, we focus on two computer vision tasks that are at the limit of the ability of current state-of-the-art algorithms, i.e., faint edge detection in noisy images and multispectral registration of images. Edge detection is one of the earliest problems that has been studied in image processing and computer vision [9], [19], [7]. Although many approaches have been proposed to address this task, they still fail to detect edges when they are faint and the images are noisy [22], [21]. Those limitations are particularly problematic as these kinds of edges can be found in most imaging domains including satellite, medical, low-light, and even natural images. See Figure 1 for the classic and DL results of the faint edge detection methods that we discuss in this paper.

With the development of multi-sensor cameras that capture images from different modalities, multispectral image alignment has become a very important computer vision task. Indeed, robust alignment between the different image channels forms the basis for informative image fusion and data fusion. For example, while robust object detection can be derived from a combination of color and infrared images, this relies on the availability of accurate multispectral alignment. However, specialized methods need to be developed as reliable cross-spectral alignments cannot be achieved by using single-channel registration methods like scale-invariant feature transform (SIFT) [17], [5] feature based registration.

Although a few comparative studies between DL and classic approaches have already been performed, this is the first that focuses on challenging ill-posed problems, exemplified by faint edge detection and multispectral image registration, which allow gaining interesting new insights. This paper is organized as follows. In Section II we review previous studies analyzing classic and DL approaches. While in Section III we compare such solutions for faint edge detection, in Section IV we focus on multispectral image alignment. Finally, we discuss the insights gained from this study in Section V and conclude this manuscript in Section VI.

II. PREVIOUS WORK

Herein, ‘classic’ approaches are defined as those that do not depend on machine learning. They are engineered algorithms that rely on theory and mathematical models, and not directly on external data. Examples of such algorithms include: the Canny edge detector [7], which uses hysteresis of gradients to identify curves in the image, the SIFT descriptor [17], which is an engineered and handcrafted representation of an image interest point, and optimization methods like in photometric stereo for example [3].

A recent study [27] compares classic and deep learning algorithms. That investigation focuses on three computer vision tasks, i.e., panorama generation, 3D reconstruction, and simultaneous localization and mapping (SLAM). They show that
each approach, classic and DL, has its advantages and limitations. In particular, they highlight that the classic development process often relies on a strong theoretical framework which gives transparency and trust, whereas DL methods, when trained with an appropriate dataset, tend to deliver much higher performance. Other studies, focused on a single application, report outcomes of experiments evaluating their difference in terms of accuracy. A recent publication [11] presents a comparison of a set of classic keypoint descriptors with their deep learning-based competitors [28], [8]. Evaluation under various geometric and illuminations shows that some combinations of classic keypoint detectors and descriptors outperform pre-trained deep models. On the other hand, performance analysis of two solutions for visual object detection, i.e., a classic feature extractor with a learned classifier and an object detector based on compact CNN (YOLO v3) [29], reaches a different conclusion [18]. They find that the classic detector fails to detect objects under varying geometry such as size and rotations, while the compact CNN-based detector deals with these variations outperforming it. Similarly, a survey of classic and DL methods for face recognition [32] confirms what is generally accepted in the community, like in boundary detection, e.g., [33], that CNNs are the state of the art as they deliver significantly better accuracy.

While performance metrics, such as accuracy, are key elements when comparing different approaches, researchers have also considered other aspects in their analysis. First, the high cost of the training phase of DL algorithms and its associated large amount of energy consumption have been highlighted [11]. Second, evaluation of the computational resource requirements for DL, for NLP algorithms in particular, has drawn attention to the fact that, although large neural networks can improve accuracy, they rely on the availability of large and costly computational devices, which may limit their applicability [31]. They report that training of an NLP standard DL model, like the one in [2], requires 120 training hours which can cost up to 180 USD of cloud computing and electricity. Third, a major limitation of current DL methods is the limited ability of humans to interpret them, i.e., the infamous black-box effect. This lack of transparency may prevent the deployment of DL-based solutions in applications where legal and ethical issues are paramount, such as autonomous driving [16].

Although previous research already provides good insight, further investigation is required in particular regarding assessing the behaviors of those classes of approaches when faced with challenging ill-posed problems. Thus, we conduct our research focusing on two tasks of that nature, i.e., faint edge detection and multispectral image registration, which are both long-standing research areas. We anticipate that the outcome of this study will inform the computer vision community about the ability of classic and DL methods to solve problems that are currently only addressed by weak solutions. Our comparison is discussed differently in detail in the thesis [26].

III. FAINT EDGE DETECTION

Faint edge detection (FED) is a challenging problem that has still not been addressed adequately. As edges at a low signal-to-noise ratio (SNR) can be found in a variety of domains, e.g., medical, satellite, low-light, and even natural images, effective solutions tend to be customized and applicable only to a very narrow range of applications [13]. Recently, a couple of related state-of-the-art approaches have been proposed to improve FED accuracy: while FastEdges is a classic method relying on a hierarchical binary partitioning of the image pixels [22] - see Figure 3 - FED-CNN takes advantage of a multiscale CNN to mimic that hierarchical tree approach [23] - see Figure 3.

Using a simulation where a set of binary images [15] are contaminated by Gaussian additive noise and edges had their contrast reduced, we compare their performance highlighting their individual strengths and limitations. Note that the standard Canny detector [17] and the more recent Holistically Edge Detector (HED) [33], a DL method based on the VGG-16 network [30], are used as baseline methods. As it is common in the evaluation of binary classifiers, the F-measure, i.e.,
Fig. 2. FED approach based on an image Rectangle-Partition-Tree [22]: this classic method searches the best concatenation of sub-curves by breaking point \( p_3 \) for every curve between every two boundary points \( \forall p_1, p_2 \). This search is performed recursively in a bottom-up dynamic programming-like approach.

Harmonic mean of the precision and recall, is used to assess the quality of the detected edges.

As Figure 4 shows, where F-scores are calculated according to signal-to-noise ratios in the range \([0,2]\), both state-of-the-art methods outperform significantly the HED and Canny detectors. However, FED-CNN systematically delivers higher F-scores than FastEdges’s. For example, for a SNR of 1, resp. 2, FED-CNN achieves a score of 0.4, resp. 0.62, while FastEdges only obtains 0.28, resp. 0.56.

When considering computational complexity and runtime, again FED-CNN performs much better than FastEdges. First, a theoretical study of the computational complexity of those two algorithms reveals that, while FastEdges is nearly linear [22], FED-CNN is linear [23]. Second, as Table I shows, using an Intel i9 Sky-Lake CPU, FED-CNN proved more than 3 times faster than FastEdges. Moreover, the processing time of FED-CNN can easily be accelerated on a GPU, here a GeForce gtx1070, improving runtime by almost two orders of magnitude and approaching the speed of the efficient Canny detector.

Although this experiment results in the DL algorithm outperforming significantly the classic one, the traditional approach has clear advantages.

First, it has strong theoretic foundations [22]. Its complexity,\

\[
C(N) \leq 6N^{1.5} \left[ \sum_{l=0}^{\infty} 2^{-l} + \sum_{l=1}^{\infty} 2^{-l} \right] = 18N^{1.5}
\]

Moreover, how faint an edge can be and still be detected by this classic algorithm is known. If \( \sigma \) denotes the noise standard deviations and \( w \) the filter width, the lower-bound of the minimal contrast that it can detect is:

\[
T_\infty = \Omega(\sigma/\sqrt{w})
\]

This limit can be explained by i) the space of possible curves of the algorithm is exponential according to the curve length, and ii) the dynamic programming method used to search for an exponential number of curves takes a polynomial time.

Second, while differences between the natures of the training and testing sets generally lead to much-reduced performance of DL algorithms due to generalization bounds [12], classic methods tend to be suitable for various imaging domains. Indeed, although the design of FastEdges assumed step edges with constant contrast and Gaussian noise, this approach also achieved accurate results on the BSDS-500 [20] dataset [22]. This demonstrates that it can still be highly competitive in other imaging domains, such as those covered by BSDS-500 with its noisy natural images. On the other hand, when applied to an imaging domain similar to the training set’s, FED-CNN
shows high flexibility to geometric variations including edge curvatures and geometric transformations [23].

While performance scores are essential when selecting an approach, the cost of its development is also important. The development processes of classic and DL solutions are quite distinct. Whereas the FED classic approach required planning, analysis, parameter optimization, and complex derivation of computational complexity and threshold, the DL one, once suitable training data were identified, could be produced quite swiftly by adapting existing DL architectures. This versatility of DL architectures allows successful designs to be easily remodeled to address applications different from the ones for which they were initially conceived. As reported in [23], FED-CNN could be effortlessly transformed so that it could be used to perform noisy image classification and natural image denoising. Actually, experiments on the CIFAR 10 and 100 datasets [14] revealed state-of-the-art accuracy [23].

IV. MULTISPECTRAL IMAGE REGISTRATION

Multispectral image alignment is another task which has not been satisfactorily addressed by computer vision. See Figure 5 for example of multispectral image pair. In this study, we focus on two recent developments which achieved consecutively state-of-the-art performance: a classic approach which relies on a handcrafted descriptor designed to be invariant to different spectra [25] - see Figure 5 - and a DL framework based on pseudo-Siamese network [24] - see Figure 7.

Table II reports the average pixel error of those two approaches and other classic techniques, i.e., correlation of Canny [7], correlation of Sobel [9], maximization of mutual-information and LGHD [1], in a task aiming at aligning visible (VIS), i.e., 0.4-0.7 $\mu$m, to Near-Infra-Red (NIR), i.e., 0.7-2.5 $\mu$m, images. This experiment was conducted using a standard dataset of cross-spectral aligned images [6]. The DL solution outperformed significantly all classic approaches. Moreover, as reported in [24], it is robust to geometric distortions: scaling applied in the [0.8,1.1] range only leads to a translation error of around 1 pixel.

| Algorithm | Average Pixel Error |
|-----------|---------------------|
| DL solution [24] | 0.03 |
| Handcrafted descriptor [25] | 0.08 |
| Canny | 0.07 |
| Sobel | 0.07 |
| Mutual Information | 0.11 |
| LGHD | 0.21 |

To evaluate if the DL approach was suitable to other imaging domains, it was applied on an alignment task of VIS to Middle-Wave Infrared (MWIR), i.e., 3 – 5$\mu$m, images. However, since it had only been trained on a VIS to NIR dataset, this led to total failure. On the other hand, the application of the algorithm with its handcrafted descriptor to VIS to MWIR image alignment continued to deliver quality results [25], demonstrating the robustness of the classic approach to various spectral channels.

As it has been seen, multispectral alignment can be performed using an approach either relying on a carefully crafted feature descriptor or learned by a CNN using a metric learning scheme. However, in terms of registration accuracy, while the DL approach excelled on images the features of which were covered in the training set and succeeded at handling geometric variations, the classic approach proved more robust to different imaging modalities.

Although registration error is a key element when comparing multispectral image registration algorithms, other important aspects could also be considered. First, as the DL approach requires a forward pass of a CNN for every keypoint, the processing time of creating a feature descriptor is faster with the classic approach. Second, while a classic approach does not require training resources, the DL method relies on the availability of a valid multispectral database with a corresponding aligned image to operate. Moreover, its accuracy also depends on the level of information available in the keypoint features in that dataset. Third, both approaches have different hardware requirements: whereas the classic methods can easily be run on a standard CPU, real-time computing can only be achieved by the DL method if its execution takes place on a GPU. Not only is an expensive processing platform required, but also this prevents its usage on some embedded systems. Finally, there is a major difference regarding the development time that was needed to produce those two solutions. While the classic method was developed with much effort, once available, it could be quite rapidly transformed into its deep learning variant.

V. DISCUSSION

This comparison of recent classic and DL algorithms addressing two challenging ill-posed problems, i.e., faint edge detection and multispectral image registration, has provided novel insights regarding those two classes of approaches. Their particular features are summarized in Table III.

| Feature/Approach | DL | Classic |
|------------------|----|---------|
| Accuracy (Acc.) | High | Moderate |
| Acc. for other domains | Low | Moderate/Fast |
| Speed on CPU | Fast | / |
| Speed on GPU | / | / |
| Theoretical basis | Moderate | High/Moderate |
| Training dataset | Essential | No |
| Geometric variability | Robust | Weak |
| Development | Fast | Slow |
| Repurposing ability | High | Low |

Although like most previous comparative studies [18], [27], and [32], ours reports that DL approaches achieve higher accuracy than classic methods. Moreover, it also underlines the fact that usage of a DL solution is very much restricted by the nature of its training set and, thus, it performs poorly...
when applied in another imaging domain. We should however note that they proved remarkably robust to geometrical transformations. As [31], our experiments also show that DL algorithms are slow on CPU-based machines, while they are appropriate for many classic solutions. Thus, GPU hardware is highly desirable when running DL solutions, which limits their applicability. Note that there are approaches of pruning and quantization that aim at minimizing inference time while preserving accuracy for DL [10].

Classic algorithms may be conceived from a strong theoretic basis, providing, e.g., in the case of faint edge detection, quantified information regarding the limit of their capacities. Unfortunately, as already mentioned by [27], this is not the case of the studied DL solutions, where, e.g., there is no practical understanding of either the CNN filter derived for FED or the invariant descriptor produced for multispectral image registration. This lack of transparency may prevent their usage in sensitive applications.

Since we had inside knowledge regarding the development of all the methods that we have investigated in this manuscript, we were in the quite unique position of being able to compare their development process. For both applications, once suitable training datasets were available, the implementation of the DL solution was much faster than the classic ones as existing CNN architectures could be quite easily adapted to fulfill the requirements of the targeted tasks. This repurposing ability can also naturally be exploited by recycling the DL algorithms investigated in this study. Indeed, FED-CNN was converted into both a noisy image classifier and a natural image denoiser by retraining the same CNN architecture using a different loss function.

Beyond accuracy, which, generally, privileges DL solutions if an appropriate training set can be assembled, we have reviewed other parameters that influence and sometimes impose the choice of a class of approaches when addressing computer vision and image processing applications. As both classes have unique strengths and limitations, it is expected that both will continue to produce useful solutions in the near future.

VI. CONCLUSION

In this paper, we reported the insights gained from a comparative study between DL and classic approaches applied to computer vision and image processing. In this investigation, we focused on challenging ill-posed problems, namely faint edge detection and multispectral image registration, analyzing the strengths and limitations of recent state-of-the-art DL and classic solutions.

Although those DL algorithms outperform classic methods in terms of accuracy and are robust to geometrical transformations, unlike the classic approaches, their performance collapses when attempting to process images outside their training space. Moreover, usage of GPUs is often mandatory to meet their generally higher computing requirements. On the other hand, the repurposing ability of DL architectures makes the development of new approaches much easier than with classic methods.

Eventually, the main concern regarding DL solutions may be that, while classic algorithms are quite transparent and are often supported by theory, the learning solutions are difficult to understand and explain. Thus, until further progress in the interpretability of deep learning models, the issue of trust may hinder their deployment in many real-life applications.

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Fig. 7. Deep-learning architecture for a learned invariant descriptor [24]. It can be seen as a pseudo-Siamese network or as a teacher-student scheme. The visible (VIS) color path is forwarded through a pre-trained classification network that was trained on the CIFAR10 dataset. Its corresponding Near-Infrared (NIR) patch is used to train the infrared network to produce a similar invariant representation. A L2 loss function is used.

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