TOWARD SCALABLE DAMAGE ASSESSMENT FOR RAPID DISASTER RESPONSE

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ABSTRACT

Current research and development efforts at DLR`s Center for Satellite Based Crisis Information (ZKI) focus on deploying automated image analysis methods as part of rapid mapping processing routines. The use of machine learning methods enables processing of large amounts of heterogeneous satellite, aerial and drone images at varying spatial scales and temporal frequencies. In this work, we introduce an automated and scalable image processing chain for rapid building damage assessment, optimize it for inference on different hardware and provide application examples from recent natural disasters. We show the scalability of the method from high-frequency live-mapping with drones on a laptop to large-scale processing of satellite and aerial images on a high-performance computing cluster.

Index Terms— Damage Assessment, Rapid Response, Siamese Convolutional Neural Network, Drones, Optical Satellite Images

1. INTRODUCTION

The emergence of machine learning techniques and the availability of remote sensing datasets on a large scale have created new opportunities for automating the analysis of remote sensing data. This enables the handling of increasing data volumes, intricate complexities, and the inherent spatio-temporal dynamics associated with disaster situations. Change detection approaches that compare pre- and co-/post-disaster images can provide valuable insights into distribution and intensity of building damages. In this context, deep learning-based approaches have been extensively studied in recent years, with Siamese Convolutional Neural Networks (CNN) being particularly favored for the task [1], [2]. To overcome issues related to misalignments of building footprints between bi-temporal input images, some studies propose complex multi-task architectures that handle building delineation and damage classification at once [3]. Other studies follow a two-step approach and train separate models for building segmentation and damage classification [4]. In this work, we introduce an automated image processing chain for rapid building damage assessment, optimize it for inference on different hardware and provide application examples from recent natural disasters to evaluate its scalability and generalization ability.

2. DATA

The globally distributed xBD benchmark dataset [5] is used for training, validation and test of a Siamese CNN for damage assessment. Additionally, we use the OpenEarthMap dataset [6] as input for training and validation of a CNN for building footprint refinement. Very high-resolution optical satellite images from the MAXAR Open Data Program [7] are acquired for large scale application examples from recent natural disasters in Morocco (earthquake, September 2023) and Libya (floods, October 2023). Moreover, we utilize aerial and drone imagery from flight surveys carried out by DLR during and after the Ahrtal floods in Germany 2021 [8].

3. METHOD

We develop an automated and scalable image processing chain that uses a LightGlue model [9] for improved co-registration of input images and a two-step approach for building damage assessment with a Siamese CNN (Figure 1).

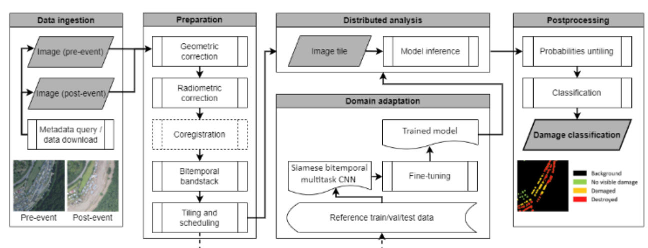
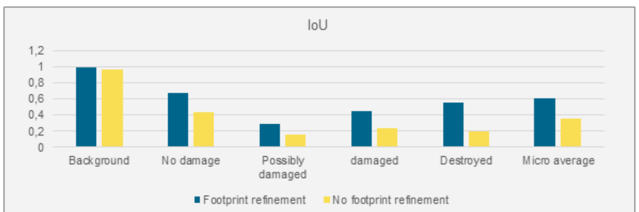


Figure 1*: Overview of the automated image processing chain for damage assessment.*

We implemented a U-Net with EfficientNet-B4 [10] encoder for building segmentation and a Siamese version of the same encoder-decoder architecture for damage classification. We train both models independently with an AdamW optimizer, initial learning rate of 1e-3, weight decay of 1e-2 and a weighted combination of binary cross entropy and Lovász Hinge loss. Encoder weights are initialized from a model that has been pre-trained on Imagenet. Training is performed with 32-bit floating-point precision (FP32) using Pytorch. Training samples are augmented with respect to brightness, contrast, scale and orientation. Model performance is assessed by reporting Intersection over Union (IoU), Precision (Prec) and Recall (Rec). We compare different inference engines and model formats to evaluate their influence on throughput, including Pytorch (FP32), ONNX (FP32) and ONNX (FP16). Model throughput is measured in megapixel per second (mp/s) and averaged across five prediction runs on 5,000 tiles with shape (256, 256, 3).

4. RESULTS

Figure 2 shows results of our approach on an independent test split of the xBD datasets and highlights the positive effect of the building footprint refinement on the performance of the Siamese U-Net with EfficientNet-B4 encoder. Improvements in model accuracy of 0.252 IoU (micro average) can be observed. The model with refinement performs well on classes “no damage”, “damaged” and “destroyed”, while the results indicate a clear drop in performance for class “possibly damaged”. All classes benefit from the building footprint refinement with class “destroyed” showing the largest increase in accuracy of 0.366 IoU.



Footprint refinement

metric	Background	No damage	Possibly damaged	Damaged	Destroyed	Micro average
IoU	0.991	0.679	0.284	0.452	0.560	0.609
Precision	0.996	0.804	0.425	0.579	0.713	0.746
Recall	0.995	0.814	0.461	0.673	0.722	0.769
Support	2283506678	51132981	5279380	5516380	3374821	2348810240

No footprint refinement

metric	Background	No damage	Possibly damaged	Damaged	Destroyed	Micro average
IoU	0.961	0.434	0.151	0.242	0.194	0.357
Precision	1.000	0.450	0.172	0.263	0.201	0.376
Recall	0.962	0.924	0.553	0.756	0.850	0.876
Support	2283506678	51132981	5279380	5516380	3374821	2348810240

Figure 2*: Accuracy assessment of the Siamese U-Net model with and without building footprint refinement on an independent test split of the xBD dataset.*

The trained models are deployed in the image processing chain via the open ONNX (Open Neural Network Exchange) format, which is built to represent machine learning models in a standard across a variety of frameworks, tools, runtimes and compilers. To improve inference speed in the production environment, we have converted the FP32 models to mixed-precision FP16 models, which effectively reduces model size and complexity without affecting the accuracy of the results. Figure 3 shows a comparison of inference throughput across a range of batch sizes for the U-Net with EfficientNet-B4 encoder on the building segmentation task.

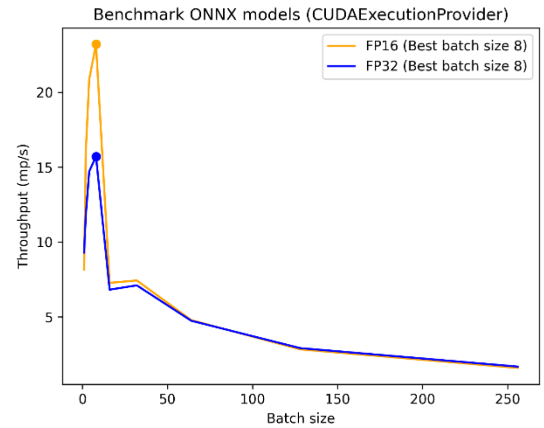


Figure 3*: Comparison of ONNX model inference throughput for different model precisions. Measured on a NVIDIA RTX A4000 GPU using ONNX-Runtime "CUDA Execution Provider" across a range of batch sizes.*

Figure 4 shows an example of a damage assessment from very high-resolution optical aerial images of the Ahr valley floods in Germany 2021. To exemplify the efficiency and scalability of the image processing chain, these images have been processed on a laptop with a standard consumer GPU. Beyond static map production, it is possible to use the deployed method for live-mapping of damages on the basis of aerial image streams and drone videos.

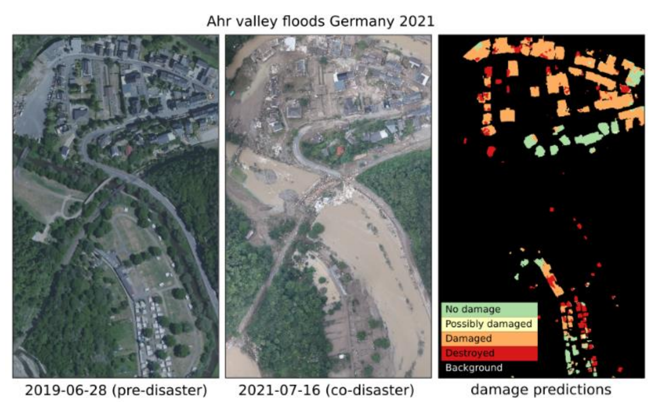


Figure 4*: Example of damage assessment from very high-resolution optical aerial images of the Ahr valley floods in Germany 2021.*

Figure 5 shows small subsets of large-scale damage assessments for the Morocco earthquake 2023 and the Libya floods 2023 based on very high-resolution satellite images of the MAXAR Open Data Program. For such purposes, a highly parallelized version of the image processing chain is being deployed on a GPU node of the Leibniz Supercomputing Centre of the Bavarian Academy of Sciences and Humanities. Resource allocation is scalable and controlled via SLURM workload manager.

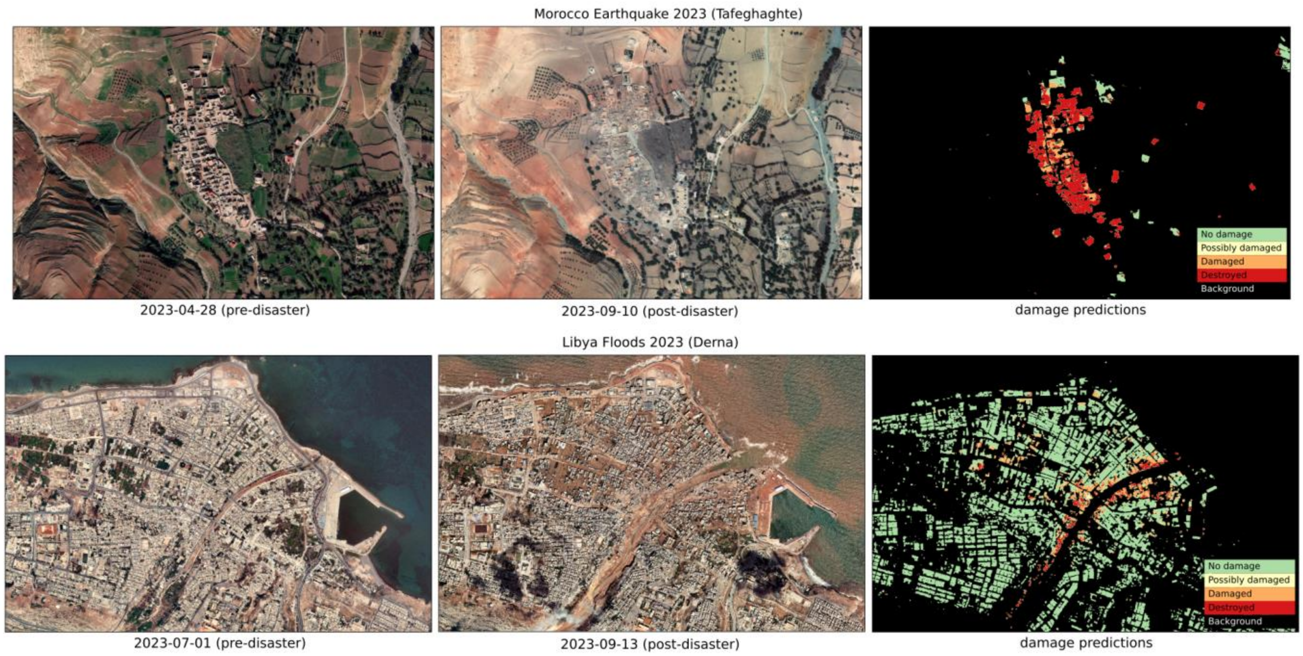


Figure 5*: Examples of damage assessments from very high-resolution optical satellite images of the Morocco earthquake 2023 and the Libya floods 2023.*

5. DISCUSSION AND CONCLUSIONS

We showed the deployment of a method for rapid damage assessment from bi-temporal satellite, aerial and drone images. The methods can produce accurate results and are scalable to different data- and hardware-availability scenarios. A good generalization ability of the image analysis method is in any case essential to cope with highly varying data availability in disaster situations like the 2021 floods in Germany. To this regard, more research is currently conducted to test the influence of different domain adaptation methods on the generalization ability of the learning machine [11]. Automated image processing routines together with pre-trained machine learning methods for image analysis can reduce the time between image acquisition and final product generation from several hours/days to just a few minutes. It therefore allows for a faster product delivery, for a higher analysis frequency and for a continuous monitoring of the situation. The inference speed achieved by the damage assessment method coupled with the real-time capabilities of modern drone systems and the flexibility of the web-services offered by DLR`s ZKI [12], would further enable the deployment of a fully automated processing chain for live-mapping, analysis and dissemination.

6. ACKNOWLEDGEMENTS

This work was supported by the European Union as part of the TEMA project [Grant No. 101093003] and by DLR internal funding as part of the RESITEK project.

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