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OpenSpeckle: Open science principles in shearography and ESPI

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ABSTRACT

Shearography and electronic speckle pattern interferometry (ESPI) have historically been developed in limited collaboration. Both techniques have a significant entry barrier for new researchers to get reliable results. The situation is even worse regarding data and code availability: only three documented and publicly available shearography datasets and very limited open software realisations exist. The data sharing aspect gets more critical. First, AI developments are well reported, while only two datasets were published. Second, developments in phase processing are reported without publicly available code. This limits reproducing and validating the results. Following an example from open data challenges in digital image correlation (DIC), this presentation highlights the Open Science issues and proposes three shearography datasets with inspection of composites. This presentation intends to initiate a discussion in the field that could lead to better practices on data and code sharing.

Keywords: speckle interferometry, shearography, ESPI, non-destructive inspection, optical metrology

1. INTRODUCTION

Speckle interferometry techniques, including shearography and electronic speckle pattern interferometry (ESPI), have been developed with limited collaboration and data sharing. Multiple research groups have published papers and books with theoretical and practical insights into optical arrangements, interferogram and phase processing, and numerous application cases. However, both techniques have a significant entry barrier. Researchers who are new to the topic have to learn and master the “art” experimentally to achieve reliable experimental results or even reproduce already reported ones. As a general overview of the field, there is a lack of well-documented best practices and industrial standards for inspection (which are limited to ASTM E2581, DIN 54180). The situation is even worse regarding data availability and code-sharing practices.

At this moment (June 2025), there are four documented and publicly available shearography datasets[1-5], a limited number of open code software realisations[6-9] and almost no pre-prints or white papers with best practices. The Open Science movement aimed at making research results accessible to researchers of all levels has limited depth in the shearography and ESPI fields.

The data sharing aspect gets more critical for at least two reasons. First, AI and machine learning (ML) developments penetrate all engineering practices. Most of the recently reported AI developments in shearography[10-14] are made by the same experimental engineers who have mastered the technique. This limits open and community-driven multi-disciplinary projects. Now, only two datasets used for training purposes[4,5] and two code realisations for the models[6-8] are publicly available. Second, novel developments in phase processing, e.g. filtering and unwrapping, are reported without code realisation and used datasets. Readers can reproduce the results assuming well-documented theoretical grounds. However, different code implementations may not give the same results. Therefore, reproduction of the results, validation and benchmarks are limited.

Relevance of open data sets for shearography inspection. Most of the reported shearography inspections and all available commercial instruments provide the out-of-plane inspection scheme where the surface gradient (with practical assumptions) equal to the out-of-plane surface strain components dw/dx or dw/dy is analysed. Verification and

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validation of the out-of-plane strain at low levels (up to 1000 microstrain) is challenging in comparison with the reference *in-plane* specimens (e.g. when validated with strain gauges).

Open science practices are well developed in the neighbouring field of digital image correlation (DIC). One of many examples is the data processing challenges[15,16] where researchers worldwide can benchmark their developments without access to the equipment.

In 2000-2010 there were several EU projects, addressing the standardisation of full-field optical measurements, namely Standardisation Project for Optical Techniques of Strain measurement (SPOTS)[17] and Validation of Numerical Engineering Simulations: Standardisation Actions (VANESSA)[18]. The main results related to this study include:

- Reference specimens for in-plane strain characterisation with full-field techniques with non-regularities (openings, holes), asymmetry and complex strain field (small and large local gradients)[19].
- Round robin exercise for optical strain measurement (including ESPI, grating interferometry, photoelasticity and thermoelasticity were benchmarked)[20].

The main practical problem is that the outcomes of these projects, including raw data, are not publicly available anymore.

This paper presents three datasets with shearography inspection data that can be used for benchmarking of shearography phase processing algorithms (filtering, unwrapping, background deformation compensation), ML and other applications.

2. DATASET 1. INSPECTION OF THICK COMPOSITE WITH CONTROLLED SURFACE TEMPERATURE

Inspection of relatively thick structures (e.g. laminates of 50 mm) requires significant heating time (reaching 10 minutes) and power (order of several kW). In such cases, the heating surface may reach high temperatures. To avoid overheating, an approach was developed to gradually decrease the heating power to allow heat to propagate through the thickness of the material while keeping the front surface at a controlled constant value. The inspection results, FEM modelling and analysis were previously reported[21].

The inspection of a 51 mm thick GFRP was done with the out-of-plane shearography configuration, five-step temporal phase shift with the shearing device based on a Michelson interferometer[21]. The experimental results and the guiding FEM estimations are shown in Figure 1 (a), the model overview in Figure 1 (b).

The reported dataset for a thick composite material[1] is presented in Table 1.

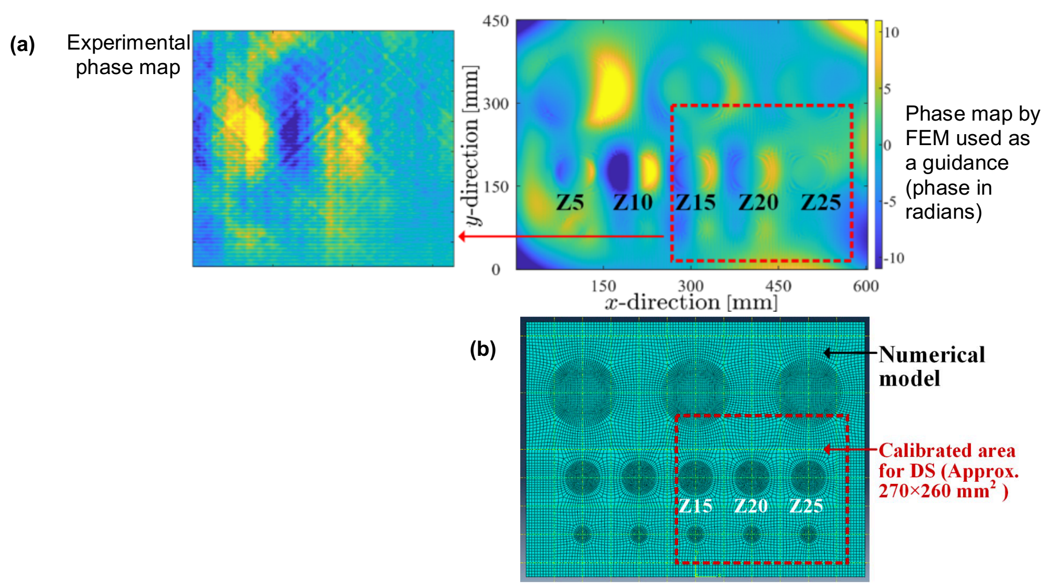


Figure 1. Thick composite inspection. (a) Comparison of the experimental phase map (left) and FEM guidance (right) for 51 mm thick GFRP specimen[21]. Phase in radians. (b) The FEM model of the specimen with mesh.

Table 1. Dataset 1. Inspection of thick composite GFRP with controlled surface temperature heating.

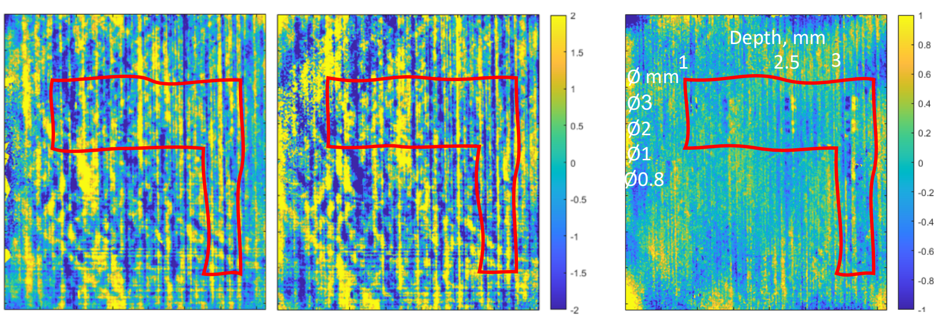
Readme	Text description of the dataset
The raw data	Raw bmp files (2456 × 2058 pixels, 8 bit) with the speckle interferograms (in sets of 5), captured before heating and during the cooling part of the inspection
Code	MATLAB code for reading the raw files, temporal phase shifting, filtering. 2D unwrapping is not included
Pre-processed data	MATLAB *.mat* files with processed phase maps (directly available pre-processed numerical results)
FEM data	FEM results based on analysis in Abaqus[21], exported to MATLAB *.mat* files with the surface displacement (w in [m]), displacement gradients dw/dx or dw/dy in [-] and reproduced phase maps $\varphi_{dw/dx}$ and $\varphi_{dw/dy}$ [in radians] where the calibrated shear distance and the laser wavelength are taken into account.
Results preview	Videos with the variation of the phase induced by the defects over time (experimental and FEM guidance)

3. DATASET 2. INSPECTION OF SUBMILLIMETER DEFECTS IN CFRP

A challenging case of small defect detection is shown in Figure 2 where flat bottom holes with diameters from 0.4 to 3 mm at depths of 1 to 3 mm are present in a composite specimen. The results highlighted in Figure 2 (c) are obtained with the newly developed and reported shearography pair method. At the same time, conventional observations during *heating* and *cooling* parts of the inspection do not reveal the defects due to extensive background fibre-induced noise (Figure 2 (a-b)). The inspection results and analysis were previously reported[22].

The inspection of a 4 mm thick aerospace grade CFRP was done in a similar way as the Dataset 1: using the out-of-plane shearography configuration, four-step temporal phase shift with the shearing device based on a Michelson interferometer[22]. During this inspection, the shearography pair method minimised the observing strain signatures of the material layup and maximised the signal-to-noise ratio[22].

The reported dataset for submillimeter defects in CFRP[2] is presented in Table 2.



(a) Compensated phase map during heating

(b) Compensated phase map during cooling

(c) Compensated phase map with corresponding shearography pair

Figure 2. Inspection of submillimeter defects in CFRP. Comparison of phase maps: (a) only during heating, (b) only during cooling, (c) following the developed and reported approach of the corresponding shearography pair (4 mm CFRP, [0/90] layup, phase in radians).

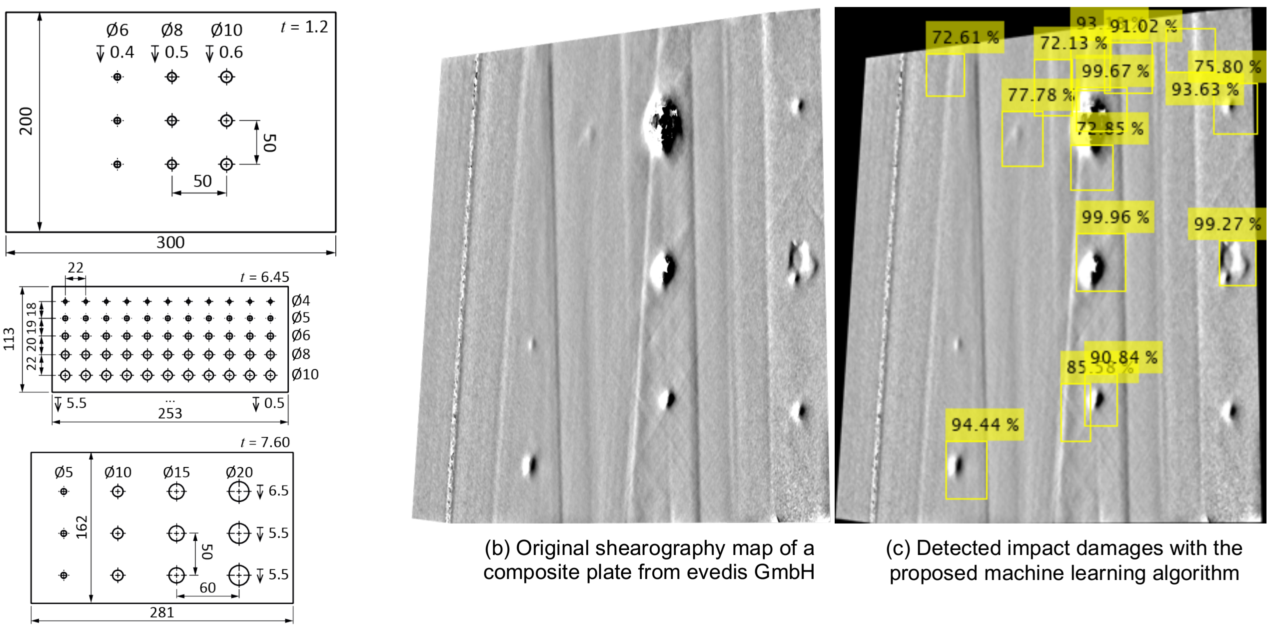
Table 2. Dataset 2. Inspection of submillimeter defects in CFRP.

Readme	Text description of the dataset
The raw data	Raw bmp files (2456 × 2058 pixels, 8 bit) with the speckle interferograms (sets of 4 interferograms), captured before heating, during heating and further in the cooling part of the inspection
Code	MATLAB code for reading the raw files, temporal phase shifting, filtering. 2D unwrapping is not included.
Pre-processed data	MATLAB *.mat* files with processed phase maps (directly available pre-processed numerical results)
Results preview	Videos with the variation of the phase induced by the defects over time

4. DATASET AND TRAINED MODEL 3. AUTOMATED DEFECT DETECTION IN COMPOSITE MATERIALS WITH SHEAROGRAPHY

In 2022, we presented one of the first applications of deep learning to shearography for non-destructive testing of composite materials at the 20th European Conference of Composite Materials in Lausanne[2]. The core of our approach was based on a Faster R-CNN architecture, adapted to detect and localize defects directly from demodulated shearographic phase maps acquired under thermal loading. The model was trained on artificially induced discrete damages such as flat bottom holes in GFRP, CFRP, and sandwich specimens, with ground truth validated by destructive sectioning, and was subsequently evaluated on specimens exhibiting more complex, diffused damage patterns such as impact and dry spots. Recently, its capability to detect impact damage on composite plates was successfully demonstrated in an industrial application by edevis GmbH, Stuttgart, achieving promising accuracy even outside the original training domain (Figure 3).

(a) Illustration of specimens with defects of defined geometry



(b) Original shearography map of a composite plate from evedis GmbH

(c) Detected impact damages with the proposed machine learning algorithm

Figure 3. (a) Specimens used for the dataset generation and (b-c) demonstration of the industrial uptake of the developed ML model.

All shearography map images were manually annotated to mark defect locations and sizes, ensuring high-quality labels for supervised training. To promote transparency and reproducibility, we publicly released the entire dataset on Zenodo[4,6] (Table 3) and the training pipeline, model, and evaluation scripts on GitHub[7].

The dataset was structured using open and human-readable formats such as JSON files to store annotation metadata, including defect positions, bounding boxes, and class labels. This format is particularly well-suited for sharing annotations linked to image data, as it is simple, transparent, and widely supported across programming environments. In addition, JSON can also store measurement parameters and metadata, effectively acting as a lightweight self-contained container.

For larger-scale applications involving high-resolution image stacks, volumetric or multi-modal data, more efficient binary formats such as HDF5 can be used[5]. HDF5 supports complex hierarchical structures, compression, and fast access to large datasets, making it ideal for storing large volumes of measurement data while maintaining a consistent structure. Both formats complement each other well – JSON for lightweight interoperability and HDF5 for scalable scientific storage.

Our results showed that even with a relatively small dataset, a well-designed deep learning model could significantly support the automation of defect detection in shearography. We hope this example encourages broader data and code sharing and interdisciplinary efforts within the shearography and NDT communities.

Table 3. Dataset 3 with the trained ML model for automatic defect detection in composites.

Readme	Two different specimen classes were selected to construct a balanced and diverse dataset: **Specimens with defined artificial defects:** Three CFRP specimens with precisely defined drilling patterns, varying in: dimensions hole layouts and depth, Laminate thicknesses (Figure 3 (a)) **Specimens with undefined and realistic defects:** - Impact damage (4 CFRP specimens), generated using varying impact energies - Dry spots (2 GFRP specimens), induced during manufacturing by adding different amounts of ammonium hydrogen carbonate (NH_4HCO_3) to introduce voids and resin-starved areas. Experiments were conducted using an SE3 shearography system from isi-sys GmbH, equipped with a 5 MPx (2452 × 2052 px) CCD sensor and a 500 mW LED laser array (wavelength $\lambda = 658$ nm). Thermal loading of the specimens was applied using a 1.2 kW halogen radiator, resulting in a measured surface temperature increase of $\Delta T = 2$ K. All specimens were examined under varying shear angles and magnitudes. The shear range extended from 10 to 40 kSt in 5 kSt increments in both horizontal and vertical directions, corresponding to a spatial shear amount between 2.63 mm and 6.98 mm, based on a fixed working distance of 833 mm.
The raw data	The shearographic phase maps are stored as (2452 x 2052) Px^2 12bit mono-chrome uncompressed *.tif files.
Code	The codebase accompanying the ShearDetect dataset is publicly available on GitHub. It is implemented in Python, with a strong emphasis on the use of open-source machine learning libraries, particularly PyTorch, for accelerated model training and inference. GPU acceleration via PyTorch enables efficient training on large datasets and supports integration with modern architectures like Faster R-CNN or custom lightweight backbones. The checkpoint of the model with all pretrained weights can be downloaded from Zenodo[6].

Pre-processed data	The data was manually annotated, and the data was stored in json file. *.json-files contain the following annotations and infos:
	{
	"fileID": "specimenName_imageName",
	"Dataset": "specimenName",
	"image": "imageName",
	"defect": [[x1, y1, x2, y2]], // list of bounding boxes of defects
	"specimen": [[x1, y1, x2, y2]] // list of bounding box of the entire specimen
	}

Results preview	The GitHub repository offers a pre-processing and post-processing modules to display detected defects as bounding box with confidence probability from ML algorithm as depicted ion Figure 3

5. POTENTIAL PUBLIC USE OF DATASETS

All datasets presented here share similarities, e.g. detection of defects in composite materials. The main differences are in the thickness and scale of the defects. The datasets and the trained model also share potential for public use:

Potential public use:

□ Development and benchmarking of new phase filtering approaches and 2D unwrapping algorithms.
□ Developing approaches to isolate, characterise and maximise the defect-induced phase and signal-to-noise ratio:
  ■ The defect-induced phase from the global or background deformation of the specimen due to bending, buckling or rigid body movements during consecutive heating and cooling (e.g. similar to the phase compensation[9]).
  ■ The defect-induced phase from the background fibre-related noise caused by the composite layup and non-uniform distribution of reinforcement fibres.
□ For training, validation and testing for existing and new ML developments.
□ Benchmarking of ML algorithms

Open challenges where the community can contribute:

□ Maximising the defect-induced phase compared to the observing fibre-induced deformation (for details see previous publications[21,22]; equivalent to maximising the signal to noise ratio).
□ Detection of smaller or deeper defects in composite materials.

- ☐ Depth estimation from time-resolved shearography: developing robust methods to extract defect depth information from temporal shearography phase data remains an open problem.
- ☐ Multimodal defect detection: combining complementary modalities – such as thermography and shearography – to improve detection reliability and defect characterisation presents technical and data integration challenges.
- ☐ Standardisation of data annotation and storage for benchmarking: establishing a common, open standard for annotating, storing, and sharing NDT data would greatly enhance reproducibility and interoperability across research groups and applications

6. CONCLUSIONS

This presentation highlights the Open Science issues and proposes three datasets and one trained model with challenging defect detection cases in composite materials, including inspection of thick GFRP material and detection of submillimeter defects in aerospace-grade CFRP. This presentation intends to initiate a discussion in the field that could lead to better practices on data sharing and start the shift towards Open Science principles.

As a further development, a round robin exercise can be executed. The possible options are:

- ☐ Option *Inspection*. The objective is to evaluate the detection sensitivity of shearography for typical defects and damage in composite materials:
  - ■ Specimen: to design a representative specimen or set of specimens to be inspected in various laboratories and companies
  - ■ Excitation: thermal excitation can be proposed as the main one. Other available options can also be benchmarked.
  - ■ Criteria to benchmark: signal-to-noise ratio for reference defects
  - ■ Deliverables: raw interferograms, phase maps, defect mapping, and inspection report.
- ☐ Option *Data*. A reference data set can be generated and shared (also, one of the existing datasets can be used):
  - ■ Data: experimental data set with a FEM modelling prediction of the surface displacement gradients.
  - ■ Criteria to benchmark: signal-to-noise ratio for reference defects, phase difference between the experimental data and FEM guidance.
  - ■ Deliverables: phase maps, defect mapping, comparison experiments with FEM and overall report.
- ☐ Option *Code*. Promote transparency and reproducibility in defect detection algorithms through the publication and benchmarking of open-source code.
  - ■ Content**:** publish reference code for preprocessing, model training, and evaluation (e.g., CNNs, U-Nets, or even Recurrent Convolutional Networks for time-resolved interpretation of measurements) on platforms like GitHub.
  - ■ Benchmarking**:** assess accuracy (IoU, mAP), inference time, and generalization across datasets.
  - ■ Deliverables**:** GitHub repository with training scripts, pretrained models, example data, and documentation.
  - ■ Goal**:** foster community contributions and establish a common baseline for ML-driven NDT.

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REFERENCES

[1] Tao, N., Anisimov, A. G. and Groves, R. M., "Dataset on shearography data for deep defect detection and characterization in thick GFRP laminates," Dataset, 2022, https://data.4tu.nl/datasets/647b474a-cc3c-4b14-b5fa-f9823a8a581b, https://doi.org/10.4121/21674780

[2] Düreth, C., Hornig, A., Koch, I., Maik, G., 2022. Application of Machine Learning Methods on the Defect Detection in Shearographic Images, in: Proceedings of the 20th European Conference on Composite Materials - Composites Meet Sustainability. Presented at the 20th European Conference on Composite Materials - Composites Meet Sustainability, EPFL Lausanne, Composite Construction Laboratory, Laussane, Switzerland. https://doi.org/10.5075/EPFL-298799_978-2-9701614-0-0

[3] Tao, N., Groves, R. M. and Anisimov, A. G., “Dataset on research data underlying the publication: Shearography pair method for reliable non-destructive inspection of millimeter and submillimeter defects in fiber-reinforced composites,” Dataset, 2025, https://data.4tu.nl/datasets/1037b955-c7b9-42a0-953d-2598783661f6, https://doi.org/10.4121/1037b955-c7b9-42a0-953d-2598783661f6
[4] Düreth, C. (2022). ShearDetect - Dataset (1.1) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.6463119
[5] Düreth, C. (2025). Torch3Dseg - Dataset [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15511228
[6] Düreth, C. (2022). ShearDetect - pretrained model (Versie 1). Zenodo. https://doi.org/10.5281/zenodo.6504390
[7] Düreth, C., “ShearDetect: shearography defect detection code,” GitHub repository (2025); https://github.com/ILKGit/ShearDetect.git
[8] Wang, Y., Zheng, Z., Liu, X., Yan, P., Li, J. and Zhu, Z., "Phase Fringe Suppression of Background Deformation for Nondestructive Testing Based on Shearography," in IEEE Transactions on Instrumentation and Measurement, vol. 74, pp. 1-7, 2025, Art no. 6001707, https://doi.org/10.1109/TIM.2025.3541693
[9] Liu, X., “Shearography background fringe suppression code,” GitHub repository (2025); https://github.com/xwl217217/shearography-background-fringe-suppression
[10] Li, W., Wang, D. and Wu, S., “Simulation dataset preparation and hybrid training for deep learning in defect detection using digital shearography,” Appl. Sci. 12(14), 6931 (2022); https://doi.org/10.3390/app12146931
[11] Saleh, N. A., Al-Areqi, F., Konyar, M. Z., Kaplan, K., Öngir, S. and Ertunç, H. M., “Bubble defect detection for tire shearography images with transfer learning based deep CNN models,” Eng. Res. Express 6(4), 045423 (2024); https://doi.org/10.1088/2631-8695/ad915b
[12] Wu, R., Wei, H., Lu, C. and Liu, Y., “Automatic and accurate determination of defect size in shearography using U-Net deep learning network,” J. Nondestruct. Eval. 44(1), 12 (2025); https://doi.org/10.1007/s10921-024-01149-7
[13] Ye, Y., Zhang, T., Liu, X., Wang, X., Su, Z., Ding, L. and Zhang, D., “Recognition of small defects in shearography based on improved YOLO network,” Opt. Laser Technol. 184, 112524 (2025); https://doi.org/10.1016/j.optlastec.2024.112524
[14] Li, G., Hu, Y., Wang, H., Hao, Q. and Zhang, Y., “Shearography-based near-surface defect detection in composite materials: a spatiotemporal object detection neural network trained only with simulated data,” Nanomaterials 15(7), 523 (2025); https://doi.org/10.3390/nano15070523
[15] Reu, P. L., Toussaint, E., Jones, E., Bruck, H. A., Iadicola, M., Balcaen, R., Turner, D. Z., Siebert, T., Lava, P. and Simonsen, M. D. I. C., “DIC challenge: developing images and guidelines for evaluating accuracy and resolution of 2D analyses,” Exp. Mech. 58, 1067–1099 (2018); https://doi.org/10.1007/s11340-018-0352-7
[16] Reu, P. L., Blaysat, B., Andò, E., Bhattacharya, K., Couture, C., Couty, V., Deb, D., Fayad, S. S., Iadicola, M. A., Jaminion, S. and Klein, M., “DIC challenge 2.0: developing images and guidelines for evaluating accuracy and resolution of 2D analyses: focus on the metrological efficiency indicator,” Exp. Mech. 62(4), 639–654 (2022); https://doi.org/10.1007/s11340-022-00822-x
[17] Burguete, R. and Patterson, E., "SPOTS project and development of a standard and reference material." EPJ Web of Conferences 6, 46001 (2010). https://doi.org/10.1051/epjconf/20100646001
[18] European Commission, “Reporting for project: Validation of Numerical Engineering Simulations: Standardisation Actions VANESSA,” CORDIS EU Research Results (Final Report, 2014) https://cordis.europa.eu/project/id/319116/reporting
[19] Patterson, E. A., Hack, E., Brailly, P., Burguete, R. L., Saleem, Q., Siebert, T., Tomlinson, R. A. and Whelan, M. P., "Calibration and evaluation of optical systems for full-field strain measurement," Opt. Lasers Eng. 45(5), 550–564 (2007). https://doi.org/10.1016/j.optlaseng.2006.08.012
[20] Mendels, D. A., Hack, E., Siegmann, P., Patterson, E. A., Salbut, L., Kujawińska, M., Schubach, H. R., “Round robin exercise for optical strain measurement,” in Proc. 12th Int. Conf. Exptl. Mech., Advances in Experimental Mechanics, C. Pappalettere, ed., McGraw-Hill, Milano, pp. 695–696 (2004).
[21] Tao, N., Anisimov, A. G. and Groves, R. M., “Towards safe shearography inspection of thick composites with controlled surface temperature heating,” NDT&E Int. 139, 102907 (2023); https://doi.org/10.1016/j.ndteint.2023.102907
[22] Tao, N., Groves, R. M., and Anisimov, A. G. "Shearography pair method for reliable non-destructive inspection of millimeter and submillimeter defects in fiber-reinforced composites". Measurement, 117980. (2025), https://doi.org/10.1016/j.measurement.2025.117980