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Review Article

Advanced spatio-temporal filtering techniques for photogrammetric image sequence analysis in civil engineering material testing

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ABSTRACT

The paper shows advanced spatial, temporal and spatio-temporal filtering techniques which may be used to reduce noise effects in photogrammetric image sequence analysis tasks and tools. As a practical example, the techniques are validated in a photogrammetric spatio-temporal crack detection and analysis tool applied in load tests in civil engineering material testing. The load test technique is based on monocular image sequences of a test object under varying load conditions. The first image of a sequence is defined as a reference image under zero load, wherein interest points are determined and connected in a triangular irregular network structure. For each epoch, these triangles are compared to the reference image triangles to search for deformations. The result of the feature point tracking and triangle comparison process is a spatio-temporally resolved strain value field, wherein cracks can be detected, located and measured via local discrepancies. The strains can be visualized as a color-coded map. In order to improve the measuring system and to reduce noise, the strain values of each triangle must be treated in a filtering process. The paper shows the results of various filter techniques in the spatial and in the temporal domain as well as spatio-temporal filtering techniques applied to these data. The best results were obtained by a bilateral filter in the spatial domain and by a spatio-temporal EOF (empirical orthogonal function) filtering technique.

1. Introduction

Civil engineering material testing has become an interesting application field for photogrammetric measurement techniques, both in laboratory environments as well as on real objects. A typical task is crack measurement, aiming at the time-resolved detection, localization and measurement of cracks. Herein, image-based techniques have the essential advantage of offering both: spatial and temporal resolution, providing a basis for the qualitative and quantitative analysis of complex crack patterns over time. Using sub-pixel accuracy image analysis techniques, cracks with a width much smaller than a pixel can be detected, and their width can be determined with subpixel accuracy. Several papers about digital photogrammetry in civil engineering material testing have been published in recent years. Whiteman et al. (2002) used stereo image sequences to analyze vertical deflections of sparse photogrammetric targets on a concrete beam during load tests. They achieved a standard deviation of 0.25 mm related to beams with a length of 6.4 m. Fraser and Riedel (2000) conducted a deformation monitoring of hot steel beams. Photogrammetric targets were observed with a trinocular camera system over 2 h. Hampel and Maas (2003) and Benning et al. (2004) presented multi-ocular photogrammetry systems for civil engineering material testing. The test bodies were prepared with a grid of targets that were tracked in an image sequence using image correlation techniques. Cracks could be located by an analysis of displacement fields of the targets, obtaining the crack width from the local target displacement itself. Measuring discrete targets offers the advantage of a high precision but the crack location resolution is small if the location of cracks in a probe is to be derived from variations in the distances between targets over an image sequence. Hampel and Maas (2009) presented a stereo image sequence based technique, which uses a cascaded image analysis approach: In the first step, least squares matching (LSM) is used to determine dense image point shift vector fields. In the second step, these vector fields are analyzed for local discrepancies, yielding the position and width of cracks. If, for instance, displacement vectors are determined for 11 × 11 pixel patches in image sequences of 4000 × 3000 px cameras, more than

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100,000 displacement vectors can be determined. This dense displacement vector field can again be considered as an image, allowing for image analysis techniques to be applied to detect local discrepancies caused by the development of cracks. Using subpixel accuracy image measurement techniques, cracks with a width of 5 μm can be detected in a $20 \times 20\,\text{cm}^2$ probe (Maas, 2012), and their width can be determined at a precision of about 1 μm. Koschitzki et al. (2011) presented a simplified technique, allowing for the quantitative analysis of crack pattern development from monocular image sequences. Barazzetti and Scaioni (2010) also conducted load tests with concrete beams and recorded image sequences with a stereo camera system. In addition to a grid of markers, a target-less method is described based on the Wallis filter for contrast improvement of the natural texture and the FAST interest operator. Correspondences were found with descriptor matching methods (SIFT and SURF). For tracking the features, cross-correlation and least squares matching is used. In Detchev et al. (2013), a target-less multi-camera and projector system is presented for deflection measurements. Qi et al. (2014) conducted experiments with range cameras for periodic surface movements, achieving half-millimeter accuracy. There are also approaches using digital image correlation techniques applied on image sequences to obtain two-dimensional dense displacement and strain fields (Guerrero et al., 2014; Fedele et al., 2014). Ghorbani et al. (2014) generated crack maps performing three-dimensional digital image correlation with a stereo system. Fedele et al. (2013) presented an approach also based on a Galerkin, finite element formulation for digital image correlation to compute displacement fields. In this context, hierarchical image pyramid techniques were applied to make it robust.

A general issue in the analysis of these spatio-temporal crack pattern development processes is noise in the measurement process, either caused by shortcomings of the image analysis procedures or by the imaging system or other external effects. The existence of noise will usually require filtering techniques to be applied in the data processing chain. Although, the method of Fedele et al. (2013) attenuates noise, we used another alternative approach to filter out noise. In the following, we will describe filtering techniques, which have been designed specifically for the requirements of the task described above. As the techniques are applied to a monocular image sequence analysis scheme as described in Koschitzki et al. (2011), their method will briefly be described in Section 2. In Section 3, we address both filters acting in the spatial domain as well as filtering acting in the temporal domain. Combining both, a spatio-temporal filtering procedure will also be presented. Finally, Section 4 will show and discuss practical results obtained by the different filtering techniques.

2. Image sequence analysis for crack patterns determinations

Fig. 1 shows an iconic image of the measurement process: A concrete beam is subject to a force F, which is increased continuously or in discrete load steps. With increasing load, the probe will deform and show cracks, which are to be detected and analyzed. When measuring a real world object rather than testing a probe in a lab, an early detection of local stress may be crucial as it can be used as an indicator for a non-destructive timely termination of a load experiment.

During an experiment, an image sequence of a concrete beam is recorded at a suitable temporal resolution. Depending on the dynamics of the load process (and the quality of the probe), the required temporal resolution may be in the order of minutes, seconds or even milliseconds. At moderate temporal resolution, the process can be observed in real-time, while high-speed camera image sequences will usually require image sequence storage and offline processing. The monocular approach requires a planar surface on the test object, with the viewing direction approximately perpendicular to the surface. This requirement will usually not pose a severe restriction. Due to the lack of sufficient surface texture of the concrete beam, a fix artificial spray texture was applied. The first image of a sequence is defined as a reference image. Therein, points with high contrast are determined, using an interest operator, such as the Harris operator (Harris and Stephens, 1988). These interest points are triangulated into a mesh using Delaunay triangulation (TIN, triangulated irregular network). In the subsequent images, the interest points are tracked with subpixel precision using LSM (Förstner, 1984; Grün, 1985). In the case of cracks in the probe, the TIN meshes containing the cracks will change in area and shape. To analyze the differences of the triangles between the epochs a strain tensor is computed for each triangle. To achieve this, the parameters of an affine transform are computed between the coordinates of the triangle points in the different epochs.

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} a_{11} + a_{12} \cdot x + a_{13} \cdot y \\ a_{21} + a_{22} \cdot x + a_{23} \cdot y \end{pmatrix} \tag{1}$$

where u, v = coordinates of a later epoch
x, y = coordinates of the reference epoch
a_{ij} = affine parameters

The parameters of the affine transform contain translation, rotation and deformation. Translation and rotation are discarded because only deformation (strain) is relevant. At first, translation can be excluded (a_{11} and a_{21} are computed but ignored in the following). The strain tensor **V** can be extracted by decomposition of the deformation matrix **F** in a symmetric and an orthogonal matrix (see Eq. (2)).

$$\mathbf{F} = \begin{pmatrix} a_{12} & a_{13} \\ a_{22} & a_{23} \end{pmatrix} = \mathbf{V} \cdot \mathbf{R} \tag{2}$$

where **F** = deformation tensor
R = rotation matrix (orthogonal)
V = left strain tensor (symmetric)

The decomposition can be obtained by the following steps: First, the left Cauchy–Green deformation tensor $\mathbf{V}^2$ is computed by multiplying **F** with its transposed.

$$\mathbf{V}^2 = \mathbf{V} \cdot \mathbf{V} = \mathbf{V} \cdot \mathbf{V}^T = \mathbf{F} \cdot \mathbf{F}^T \tag{3}$$

In a 2nd step, the eigenvalue decomposition of $\mathbf{V}^2$ is performed.

$$\mathbf{V}^2 = \mathbf{C} \cdot \mathbf{\Lambda} \cdot \mathbf{C}^T \tag{4}$$

where **C** = eigenvector matrix (orthogonal matrix)
Λ = eigenvalue matrix (diagonal matrix)

Finally, **V** can be computed by manipulating the matrix **Λ** containing the eigenvalues of $\mathbf{V}^2$ and multiplying the matrices as follows:

$$\begin{aligned} \mathbf{V} &= \mathbf{C} \cdot \mathbf{\Lambda}^{0.5} \cdot \mathbf{C}^T \\ \mathbf{R} &= \mathbf{V}^{-1} \cdot \mathbf{F} = \mathbf{C} \cdot \mathbf{\Lambda}^{-0.5} \cdot \mathbf{C}^T \cdot \mathbf{F} \end{aligned} \tag{5}$$