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1 Shape Measurement Using a New Multi-Step Stereo-DIC
2 Algorithm That Preserves Sharp Edges

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5 Michel Devy

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7 Abstract Digital Image Correlation is widely used for shape, motion and deforma-
8 tion measurements. Basically, the main steps of 3D-DIC for shape measurement
9 applications are: off-line camera calibration, image matching and triangulation.
10 The matching of each pixel of an image to a pixel in another image uses a so-
11 called subset (correlation window). Subset size selection is a tricky issue and is
12 a trade-off between a good spatial resolution, achieved with small subsets that
13 preserve image details, and a low displacement uncertainty achieved with large
14 subsets that can smooth image details.

15 In this paper, we present a new multi-step DIC algorithm specially designed
16 for measuring the 3D shape of objects with sharp edges. With this new algorithm

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17 an accurate 3D reconstruction of the whole object, including sharp edges that are
 18 preserved, can be achieved.

19 Keywords Shape Measurement · Stereovision · Digital Image Correlation (DIC) ·
 20 Edge Preservation · Accurate 3D reconstruction.

21 1 Introduction

22 The problem of improving the accuracy of the 3D reconstruction of a complex
 23 object is addressed by using a DIC-based shape measurement technique. The DIC
 24 technique requires choosing a correlation criterion, the size of the correlation win-
 25 dow (also called subset) and the window transformation model (subset shape func-
 26 tion). The choice of the subset size is a tricky issue [1–4] and is a trade-off between
 27 a good spatial resolution, achieved with small subsets that preserve image details,
 28 and a low displacement uncertainty achieved with large subsets that can smooth
 29 image details (see figure 1 and table 1).

subset size	displacement uncertainty	shape details
small	high	preserved
large	low	smoothed

Table 1 Trade-off between displacement uncertainty and shape details preservation

30 In order to increase the accuracy of the shape reconstruction, several authors
 31 have proposed to use a multi-view stereo method that exploits a large number of
 32 images [5–8] and that allows using a small subset size.

33 In this paper, we address the problem of providing an accurate 3D reconstruc-
 34 tion of an object by using the classical two-views 3D-DIC technique.

35 In the classical DIC-based matching technique, discontinuities (e.g. cracks
 36 in 2D-DIC-based displacement/strain measurements, sharp edges in stereo-DIC-
 37 based shape measurements) are difficult to handle and several authors have pro-
 38 posed new DIC formulations specially designed for DIC matching in presence of

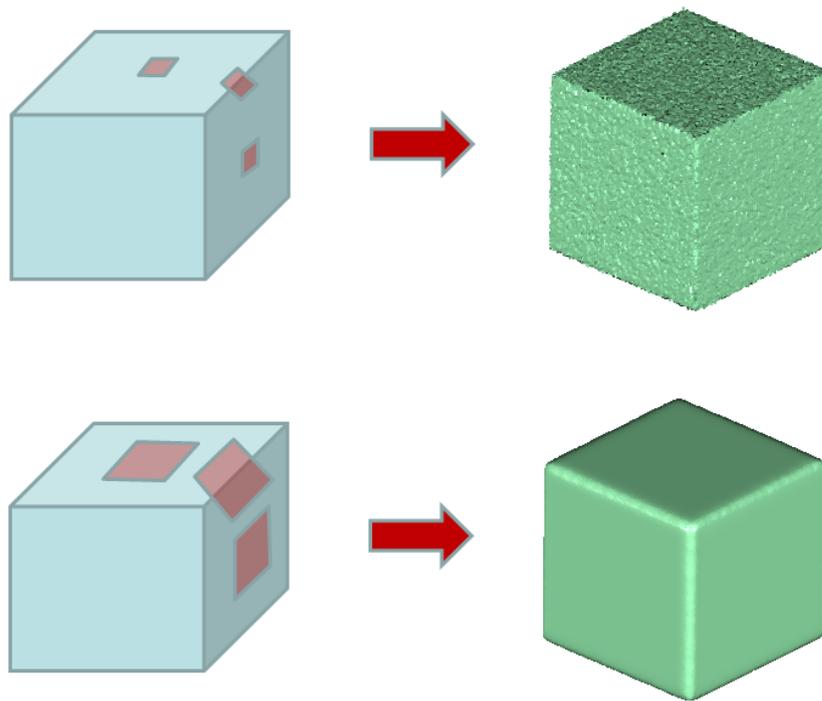


Fig. 1 3D reconstruction using a small subset (top) and 3D reconstruction using a large subset (bottom)

39 discontinuities [9–12]. Most of these works deal with 2D discontinuities and there
40 is no work to the authors knowledge that deals with discontinuities for 3D-DIC.

41 The extraction of edges can be performed after the 3D shape measurement,
42 using a 3D mesh like in [13]. An analysis of the 3D mesh allows a fine extraction
43 of the surface discontinuities, then of the edges. In our method, sharp edges are
44 obtained using DIC and are extracted directly from the 3D points cloud generated
45 by the stereo-DIC-based method, without building a 3D mesh.

46 We propose a new DIC method, based on a new correlation criterion and a
47 new window transformation model, specially designed to preserve the sharp edges
48 that can be present on many machined objects.

49 2 Overview

50 The presented method is an extension to the standard stereo-vision 3D recon-
51 struction. It aims to refine the reconstruction accuracy for points near sharp
52 edges. These points are generally badly estimated due to an over-smoothing effect.
53 Standard stereo-vision uses the approximation that the observed surface is locally
54 continuous and almost planar. This assumption becomes false near sharp edges
55 causing a false estimation of the surface. Due to the planar approximation, stan-
56 dard stereo-vision tends to measure edges as curves. To achieve the sharp edges
57 preservation, our proposed method performs an iterative refinement of the areas
58 where the planar approximation fails. It starts from an initial 3D reconstruction
59 of an object.

60 The initial 3D reconstruction is obtained using a standard stereo-vision method
61 and is briefly presented in section 4. It provides a 3D point cloud representation of
62 the surface, and equally computes normals and confidence values of the measured
63 points.

64 From this initial reconstruction, our edge-optimized method refines iteratively
65 the position of the edges. Our algorithm is composed of three steps.

66 Firstly, it detects regions with high curvature. These regions are considered candi-
67 dates to the edge refinement. This allows us to reduce the number of points which
68 need to be processed. It is presented in section 5.

69 Secondly, the algorithm computes a first estimate of the possible location of the
70 edges for each area (section 6).

71 Finally, every considered point is estimated using our new "bi-plane" model. This
72 model is based on the two planes which compose an edge, and is refined minimizing
73 a correlation criterion. It is presented in section 7.

74 The proposed strategy to improve the accuracy near sharp edges is itself based
75 on a two-planes assumption, i.e. the neighborhood of every point on the object
76 surface can be approximated by two planes. In some situations (chamfers perceived
77 from a far viewpoint), this assumption can be violated. An additional step is

78 necessary to validate the results. The residual error from the standard stereo-vision
 79 method and the residual error from our new edge-optimized method are compared.
 80 The reconstruction which provides lower error is chosen. This ensures that high
 81 curvature areas not representing actual sharp edges would not be "sharpened" by
 82 error.

83 3 Problem formulation and notation

84 We consider a stereo-vision system with two digital cameras rigidly attached. We
 85 associate to each camera an euclidean coordinate frame. Respectively \mathcal{C}_0 and \mathcal{C}_1
 86 for the principal camera and the secondary one: 3D points are reconstructed in
 87 the reference frame of the principal camera. Every camera is calibrated using the
 88 method from [14], modified to allow automatic initialization; the rigid transfor-
 89 mation between the reference frames of the two cameras is also estimated using
 90 the standard stereo calibration toolbox. Images are considered distortion free –
 91 i.e. the images are provided by a perfect distortion free system or the images have
 92 been corrected from their distortion using the calibration parameters. Moreover,
 93 images and transformations are considered in the epipolarly rectified space. This
 94 transformation between the cameras is noted $[\mathbf{I}_{3 \times 3} | \mathbf{t}_{\mathcal{C}_1 \mathcal{C}_0}] \in SE(3)$, where $\mathbf{I}_{3 \times 3}$ is a
 95 3×3 identity matrix and $\mathbf{t}_{\mathcal{C}_1 \mathcal{C}_0}$ is the translation between the origins of the camera
 96 frames, with only the baseline along the X axis.

97 The stereo-imaging process can then be represented using a linear model re-
 98 lating a 3D point in the world (reference) coordinate frame $\mathbf{m}_{\mathcal{W}} = (X, Y, Z, 1)^T$
 99 to two image points $\mathbf{m}_{\mathcal{I}_0} = (sx_0, sy, s)^T$ and $\mathbf{m}_{\mathcal{I}_1} = (sx_1, sy, s)^T$ the projections of
 100 $\mathbf{m}_{\mathcal{W}}$ in, respectively, the image coordinate frames \mathcal{I}_0 , related to the camera \mathcal{C}_0 , and
 101 \mathcal{I}_1 , related to the camera \mathcal{C}_1 . Due to the epipolar rectification, images of the same
 102 3D points lie on the same image line and have then the same y coordinate [15].

The imaging process can be formulated as follow.

$$\mathbf{m}_{\mathcal{I}_0} = \mathbf{K}_0 [\mathbf{R}_{\mathcal{C}_0\mathcal{W}} | \mathbf{t}_{\mathcal{C}_0\mathcal{W}}] \mathbf{m}_{\mathcal{W}} \quad (1)$$

$$\mathbf{m}_{\mathcal{I}_1} = \mathbf{K}_1 [\mathbf{I}_{3 \times 3} | \mathbf{t}_{\mathcal{C}_1\mathcal{C}_0}] [\mathbf{R}_{\mathcal{C}_0\mathcal{W}} | \mathbf{t}_{\mathcal{C}_0\mathcal{W}}] \mathbf{m}_{\mathcal{W}} \quad (2)$$

103 where \mathbf{K}_0 and \mathbf{K}_1 are the calibration matrices of, respectively, cameras \mathcal{C}_0 and
 104 \mathcal{C}_1 , formed from the cameras independent intrinsic parameters, and $[\mathbf{R}_{\mathcal{C}_0\mathcal{W}} | \mathbf{t}_{\mathcal{C}_0\mathcal{W}}] \in$
 105 $SE(3)$ is the transformation between the world frame \mathcal{W} and the principal camera
 106 frame \mathcal{C}_0 . This transformation is called the pose of the system.

107 4 Initial reconstruction

108 Standard stereo-vision reconstruction is the process of finding the 3D point coor-
 109 dinates $\mathbf{m}_{\mathcal{W}}$ from its image points $\mathbf{m}_{\mathcal{I}_0}$ and $\mathbf{m}_{\mathcal{I}_1}$.

110 A common stereo-reconstruction approach is to try to match pixels in the
 111 pair of images using the luminance information of the images. This is achieved by
 112 determining the point $\mathbf{m}_{\mathcal{I}_1}$ matching the point $\mathbf{m}_{\mathcal{I}_0}$. This is done by observing and
 113 matching luminance information in both images, \mathcal{I}_0 and \mathcal{I}_1 . Luminance functions
 114 are noted $\mathbf{I}_0(\mathbf{p})$ and $\mathbf{I}_1(\mathbf{p})$, respectively for images \mathcal{I}_0 and \mathcal{I}_1 . To avoid ambiguities,
 115 the matching point is found by comparing local appearance around the pixel $\mathbf{m}_{\mathcal{I}_0}$.
 116 Surface can be approximated locally by tangent planes to observed points. The
 117 matching process is the similarity measurement of the projections of an area of this
 118 approximated plane in the images. The transformation relating the projections in
 119 each image is an homography (figure 2).

120 From [8] we have the following homography formulation:

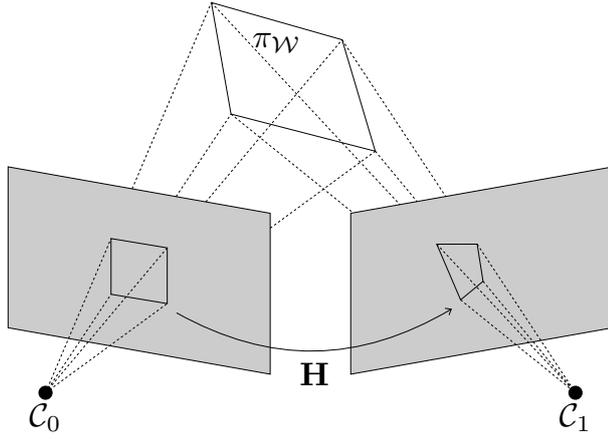


Fig. 2 An homography is a projective transformation relating the projections of a plane in two images

$$\mathbf{H} = \mathbf{K}_1 [\mathbf{I}_{3 \times 3} | \mathbf{t}_{C_1 C_0}] \mathbf{S} \mathbf{K}_0^{-1} \quad (3)$$

$$\mathbf{S} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \\ n_x & n_y & n_z \end{bmatrix} \quad (4)$$

121 where $(n_x, n_y, n_z)^T$ is the normal of the tangent plane to the surface at \mathbf{m}_W .

122 The structure of the scene, from two images acquired at the same time, is
 123 obtained by minimizing dissimilarities between the luminance function $\mathbf{I}_0(\mathbf{p})$ in
 124 the region W of image \mathcal{I}_0 and the luminance function $\mathbf{I}_1(\mathbf{p})$ in the transformed
 125 region $\mathbf{H}(W)$ of image \mathcal{I}_1 . If we note $\mathbf{x} = (n_x, n_y, n_z)$, we try to find

$$\underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i \in W} \left(\mathbf{I}_0 \left[\mathbf{p}_{\mathcal{I}_0}^i \right] - \mathbf{I}_1 \left[\mathbf{H}_i \left(\mathbf{p}_{\mathcal{I}_0}^i, \mathbf{x} \right) \right] \right)^2 \quad (5)$$

126 Equation (5) introduces the minimization criterion used to find, for a given
 127 point m_{I_0} , the matched point m_{I_1} , using only the parameters of the tangent plane

128 defined by the correlation of two pixel regions in two stereo images. This problem
129 can be solved using standard non-linear least-squares methods.

130 This approach is valid and has proved to work well on nearly planar surfaces.
131 The assumption that the observed region W is a plane tangent to surface at \mathbf{m}_W
132 introduces an approximation resulting in a surface smoothing (figure 3).

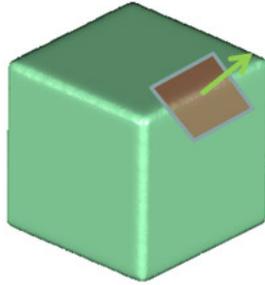


Fig. 3 The plane model does not fit the surface along the edges

133 The reconstruction process on very non-planar surfaces is a trade-off between
134 accuracy and stability by tuning the size of the region W .

135 Particularly, when the region W contains sharp edges, the tangent plane-
136 induced homography is not a valid model. It tends to reduce the discontinuity
137 of the surface. Our method proposes to correct the result of the process we have
138 described by detecting sharp edges in the model and re-correlating the erroneous
139 points using a "bi-plane" model.

140 5 Edge detection

141 The aim of our proposed method is to refine the initial reconstruction we have
142 presented to allow reconstruction of sharp edges. Only the points near sharp edges

143 have to be refined. To avoid processing unnecessary points, we add an edge detec-
 144 tion step.

145 Since the method we have described tends to smooth discontinuities due to the
 146 approximation of the local surface, edges are reconstructed as short arc curves.
 147 For each 3D point \mathbf{p}_0 , with its normal \mathbf{n}_0 , let us consider the neighborhood W
 148 consisting of nearest points $\mathbf{p}_i \in W$ around \mathbf{p}_0 . Each point \mathbf{p}_i is associated with
 149 its normal \mathbf{n}_i . We compute the mean normal $\bar{\mathbf{n}}$, the mean μ and the standard
 150 deviation σ of the dot products to this mean normal in W .

$$\bar{\mathbf{n}} = \frac{1}{\|\sum_{i \in W(\mathbf{p}_0)} \mathbf{n}_i\|} \sum_{i \in W(\mathbf{p}_0)} \mathbf{n}_i \quad (6)$$

$$\mu = \frac{1}{\text{card}(W(\mathbf{p}_0))} \bar{\mathbf{n}} \cdot \sum_{i \in W(\mathbf{p}_0)} \mathbf{n}_i \quad (7)$$

$$\sigma = \sqrt{\frac{1}{\text{card}(W(\mathbf{p}_0))} \sum_{i \in W(\mathbf{p}_0)} (\bar{\mathbf{n}} \cdot \mathbf{n}_i - \mu)^2} \quad (8)$$

151 Points on short arc curves are identified from high deviation regions to ensure
 152 that we select regions with high curvature. The standard deviation σ of the dot
 153 products represents the variability of the normal distribution in W and is then
 154 used as the deviation measurement.

155 The detection process consists in thresholding the standard deviation σ . The
 156 criterion is used to build a selection function $\Pi(\mathbf{p})$.

$$\Pi(\mathbf{p}_0) = \begin{cases} 1 & \text{if } \sigma(\mathbf{p}_0) > \alpha \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

157 where α is the threshold, allowing to be more or less selective on the edge
 158 detection. A higher threshold will reject more points, increasing the probability of
 159 non-detection. A lower threshold will result in a less selective behavior, increasing
 160 the probability to select non-edges points.

161 The edge selection process allows us to save time by processing less non-edge
162 points. The results of our method is not likely to improve points that do not lie
163 on edges. We discuss in section 7.2 this matter and how we deal with wrongly
164 selected points.

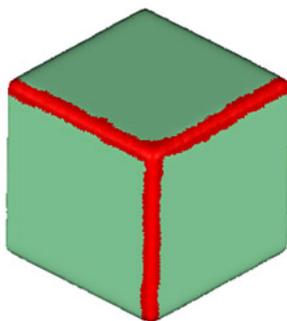


Fig. 4 Selection (red) of the edges of the cube

165 6 Initial edge estimation

166 An initial estimate of the edge model is computed for each selected point, and this
167 estimate is refined later (as described in section 7). The edge model consists of two
168 mean normals each of which describes one face of the edge. In order to compute
169 these two normals, we consider a region around the edge and then we classify
170 the points and their normal in two groups using a modified k-means clustering
171 algorithm. In section 5 the standard deviation σ of the dot products to the mean
172 normal was computed for each point. This value is introduced in the clustering
173 process, in order to filter points with a large σ . A plane is then fitted to each
174 cluster of points. The result provides the two mean normals.

175 7 Edge preservation

176 7.1 Edge matching

177 In order to refine points along edges, we introduce a new surface model. This
 178 model is represented by two planes which intersect as a 3D line \mathcal{L} (figure 5).

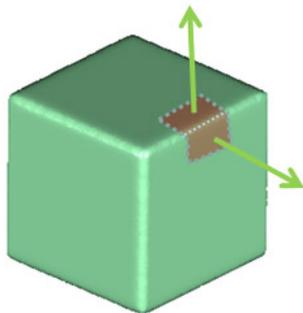


Fig. 5 The "bi-plane" model is represented by two planes defined by their normals (green)

179 The intersection can be expressed as Plücker axial coordinates:

$$\mathcal{L} = [\mathbf{L}_{23} : \mathbf{L}_{31} : \mathbf{L}_{12} : \mathbf{L}_{01} : \mathbf{L}_{02} : \mathbf{L}_{03}] \quad (10)$$

180 with \mathbf{L} the Plücker matrix.

181 Given two planes $\pi_0 = (\mathbf{n}_0, 1)^T$ and $\pi_1 = (\mathbf{n}_1, 1)^T$, with \mathbf{n}_0 and \mathbf{n}_1 the normals
 182 of the planes, Plücker axial coordinates of their intersection are defined as:

$$\mathcal{L} = [\mathbf{n}_1 - \mathbf{n}_0 : \mathbf{n}_0 \times \mathbf{n}_1]^T \quad (11)$$

183 where \times is the cross product.

184 The projection of a 3D line \mathcal{L} on a 2D line l in \mathcal{C}_i coordinate frame is written:

$$l_{c_i} = f(\mathcal{L}, \mathbf{K}_i [\mathbf{R}_{c_i \mathcal{W}} | \mathbf{t}_{c_i \mathcal{W}}]) \quad (12)$$

185 Using this projection, we can apply an homography. Its parameters will change
 186 depending on which side of the line the image points are. If we note $\mathbf{x} = (\mathbf{n}_0^T, \mathbf{n}_1^T)^T$,
 187 the new cost function becomes:

$$\underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i \in \mathcal{W}} \phi \Delta(i, \mathbf{n}_0) + (1 - \phi) \Delta(i, \mathbf{n}_1) \quad (13)$$

188 with

$$\phi = \begin{cases} 0 & \text{if } l_{c_0} \cdot x < 0 \\ 1 & \text{otherwise} \end{cases} \quad (14)$$

$$\Delta(i, \mathbf{n}) = \left(\mathbf{I}_0 [\mathbf{p}_{\mathcal{I}_0}^i] - \mathbf{I}_1 [\mathbf{H}_i (\mathbf{p}_{\mathcal{I}_0}^i, \mathbf{n})] \right)^2 \quad (15)$$

189 This new "bi-plane" model allows the shape of the edge to be accurately refined
 190 as seen in Figure 6.

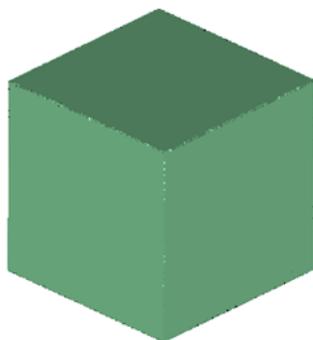


Fig. 6 3D reconstruction of the cube using the edge-optimized method (to be compared with figure 1)

191 7.2 Edge consistency

192 The proposed edge model produces good results along sharp edges made of two
193 faces. However, problems may occur when the edge model is used on surfaces with
194 chamfers, spikes, small radii edges of fillets.

195 Both chamfers and spikes are composed of more than two planes. Small radii
196 are not a surface discontinuity. In any case, our edge model cannot fit the surface
197 perfectly. In the case of important noise on the surface, the algorithm may be
198 biased and result in incorrect bi-plane fitting.

199 To prevent our method to include sharp edges in the model where they must
200 not be or to accept inconsistent results we have added a verification step.

201 In order to discard wrong results produced by the edge optimization, we com-
202 pare results obtained by the standard criterion to results obtained by the edge
203 optimization and choose the best one. This works as both methods minimize a
204 sum of squared differences on pixel intensity.

205 In addition we can set a threshold on the angle between the two-plane fitted by
206 our algorithm to reject flat angles, that are mostly inconsistencies due to surface
207 noise.

208 8 Results and discussion

209 The results presented in this section have been processed from images of a home-
210 made stereo-vision system. It is composed of two 1024×768 CCD cameras with
211 8 mm lenses and a pattern projector. The stereoscopic baseline is 140 mm long
212 and the cameras are oriented with a 15° angle. The working distance is about
213 400 mm and the pixel size is about 0.23 mm . During the image correlation process,
214 11×11 pixel correlation windows are used, leading to a spatial resolution of about
215 $2.5 \times 2.5\text{ mm}^2$. The whole setup has been described and evaluated by Coudrin
216 et al. [7]. The cameras and the projector are synchronized. We use a pattern
217 projection to provide a dense 3D information from the pair of cameras, regardless

218 of the texture on the object surface. When the system is triggered, the pattern is
219 projected on the scene. Then the two cameras acquire images simultaneously. The
220 pair of images is used in a reconstruction algorithm, providing a 3D point cloud by
221 a stereo-vision surface reconstruction method. Points are expressed with respect
222 to the frame \mathcal{C}_0 of the principal camera.

223 Figure 7 presents two 3D reconstructions of a mechanical part. The part con-
224 tains both sharp and curved edges. On the left, one can see the result of the initial
225 reconstruction. Sharp edges are rounded. On the right, one can note that the sharp
226 edges have been corrected and are sharper. Curved edges have not been modified.

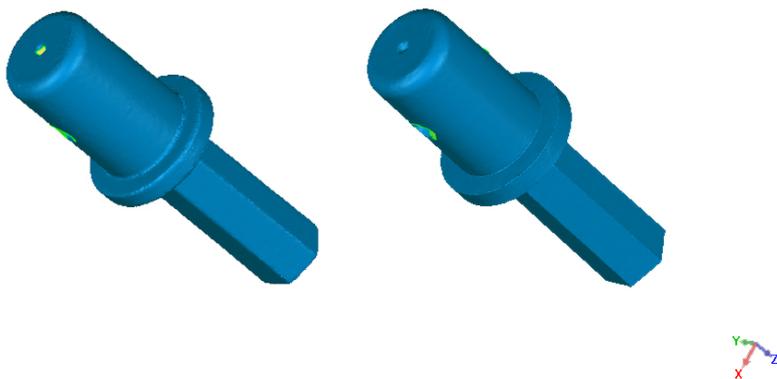


Fig. 7 Result of standard 3D reconstruction (left) and edge-optimized 3D reconstruction (right)

227 To illustrate the improvement of the new method, the deviation between the
228 two results has been computed using Geomagic Qualify software (figure 8). The
229 color map describes the signed euclidean distance between the two shapes and lies
230 within the range $[-0.5mm, +0.5mm]$. The largest errors can be observed along the
231 edges. It shows that points on edges have moved up to $0.5mm$ from their initial
232 position.

233 Figure 9 shows a cylindrical gauge block. It is composed of a section of a
234 cylinder with flat surfaces on the top and the bottom and perfectly circular surface

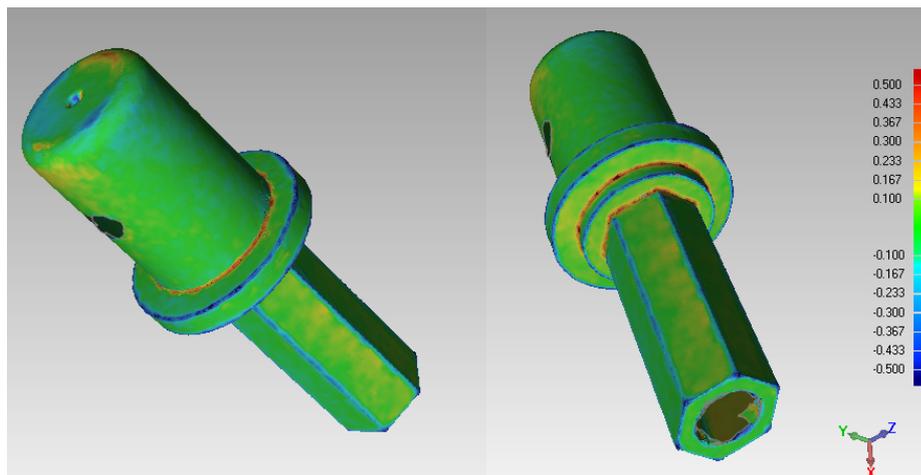


Fig. 8 Comparison between standard 3D reconstruction and edge-optimized 3D reconstruction. The color map represents the euclidean deviation between the two shapes

235 on the inside. The CAD model of this part is known and accurate up to $1\mu m$.
236 Figure 9 shows the initial reconstruction of the cylinder. Figure 10 presents the
237 qualitative result of edge optimization. The edge at the intersection of the inner
238 cylinder and the top surface has been sharpened. The other edges have not been
239 altered since they are not actual sharp edges.

240 Since the CAD model is known for this part, we have evaluated the accuracy of
241 our method by comparing the 3D reconstruction results to the theoretical surface.
242 We have used the Geomagic QualifyTM software to align and compare our result
243 to the CAD model ground truth. The software gives a comparison by projecting
244 orthogonally each point of our 3D reconstruction to the surfaces of the CAD model.
245 The result of the comparison is a distance map. Small projection distances are
246 displayed in green, and tend to dark red or dark blue when the distance increases.

247 Figure 11 shows the distance map of the initial 3D reconstruction to the CAD
248 model. The error increases strongly on the edge. Indeed, the initial reconstruction
249 over-smoothes this sharp edge. Consequently, the points have been estimated far
250 behind the actual surface. After the edge optimization process, Figure 12 shows

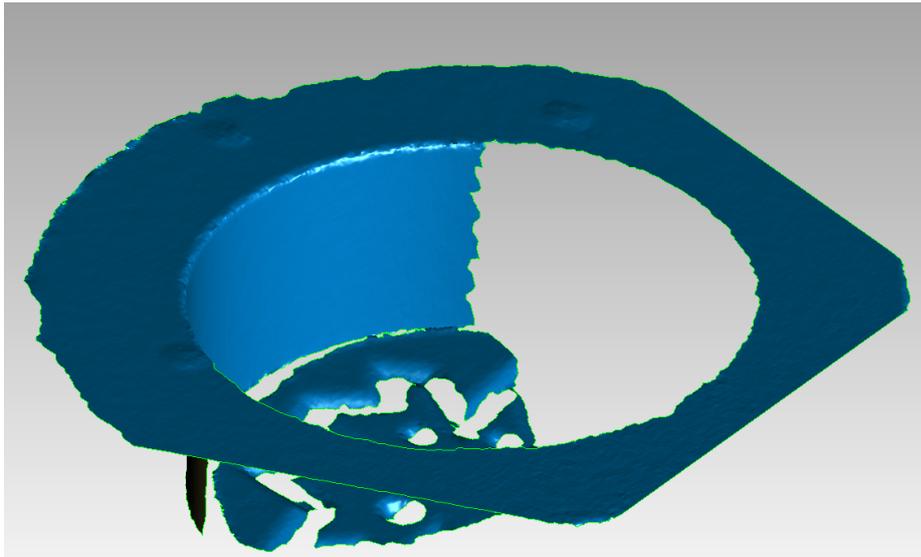


Fig. 9 Initial 3D reconstruction of a cylinder

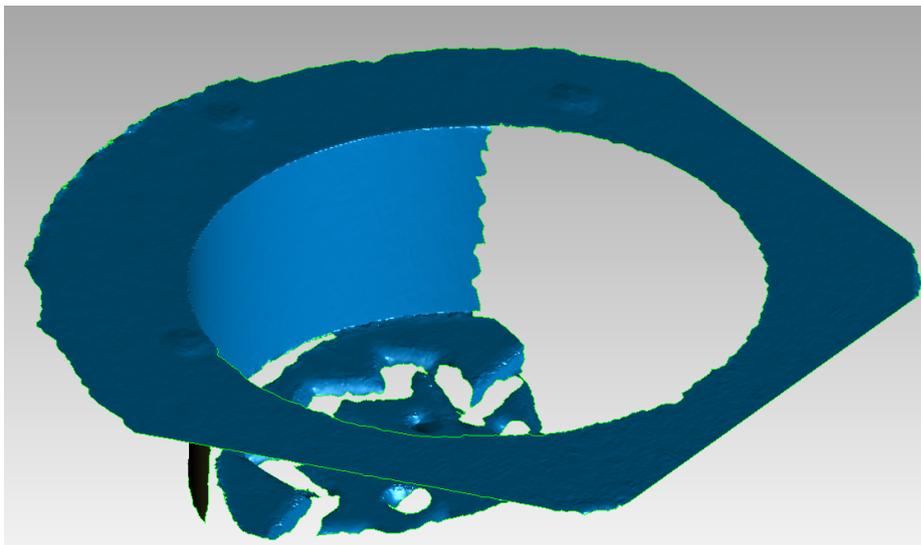


Fig. 10 Edge-optimized 3D reconstruction of the cylinder

251 the improved result. The edge has been accurately reconstructed and all the points
252 on the edge are in the acceptable green range.

253 As a side effect of our method, one can note that the top surface contains a
254 certain amount of error in figure 11 that is minimized in figure 12. This is due to the

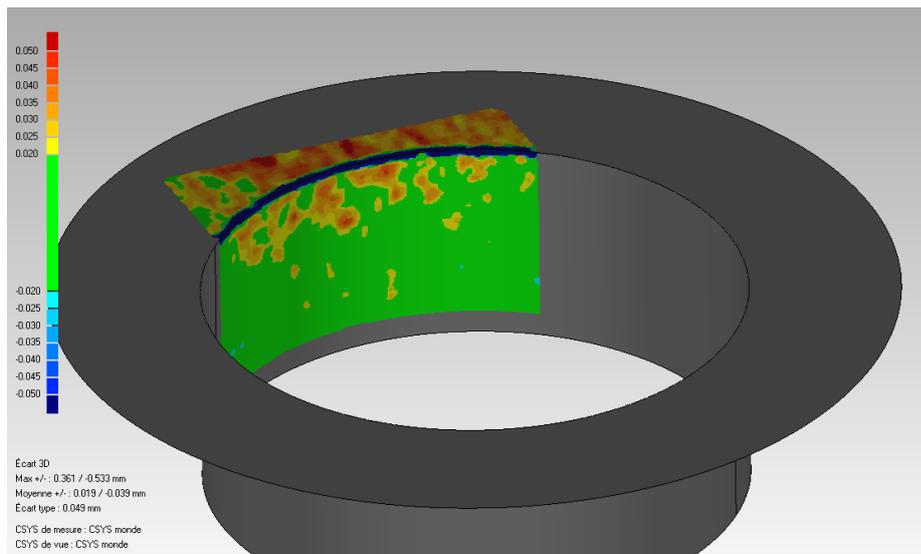


Fig. 11 Distance map of the initial 3D reconstruction to the CAD model

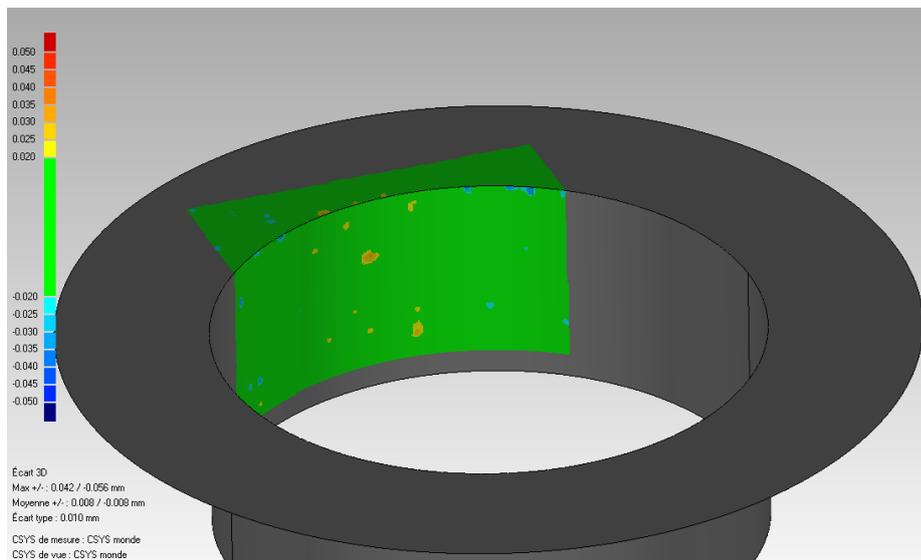


Fig. 12 Distance map of the edge-optimized 3D reconstruction to the CAD model

255 alignment step of the Geomagic Qualify software. Since the initial reconstruction
256 contains more error, it is harder to align with the actual surface. With the edge
257 improvement, the 3D reconstruction is more accurate and can be more easily
258 aligned to the CAD model.

259 It should be noted that we have shown in [8] that the standard stereo-DIC
260 approach does not perform well with a small window size (3×3 or 5×5 pixel
261 windows). Indeed, reducing the window size increases ambiguities in correlation
262 and causes drifts in the stereo matching process, causing noise and holes in the 3D
263 reconstruction. On the contrary, with a 11×11 pixel window, the noise is reduced
264 and no holes appear, but the window becomes too large compared to the size of
265 some small details, causing a smoothing effect (see Figure 10 in [8]). With the new
266 multi-step stereo-DIC method proposed in this paper, a 11×11 pixel window can
267 be used while reducing the smoothing effect.

268 8.1 Accuracy comparison

269 To give an absolute reference of the results provided by our method, we used a
270 gauge block with a known geometry.

271 This part has been designed for measurement device calibration. It has been
272 accurately manufactured and has an accurately known geometry. It is composed
273 of several simple geometrical primitives (figure 13).

274 The ground truth CAD model (figure 14) is available and used to evaluate the
275 reconstruction error.

276 We compare our edge-optimized method to the standard pairwise stereovision
277 approach. As we have seen previously, this approach tends to smooth details and
278 edges. The gauge block is made of a large plane and geometrical primitives inter-
279 secting the plane, creating sharp edges. We also provide results obtained with the
280 multi-view stereovision (MVS) method presented in [8].

281 Models resulting from the three methods (pairwise stereovision, edge sharpen-
282 ing in pairwise stereovision and our multi-view stereovision method) are registered
283 on the CAD model of the gauge block. Points are projected orthogonally on the
284 surfaces of the theoretical model and projection distance is measured for each
285 point. This distance is considered as the reconstruction error of the point. Figure
286 15 represents these errors using a color map. Green areas are measured inside

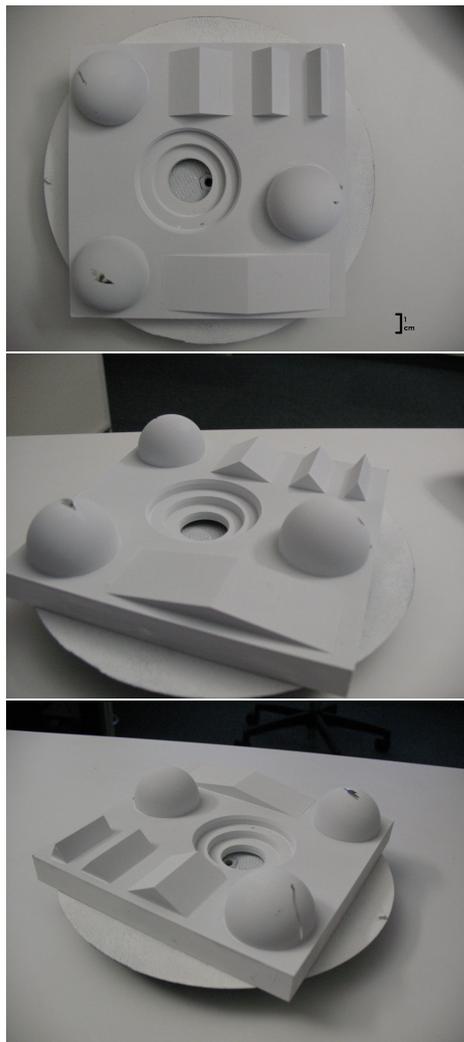


Fig. 13 The gauge block composed from simple geometrical primitives. It contains several sharp edges

287 the tolerance range $[-25\mu m, +25\mu m]$. Points with a larger positive error are rep-
288 resented on a scale from yellow to red. Points with a larger negative error are
289 represented on a scale from light to deep blue.

290 As expected, the error map of the pairwise stereovision method shows a large
291 error near edges of the model. Due to the smoothing effect of the surface ap-
292 proximation in the reconstruction process, edges are rounded. The error on the
293 dominant plane is essentially contained in the tolerance range. The edge-optimized

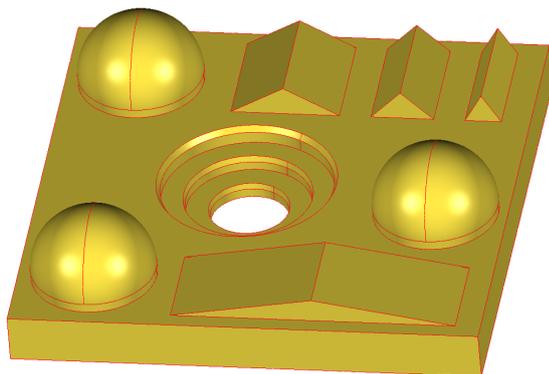


Fig. 14 The CAD model of the object is used as ground truth

	Pairwise stereo	Edge optimization	MVS optimization
Max error (mm)	0.553	0.478	0.452
Min error (mm)	-0.606	-0.286	-0.446
Pos. mean (mm)	0.036	0.037	0.023
Neg. mean (mm)	-0.032	-0.031	-0.020
Std. dev. (mm)	0.066	0.049	0.033

Table 2 Reconstruction error to the ground truth of the gauge block. Max/Min error : maximal positive and negative errors. Pos./Neg. mean : means of, respectively, positive and negatives errors. Std. dev : standard deviation on the error set

294 method performs a lot better along the edges. Maximal errors are now mainly lo-
 295 cated near complex edges – intersection of more than two surfaces – and along
 296 the chamfer of the central drilling. However, a small error on the edges remains.
 297 With our method, error is still mainly located near edges, but the model is more
 298 homogeneously inside the tolerance. The chamfers in the central drilling are now
 299 more finely reconstructed. It is to be noted that the dominant plane is also more
 300 finely reconstructed. A significantly larger part of the object is considered inside
 301 the tolerance comparing to the other methods.

302 Table 2 summarizes the results for this experiment. The results are presented
 303 showing maximal and minimal errors. The mean error should be 0 mm, since the
 304 models are registered minimizing the distance between point clouds and the surface

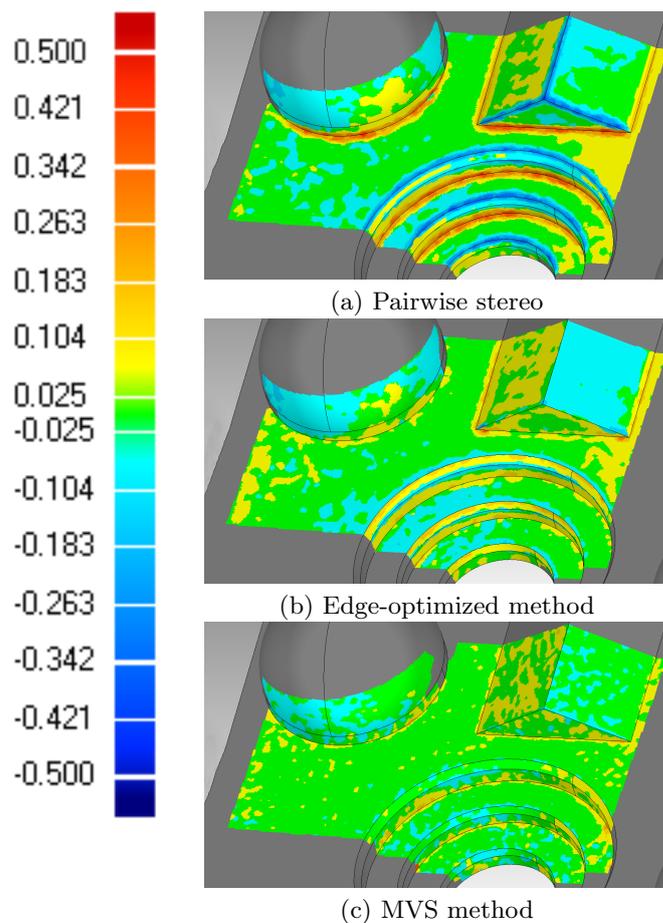


Fig. 15 Comparison of reconstruction error using pairwise stereovision, pairwise stereovision with our edge detection and correction method, and our multiview stereovision method

305 of the CAD model. It is then more meaningful to present average errors in positive
306 and negative parts. The standard deviation on the error set is also presented.

307 As it was pointed in figure 15, our edge-optimized algorithm and our MVS
308 method present better results and a higher accuracy in terms of deviation to
309 the theoretical surface. The MVS method offers the best results, with the lowest
310 deviation, but requires more images to be efficient.

311 8.2 Discussion

312 We have introduced a new bi-plane model and a new correlation criterion in order
313 to achieve a high accuracy 3D reconstruction along sharp edges. Standard window-
314 based methods suffer from the tradeoff between higher accuracy obtained with
315 large subsets and more details obtained with small subsets. Our model permits
316 to use larger subsets with the advantage of having both more details (reduced
317 smoothing effect) and higher accuracy along the edges.

318 The main advantage of our method is that it performs well with a single stereo
319 pair of images. Most of the state of the art methods which produce high accuracy
320 3D reconstruction rely on multiple views. Even if most of these methods perform
321 better than our new bi-plane model, our method allows to improve the reconstruc-
322 tion along sharp edges when a multiple view configuration is not possible. This
323 may be the case for those industrial applications where the number of cameras is
324 limited or when the shape to be measured is not easily accessible.

325 The actual limitation of our method is that it only handles one kind of discon-
326 tinuity: a bi-plane edge. With this model, more complex edges are not correctly
327 modeled and are generally smoothed. Nevertheless, the general methodology de-
328 scribed in this paper could be extended to handle more complex edge models
329 (and associated correlation criterion) and a model switching mechanism could be
330 implemented. By using the verification step described in section "7.2 Edge consis-
331 tency" the model leading to the minimal correlation score could be kept locally.
332 The choice of the best model could be even made easier in situations where the
333 CAD model of the object to be reconstructed in 3D is available.

334 9 Conclusions and Future Work

335 We have developed a new multi-step stereo-DIC algorithm, based on a new cor-
336 relation criterion and a new window transformation model, specially designed for
337 measuring the 3D shape of machined objects with sharp edges.

338 With a standard stereo-DIC-based shape measurement technique, sharp edges
339 are generally smoothed. This effect can be minimized by choosing small size subsets
340 but this increases the stereo matching uncertainty.

341 With our new method, reducing the subset size to avoid smoothing sharp edges
342 is not necessary.

343 Results on real machined objects show that, with our new method, an accurate
344 3D reconstruction of the whole object, including the sharp edges that are preserved,
345 can be achieved.

346 Many methods for 3D reconstruction are iterative and multi-resolution, im-
347 proving an initial low-resolution model up to a representation with the required
348 resolution and accuracy. Future work will be devoted to such a method, including
349 using a prior knowledge provided by the object CAD model when available, in
350 order to make simpler and more accurate the modeling process.

351 We also compared our method to a MVS method. Although the accuracy of
352 MVS methods is better than our edge-optimized method, the latter requires only
353 one pair of images and is able to produce honorable results. MVS methods require
354 several images. It is legitimate to ask if combining both methods (MVS and edge
355 optimization) and working with several images would improve the results.

356 DIC is widely used for shape and strain measurement. This work focused on
357 shape measurement and we did not explore the eventual contribution of the edge-
358 optimized method to strain measurement. This will be part of further studies.

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