Flexible registration method for light-stripe sensors considering sensor misalignments

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ABSTRACT

In many application areas such as object reconstruction or quality assurance, it is required to completely or partly measure the shape of an object or at least the cross section of the required object region. For complex geometries, therefore, multiple views are needed to bypass undercuts respectively occlusions. Hence, a multi-sensor measuring system for complex geometries has to consist of multiple light-stripe sensors that are surrounding the measuring object in order to complete the measurements in a prescribed time. The number of sensors depends on the object geometry and dimensions. In order to create a uniform 3D data set from the data of individual sensors, a registration of each individual data set into a common global coordinate system has to be performed. State-of-the-art registration methods for light-stripe sensors use only data from object intersection with the respective laser plane of each sensor. At the same time the assumption is met that all laser planes are coplanar and that there are corresponding points in two data sets. However, this assumption does not represent the real case, because it is nearly impossible to align multiple laser planes in the same plane. For this reason, sensor misalignments are neglected by this assumption. In this work a new registration method for light-stripe sensors is presented that considers sensor misalignments as well as intended sensor displacements and tiltings. The developed method combines 3D pose estimation and triangulated data to properly register the real sensor pose in 3D space.

Keywords: 3D registration, light-stripe sensors, 3D pose estimation, ICP algorithm, rigid body transformation

1. INTRODUCTION

Reflective optical 3D metrology is used in many areas, such as reverse engineering, object reconstruction, and quality assurance. Due to its non-contact measuring principle, it is suitable for non-destructive measurements on sensitive objects. Reflective optical measuring methods use light which is reflected by the measuring object. The reflected light is then captured by optics and focused on an imaging sensor. Furthermore, the detected light from the imaging sensor is used to determine the 3D coordinates of the object. Reflective optical methods are divided into two groups, using passive or active light. Passive light methods find application for instance in passive stereo vision systems (passive triangulation with two camera units), where light from the environment is used, emitted from the sun or lamps. Passive stereo triangulation requires objects with strong features to detect corresponding points in the images of both sensors. Active light methods are used in interferometry, active triangulation or time delay techniques (time of flight cameras). Active methods use projector units to illuminate the object. Following, only the structured light that is reflected by the object is then used for 3D object reconstruction.

For measurements on complex geometries, like highly curved objects or objects with undercuts or occlusions, multiple views from different locations are needed to completely capture their geometry. There are two approaches to deal with undercuts and occlusions on complex geometries: firstly, usage of one sensor and realigning either the sensor or the measuring object and secondly, usage of multiple (at least two) sensors, that are surrounding the measuring object. The first approach goes along with time expenses due to the need of realignment. Furthermore not all objects to be measured can be realigned easily or at all. The second approach, to create a multi-sensor, is a less time-consuming solution. In both cases a registration has to be performed in order to transform the measuring data from all views or sensors into a common global coordinate system.

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The problem of correct registration is getting more and more difficult with increasing measuring range. Especially for light-stripe sensors, where in the state-of-the-art registration methods all involved laser planes are assumed to be coplanar. Thus, on wide distances even small sensor misalignments can result in big deviations after registration in the global coordinate system. Additionally, sensor noise and limited resolution have a bigger impact on large measuring ranges. State-of-the-art registration methods for laser-stripe sensors use only the triangulated range data of the sensors and neglect any sensor misalignments. The deviations resulting from sensor misalignments are also neglected because the registration is applied either on small measuring ranges or the required tolerances are correspondingly large.

In this paper, a new registration method for light-stripe sensors is developed in order to improve the accuracy of the overall model in the global coordinate system. The proposed method is based on 3D pose estimation, using a Perspective-n-Points (PnP) algorithm, and triangulated data of a reference object. As a reference object a simple 2D checkerboard pattern is used. First, an estimation of the 2D checkerboard is performed which is initially faulty due to estimation accuracy.[1,2] Afterwards, laser projections on the 2D checkerboard in the same pose are also estimated in 3D space. Here triangulation of these projections is regarded as the ground truth, which is further used to compute the proper pose of the 2D checkerboard with a rigid body transformation. Extrinsic parameters of the proper pose are finally used for the registration. The developed method allows for the correct determination of sensor misalignments as well as of intended sensor displacements and tiltings. For this reason, the proposed method can especially be applied in dimensional measurements like in object reconstruction, where there is no need for perfect cross sections, because of polygonizing the measured data points to a mesh. Considering sensor displacements in the registration, an accurate and time-consuming adjustment of the sensors becomes incidental. The results of the developed registration method are shown on a measuring object and compared with results from the Trimmed ICP (TrICP) algorithm,[3] a state-of-the-art registration method.

2. STATE-OF-THE-ART REGISTRATION METHODS

In this section different state-of-the-art registration methods for multiple optical 3D sensors are presented with regard to the light-stripe sensors.

In Stoecher et al.[4] a calibration method for a multi-sensor consisting of at least two cameras and a laser plane is presented. The laser plane is spanned by at least one laser projector unit. If more than one projector unit is used, the planes are aligned and assumed to be coplanar. Depending on the constellation of the multi-sensor, it is a multi-view laser stripe sensor or a multi-sensor with multiple laser-stripe sensors. For calibration, which includes the registration of all cameras respectively light-stripe sensors, only the sensor range data of a wire-frame reference object is used which has to be precisely moved by a translation stage. At least five significant points are needed which are computed through intersection of three planes fitted in the range data. As a reference object a self-made wire-frame model of a cube is used, consisting of standard aluminium profiles. Attention has to be paid to the alignment of the reference object to avoid occlusions for other cameras.

In Schoch et al.[5] the registration of multiple laser-stripe sensors in a radial arrangement is tested in a simulation environment. The condition for this method is also that all laser planes have to be in the same plane. For registration, a special reference object has to be measured with each sensor. The reference object is composed of a circular plate which is divided into four equal sectors with unique boundaries. The unique sector boundaries consist of cylinders, placed in defined distances, and cuboids with different edge lengths between them. The dimensions of the cylinders and cuboids are known in advance. For this purpose at least two sector boundaries need to be positioned in the measuring range of each sensor. Owing to the special reference object, there is no need for overlapping of the measuring ranges of adjacent sensors. As in Stoecher et al.,[4] due to occlusions, care has to be taken at the alignment of the reference object. The registration is then performed by assignment of the measurements of cylinders and cuboids of each sensor to the unique sector boundaries.

In Zhang et al.[6] calibration and registration procedures for a multi-sensor system consisting of four cameras and four to six laser line sources surrounding the measuring object is presented. The cameras have different measurement ranges in order to provide a multiresolution measurement system. Moreover, the cameras are adjusted under the Scheimpflug condition to direct their focus on the laser planes. Zhang et al. also assume the laser planes to be coplanar. For registration of the sensors in a global coordinate system, an Iterative Closest Point (ICP) algorithm is applied. Therefore the measuring ranges of adjacent sensors have to overlap on the reference object. As a reference object a cylinder is used. Furthermore, a non-linear technique called empirical mode decomposition (EMD) is used to improve the results in sense of data merging.

The Iterative Closest Point (ICP) algorithm is a widespread approach for registration of 3D data sets with unknown point correspondences and different number of points in both data sets. For successful registration, a good initial guess of the pose is required in order not to get in a local minimum. Over the years, many modifications of the ICP were developed in terms of selection and matching of points and minimization algorithms for the rigid body transformation. In Rusinkiewicz et al.[7] several ICP variants are compared in terms of convergence speed. Chetverikov et al.[3] propose a trimmed version of ICP, called Trimmed ICP (TrICP), where the percentage of overlap can either be defined by the user or automatically estimated by minimizing an objective function.

If the correspondences of two 3D data sets are known, closed-form solutions can be applied to compute the 3D rigid body transformation that consists of a rotation and a translation in 3D space. In Eggert et al.[8] four popular algorithms, based on singular value decomposition (SVD), eigensystem computation and eigensystem analysis from unit and dual quaternions, are comparative analysed. Differences in accuracy and stability are only reported for ideal (noise-free) data. However, for practical applications there is only a difference in the computation time. Each of these algorithms was designed to solve a least squares problem and can be used for the ICP algorithm mentioned above.

All above presented registration methods for 3D data points meet the assumption that all laser planes are coplanar or that there exist corresponding points in two data sets, which is particularly the same in the case of the light sectioning method. For points that have been measured in the same laser plane, this assumption makes sense. However, in real environment it is nearly impossible to align two laser planes perfectly coplanar due to six degrees of freedom (DOF) for each sensor, where especially the three rotatory DOF are difficult to adjust. Because of this fact there will almost never be real corresponding points in two data sets measured by two laser-stripe sensors. Neglecting this fact can result in errors in the overall model after registration.

Therefore, a new method is developed which considers sensor misalignments as well as intended displacements and tiltings. The developed method is based on pose estimation and rigid body transformations between the 3D reconstructed and the triangulated data and provides flexibility regarding to algorithms used for pose estimation as well as to the used reference object. At the alignment of the reference object it is only to be noted that the reference object has to be in the measuring volume overlap of the adjacent sensors and intersected by the laser planes. In this work, as reference object a simple 2D checkerboard pattern is used.

3. NEW REGISTRATION METHOD

In this section the developed registration method is described. In order to obtain the relative 3D orientation between two adjacent light-stripe sensors, initially a pose estimation technique is used. The estimated poses are corrupted by uncertainties regarding to limited sensor resolution but mostly by noise[1,2] that is affecting on the feature detection in images. For this reason, the estimated poses are further corrected by use of triangulated sensor data, which is assumed to be the ground truth. The correction transformations are computed by application of rigid body transformations between estimated 3D reconstructions and triangulations of projected laser stripes on the reference object, minimizing the least squares error with a weighting approach. For the next steps intrinsic camera and lens distortion parameters for pose estimation as well as algorithms for feature detection of the reference object and laser stripe detection and evaluation are assumed to be available.

3.1 Pose estimation with a Perspective-n-Point approach

Perspective-n-Point (PnP) is a problem of estimating the pose of a camera in world respectively camera coordinates from a single image. For this purpose, the intrinsic camera parameters, a set of n 3D points in world coordinates $\mathbf{p}_i^w = [x_i, y_i, z_i]^T$ and its 2D projections on the imaging sensor $\mathbf{u}_i = [u_i, v_i]^T$ in image coordinates, have to be known. Intrinsic parameters are contained in the camera matrix $\mathbf{K}_{3\times3}$, where f_u, f_v are the focal length coefficients in u- and v-direction, γ is the shear distortion parameter and c_u, c_v are the principal image point coordinates. For real applications, additional lens distortion parameters $d = [k_1, k_2, k_3, \ldots, p_1, p_2, \ldots]$, consisting of radial parts denoted by k and tangential parts denoted by p, have also to be known in order to undistort the images. Intrinsic camera and the distortion parameters are the results from the camera calibration.

$$\mathbf{K} = \begin{bmatrix} f_u & \gamma & c_u \\ 0 & f_v & c_v \\ 0 & 0 & 1 \end{bmatrix}, \tag{1}$$

The camera pose is defined by extrinsic parameters, consisting of a rotation matrix $\mathbf{R}_{3\times3}$ and a translation vector $\mathbf{t}_{3\times1}$. To find this parameters is the aim of the PnP by calculating the depth of given 3D world and 2D image point correspondences.
In this work the Efficient Perspective-n-Point (EPnP) algorithm,[1] a non-iterative PnP approach, is applied. In contrast to most approaches, in EPnP, n corresponding reference points are expressed as a weighted sum of virtual control points. For general configurations four control points are required to determine the 3D-2D projective mapping. In the case of a planar reference object, like the used 2D checkerboard, only three control points are needed.

$$\mathbf{p}_i^w = \sum_{j=1}^{3} \alpha_{ij}\mathbf{c}_j^w, \quad \text{with} \quad \sum_{j=1}^{3} \alpha_{ij} = 1 \quad \text{and} \quad i = 1, \ldots, n, \quad j = 1, 2, 3 \tag{2}$$

$$\mathbf{p}_i^c = \sum_{j=1}^{3} \alpha_{ij}\mathbf{c}_j^c \tag{3}$$

Here $\mathbf{c}_j$ are the control points, where superscripted ^{w} and ^{c} denote the world respectively the camera coordinate system and α_{ij} represent the homogeneous barycentric coordinates. The projective mapping from 3D world to 2D image coordinates is then defined as

$$s_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = \mathbf{K} \sum_{j=1}^{3} \alpha_{ij} \begin{bmatrix} x_j^c \\ y_j^c \\ z_j^c \end{bmatrix} \tag{4}$$

with control points $\mathbf{c}_j^c = [x_j^c, y_j^c, z_j^c]^T$ turning to unknowns containing the wanted extrinsic parameters $\mathbf{R}$ and $\mathbf{t}$, here expressed as homogeneous coordinates $\tilde{\mathbf{c}}_j^c$

$$\tilde{\mathbf{c}}_j^c = \begin{bmatrix} x_j^c \\ y_j^c \\ z_j^c \\ 1 \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{R}_{3\times3} & \mathbf{t}_{3\times1} \\ \mathbf{0}_{1\times3} & 1 \end{bmatrix}}_{\mathbf{T}_{4\times4}} \begin{bmatrix} x_j^w \\ y_j^w \\ z_j^w \\ 1 \end{bmatrix}. \tag{5}$$

After further forming steps of equation (4), a linear formulation as $\mathbf{Mx} = \mathbf{0}$ is set up and solved. As a result extrinsic transformation $\mathbf{T}_{4\times4}$ from world into camera coordinates is obtained.
Image data which is located on the 2D reference object can be reconstructed on this plane in 3D using the inverse camera matrix and the information from extrinsic transformation obtained from EPnP.

$$\mathbf{p}_{n_i}^{\ c} = \begin{bmatrix} x_{n_i}^{\ c} \\ y_{n_i}^{\ c} \\ z_{n_i}^{\ c} \end{bmatrix} = \mathbf{K}^{-1} \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} \tag{6}$$

$$\mathbf{p}_i^c = \begin{bmatrix} x_i^c \\ y_i^c \\ z_i^c \end{bmatrix} = s_i \begin{bmatrix} x_{n_i}^{\ c} \\ y_{n_i}^{\ c} \\ z_{n_i}^{\ c} \end{bmatrix} \tag{7}$$

$$s_i = \frac{\mathbf{n} \cdot \mathbf{t}}{\mathbf{p}_{n_i}^{\ c} \cdot \mathbf{n}} \tag{8}$$

Parameter s_i is the depth of a detected feature point and can be interpreted as a scale factor for each normalized point $\mathbf{p}_{n_i}^{\ c}$ which is to calculate for the intersection with the 2D reference plane. Normal vector $\mathbf{n}$ of the reference

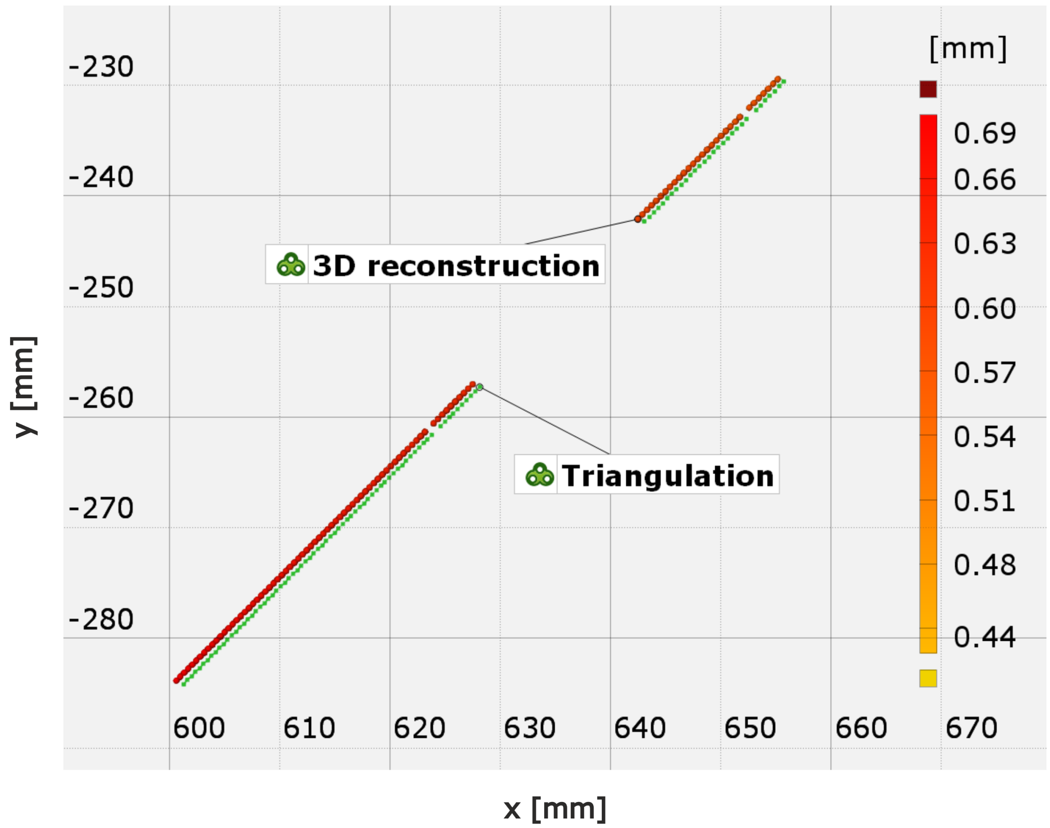


Figure 1: Deviation between 3D reconstruction (red) using EPnP and triangulated data (green) representing the ground truth. For both data sets a line fit is performed. Deviations can be seen in the color bar legend by means of orthogonal projections of the 3D reconstructed line on the triangulated line.

plane is the third column of the estimated rotation matrix $\mathbf{R}$. The results of a 3D reconstructed and a triangulated laser stripe on the same reference pose are shown in Fig. 1. It can be seen that the 3D reconstruction of the laser projection based on pure EPnP is distinctly deviating from triangulated data, which is assumed to be the ground truth.
Applying EPnP with two adjacent sensors on the 2D checkerboard in the same pose, for each sensor an extrinsic transformation $\mathbf{T}_1$ and $\mathbf{T}_2$ is obtained. Registration from $Sensor_1$ to $Sensor_2$ can be performed in the form

$$\mathbf{T}_{12} = \mathbf{T}_2\mathbf{T}_1^{-1}. \tag{9}$$

However, the deviation in the pose estimation has the consequence that the registered data is incorrectly arranged in the overall model. The impact of the deviation is shown in Fig. 4.

3.2 Computing correction transformation

In order to correct the initially computed poses, a rigid body transformation between reconstructed and triangulated data has to be performed. However, two corresponding lines are not sufficient. Therefore, at minimum two laser stripes on different poses of the reference object have to be reconstructed and triangulated. Hence, the reference object is placed in an additional pose and pose estimation as well as 3D reconstruction and triangulation are repeated. While the triangulated data of the projected laser stripes is coplanar, the estimated 3D reconsruction does not necessarily have to be, due to errors in the pose estimation. For this reason, a weighting approach is appropriate to minimize the least squares error

$$error = \sum_{i=1}^{n} w_i \left\|\mathbf{d}_i - \mathbf{R}\mathbf{m}_i + \mathbf{t}\right\|^2 \tag{10}$$

for the determination of a rigid transformation between two corresponding 3D data sets $\mathbf{d}_i$ and $\mathbf{m}_i$. For solving the minimization function from equation (10), singular value decomposition[8,9] (SVD) is applied.
First, triangulated and 3D reconstructed data at the two poses are concatenated each to a common data set, $\mathbf{d}$ and $\mathbf{m}$. Regarding to the two poses, two sets of extrinsic parameters are obtained which can be used for further correction. Next, the correction based on the first pose is performed. Therefore, weights for the first triangulated stripe are chosen to 10^6, while weights for the second stripe remain by 1. This ensures the proper determination of the correction transformation for the first pose. The corrected transformation from equation (9) is then defined as

$$\mathbf{T}_{12corr} = \mathbf{T}_{2corr}\mathbf{T}_2\mathbf{T}_1^{-1}\mathbf{T}_{1corr}^{-1}. \tag{11}$$

$\mathbf{T}_{1corr}$ and $\mathbf{T}_{2corr}$ are the extrinsic correction transformations between the 3D reconstruction from the EPnP and the triangulated data.

4. RESULTS

The experimental results of the proposed registration method are shown on measurements of a complex shaped aluminium profile with two light-stripe sensors, shown in Fig. 2. As global coordinate system for the overall model, coordinate system of $Sensor_2$ is chosen, where the measuring data from $Sensor_1$ is registered. The

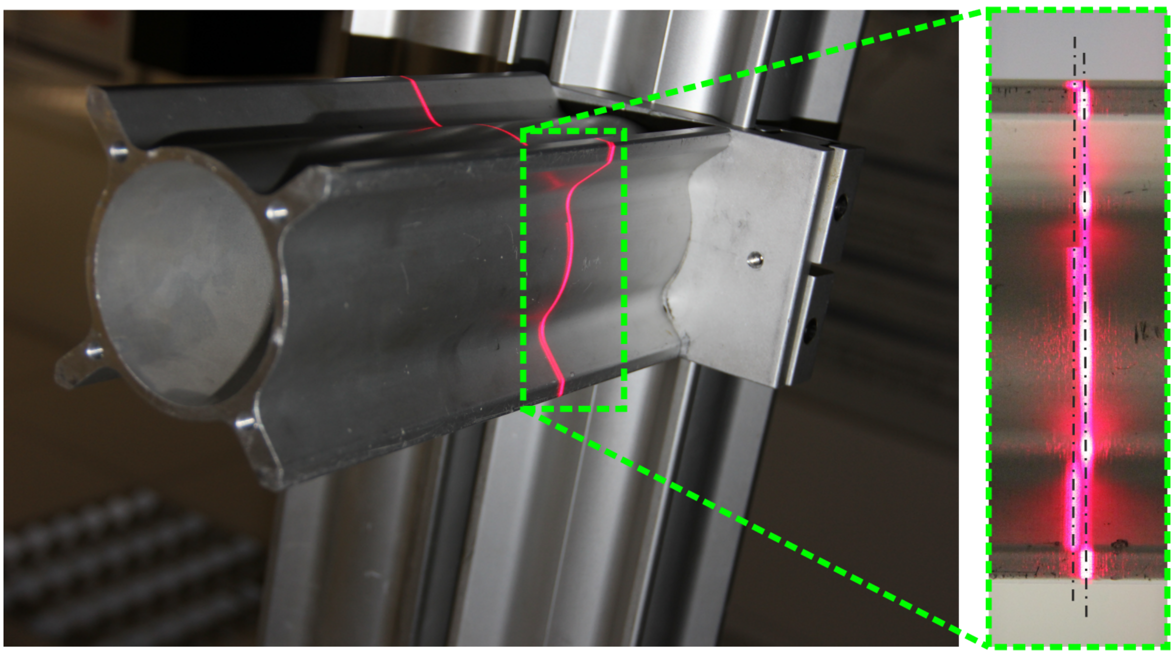
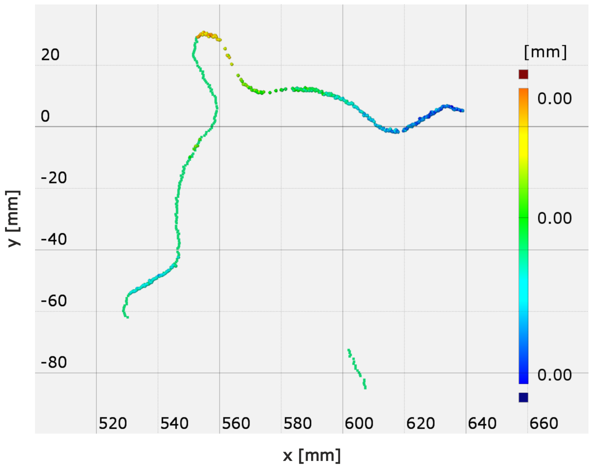
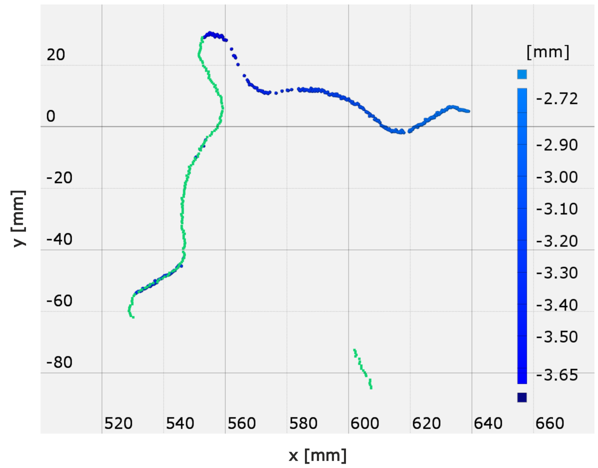


Figure 2: Complex shaped aluminium profile as measuring object. Intended laser plane displacements are clearly visible.

sensors are intended to be misaligned so that there is a significant offset between the laser projections, also seen in Fig. 2. In Fig. 3a, registration is performed with TrICP[3] as example for state-of-the-art methods that are based on point correspondences in triangulated data. It can be seen that, although there is a clearly visible displacement between both laser planes, shown in Fig. 2, state-of-the-art registration methods are not able to detect these sensor misalignments due to the assumption of coplanar laser planes and corresponding points in two data sets. Registered data from $Sensor_1$ is in the laser plane of $Sensor_2$, what does not correspond to reality. Fig. 3b shows the registration results with the developed method. As can be seen, the intended sensor misalignment is detected and data is properly registered in the overall model. In Fig. 4, registration results with pure EPnP versus the new registration method are shown. It is to be noted that diverging pose deviations in EPnP occur, which are distorting the overall model, the deviation in translation being much greater than

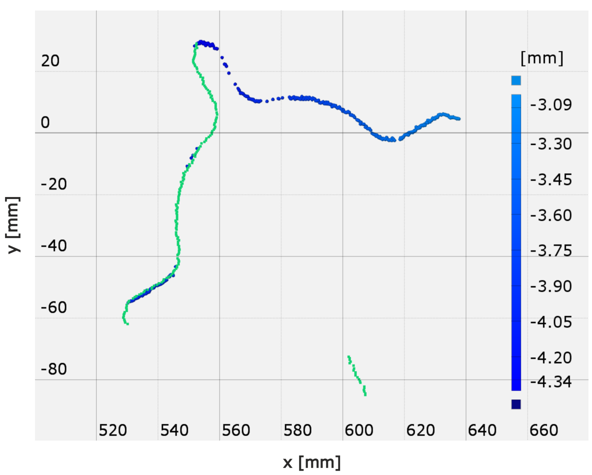


(a) Registration with TrICP

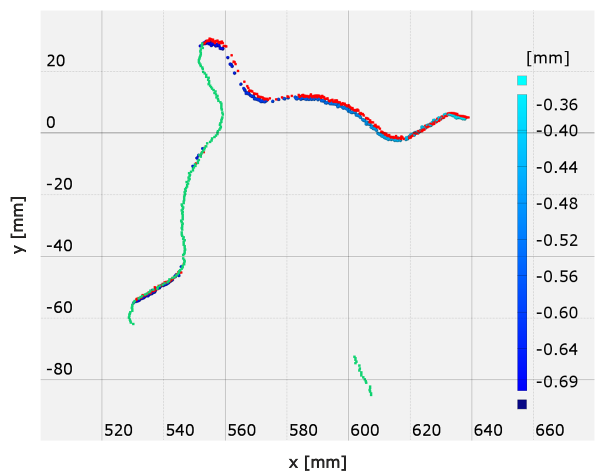


(b) Registration with the new method

Figure 3: Comparison of a state-of-the-art registration method TrICP and the developed registraion method in measurements with an intended sensor misalignmnet. No sensor misalignments are detected with TrICP (a). Sensor misalignment detected with the new method (b). Detected sensor misalignments are shown in the color bar legend by means of orthogonal projections of registered data from $Sensor_1$ to the laser plane of $Sensor_2$.



(a) Registration with pure EPnP



(b) Deviation between pure EPnP and the new method

Figure 4: Comparison of the registration results provided by pure EPnP and the developed registration method. Detected sensor misalignments with pure EPnP (a). Direct comparison of EPnP (blue) with the developed method (red), deviations between pure EPnP and the new method are shown by means of orthogonal projections of registered data with EPnP to the plane of the registered data with the new method in the color bar legend (b).

in rotation. Deviations in the registration with TrICP and pure EPnP in comparison to the new method are summarized in Table 1. In Fig. 5, $Sensor_1$ is translated by a translation stage by 2mm, 5mm, and 12mm, $Sensor_2$ remains at the same position. On each position the developed registration method is performed. It can be seen that the translations are detected and proper arranged in the overall model.

Figure 5: Pure translation of $Sensor_1$ by 2mm, 5mm, and 12mm. Results of the detected sensor translations and their distributions can be seen in the legend.

Table 1: Deviations in rotation and translation from TrICP and pure EPnP to the developed registration method. Calculated by means of a (non-weighted) rigid body transformation using SVD. For better comparison, for each pose the root mean squared error ($RMSE$) is also given.

	$\Delta\phi_x[°]$	$\Delta\phi_y[°]$	$\Delta\phi_z[°]$	$\Delta t_x[mm]$	$\Delta t_y[mm]$	$\Delta t_z[mm]$	$RMSE[mm]$
TrICP	-0.486	-0.221	-0.309	2.123	-8.316	0.003	3.320
TrICP Δ 2mm	-0.428	-0.187	-0.282	1.686	-9.448	0.491	5.088
TrICP Δ 5mm	-0.414	-0.189	-0.255	1.752	-12.016	1.440	7.901
TrICP Δ 12mm	-0.505	-0.228	-0.343	2.196	-20.013	3.948	15.347
EPnP	0.184	-0.249	0.160	3.173	2.825	1.107	1.566
EPnP Δ 2mm	0.305	-0.124	0.288	2.120	4.791	0.504	1.950
EPnP Δ 5mm	0.299	-0.168	0.277	2.387	4.629	0.742	1.853
EPnP Δ 12mm	0.183	-0.210	0.160	2.848	2.833	1.006	1.531

5. CONCLUSION

State-of-the-art registration methods for light-stripe sensors meet the assumption that two laser planes of adjacent sensors are coplanar and that there are corresponding points in two data sets. For this reason, the individual data sets appear in the same plane in the overall model (Fig. 3a), which does not correspond to reality.
In this work, a new registration method for light-stripe sensors is presented. With the developed registration method, sensor misalignments and intended displacements and tiltings can be detected and properly registered in the overall model. The proposed method combines both pose estimation, performed with the EPnP algorithm,

and a weighting least squares approach for the determination of a rigid body transformation to the ground truth that is given by triangulated data for each sensor. The flexibility of the proposed method is referred to its generality regarding to other algorithms for the pose estimation like epipolar geometry[10, 11] as well as to the used reference objects (2D or 3D) which also can remain geometrical primitive. For example, the poses even can be estimated by using the direct linear transformation (DLT) and the reference object which are used for camera calibration in advance. It has only to be cared for that enough information of the reference object is seen in the overlap of both adjacent camera systems and that laser planes are intersecting the reference object.

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