

Motion compensation for three-dimensional measurements of macroscopic objects using fringe projection

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For three-dimensional reconstruction using fringe projection and under motion point correspondences between different 2D images and global phase shifts are no longer constant during the complete process. One possibility to address this issue is the use of motion compensation as described in this article. Simulation results and remaining limitations are indicated.

1 Introduction

Three-dimensional reconstruction with measurement systems using fringe projection is widely used in non-static applications such as measurement of teeth in-side mouth, measurements using hand-held sensors [1], and inspections at assembly lines. In particular, in the last few years the demand of fast and cost-effective measurement systems becomes evident. Therefore, it is recommended to measure moving objects continuously instead of the current start-stop regimes. There are two potential approaches to address this issue: 1. the usage of high-speed components for projection and image acquisition ($\hat{=}$ quasi-static situation for 3D measurements) or 2. algorithms for motion compensation. In the current study, standard hardware was used and a novel algorithm for motion compensation was developed.

2 (Quasi-)Static situation

For 3D reconstruction it is required to find correspondences between at least two images I_n^c from different cameras c , in which one camera also could be a projector ($\hat{=}$ inverse camera). This is achieved in a successive process for each point of the master image (arbitrary selected): Determine 2D point in the master image, search for the corresponding point in the second image, and finally triangulate with a known system setup. The 2D search area for correspondences will be constraint through the active projection of the fringe pattern in two projection directions to only one 2D point. To accomplish high robustness and accuracy in 3D reconstruction, a complex sequence of pattern is needed which requires a long acquisition time using standard hardware.

In more detail, the procedure for 3D reconstruction with static setup is performed as follows:

1. Acquisition of fringe pattern with phase shifting:
Each image can be described with

$$I_n^c(x, y) = a(x, y) + b(x, y) \cdot \cos[\phi^c(x, y) + \Delta\phi_n] \quad (1)$$

where $\Delta\phi_n$ is the phase shift between two sequentially fringe pattern in degree.

2. Calculate raw fine phases $\Phi^c(I_k^c) \in [-\pi, \pi]$ with

$$\phi^c(x, y) = \arctan \frac{I_4^c(x, y) - I_2^c(x, y)}{I_1^c(x, y) - I_3^c(x, y)} \quad (2)$$

if you use $k = 4$ fringe pattern per direction.

3. Unwrap raw fine phases by using e.g. gray code pattern to get global unique fine phases $\Phi^{c'}$.
4. Calculate final 3d point cloud by triangulation between the fine phase maps $\Phi^{c'}$ of at least two cameras c (or camera and projector).

3 Measurements under motion

In case of measurements with moving objects and/or sensor systems at least two previous assumptions are no longer given:

- uniform global phase shift $\Delta\phi_n$
- unique pixel correspondences (x, y) over the whole measurement sequence, which are required for equation (2)

These given facts can be corrected by refinement of the static situation. Therefore, two important functions have to be added: First, a step of motion estimation with the result of motion vectors $T \in \mathbb{R}^6$ and second, a step of motion compensation using T .

6D motion estimation is unfeasible using 2D input data. Certainly, there are methods existing to estimate motion out of 2D images, e.g. autocorrelation. However, several kinds of motion are not convenient. To bypass this restriction, we used 3D data for motion estimation. An established algorithm to minimize errors or distances of point clouds is the approach of iterative closest points (ICP) [2]. It estimates the best transformation between two sets of given points independent of their dimension. The first step of analysis is the correlation of two 3D sets which requires

3D input data and is realised by fourier analysis of each individual 2D fringe image [3]. As result, a coarse 3D point cloud for each 2D fringe image is created that is distinct from the final 3D point cloud but sufficient as input for the ICP algorithms.

The motion compensation as second step comprises both a rear projection of the coarse 3D point clouds with known motion in the camera images and a rear projection to the projection plain. The last-mentioned step is required for determination of the local phase shifts $\Delta\phi_n(x, y)$ in projection, which are now depending on the local object height and the local motion. Due to the previous system calibration, the projection matrices are known. Rear projection of 3D point clouds into the camera images result in new aligned intensity images $\hat{I}_n^c(x_1', y_1')$. These new intensity images fulfil the equation (2).

4 Results and limitations

Figure 1 illustrates the differences between motion compensation and non-compensated input images and phase shift values $\Delta\phi_n(x, y)$ for the final 3D result. Without compensation (Fig. 1, left) various errors occur, particularly at object parts with distinctive 3D structure. In contrast, using motion compensation (Fig. 1, right) a smooth and for one point of view complete 3D result is generated.

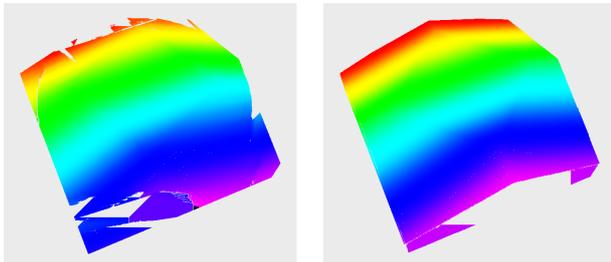


Fig. 1 Final 3d result (color-coded). Left: Disturbed image without compensation. Right: Smooth image using motion compensation.

The results look promising, however, there are still remaining limitations, e.g. changes in lighting during the measurement sequence. This is described by $b(x, y)$ in equation (1) and is constant for static scenes, the most translations and rotations around an axis which is parallel to the principal axis of the projector. For arbitrary relative motion between the measurement object and the projection system lighting alterations have to be integrated in the compensation model which is part of further research.

In addition, the accuracy of the current framework is limited by two error sources: Error in motion estimation and motion blurred input images. The first mentioned error source is mainly affected by poorly 3D point clouds as result of fourier analysis of individual fringe images. Figure 2 demonstrates the correlation

between the error of motion vector estimation and the relative 3D error in the simulation setup.

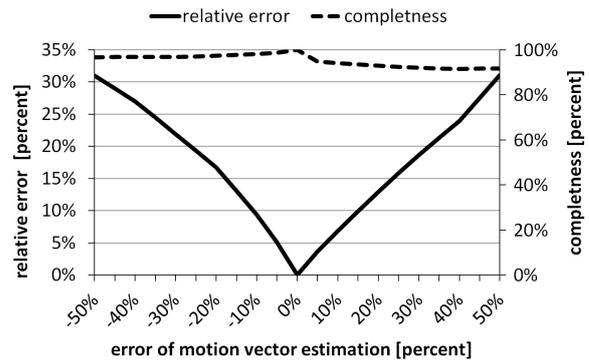


Fig. 2 Influence of motion vector estimation errors $\epsilon(T)$ on the relative 3D error.

The influence of blurred input images on the final 3D error is indicated in figure 3. Exemplary the worst case (fringe shifting and motion direction are parallel to each other) is presented. In case of fringe shifting is orthogonally to the motion direction, the influence of blurred images is quite low.

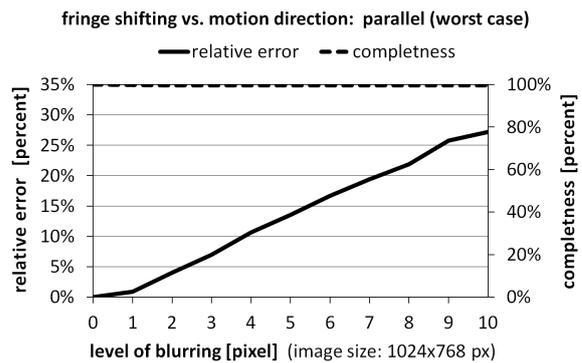


Fig. 3 Influence of motion blurred input images on the relative 3D error.

5 Conclusion

The general approach for 3D reconstruction of macroscopic objects in motion is reliable in the majority of cases, particularly in translations, agitations and minor motion. However, there are still remaining challenges, e.g. changes in lighting and major motion (blurred input images). Thus, further studies will be needed to overcome these limitations.

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