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Optimized Data Processing for an Optical 3D Sensor Based on Flying Triangulation

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Abstract. We present data processing methods for an optical 3D sensor based on the measurement principle “Flying Triangulation”. The principle enables a motion-robust acquisition of the 3D shape of even complex objects: A hand-held sensor is freely guided around the object while real-time feedback of the measurement progress is delivered during the capturing. Although of high precision, the resulting 3D data usually may exhibit some weaknesses: e.g. outliers might be present and the data size might be too large. We describe the measurement principle and the data processing and conclude with measurement results.

Keywords: Data Processing, Optical 3D Sensor, Motion-robust Acquisition, Outlier Removal.

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MEASUREMENT PRINCIPLE “FLYING TRIANGULATION”

Flying Triangulation is a recently developed optical 3D measurement principle [1, 2] which enables a motion-robust surface acquisition of even complex objects with real-time display of the current measurement status. The measurement principle will be described next (see Figure 1).

FIGURE 1. Flying Triangulation workflow: A single-shot triangulation sensor delivers camera images. From each image, sparse 3D views can be generated with data along the observed pattern. Supplying two orthogonal alternating patterns enables a robust registration of the 3D views. The current registered measurement result is displayed in real time, hence ensuring an efficient acquisition of the object. Within a few seconds, a dense 3D model of the object is obtained.

As for all line-sectioning systems, each camera image yields 3D data along projected lines, in our case for multiple-line patterns with a frame rate of 30 Hz. These data are then aligned to each other in real time. To ensure a robust alignment, orthogonal line patterns are projected alternately. The current registration result is displayed in real time, enabling a dense caption of the surface under test within some seconds.

The principle is scalable and allows measurements of small objects such as teeth up to large-sized objects such as human bodies or even entire rooms. Figure 2 shows the currently realized Flying Triangulation sensor family consisting of an intraoral tooth sensor [3], a sensor for measuring face-sized objects [4], and a sensor for the acquisition of body-sized objects [5]. More details about the sensor can also be found in [6].

FIGURE 2. The measurement principle Flying Triangulation enables a motion-robust 3D acquisition of a wide range of objects, from object sizes of some mm (e.g. teeth, fingerprints) to object sizes in the meter range (e.g. entire persons).

Although each Flying Triangulation sensor is optimized to acquire 3D data with minimal measurement uncertainty (e.g., for the tooth sensor, within the entire measurement volume of 20mm×15mm×15mm the uncertainty is below 30 μ m), still some data processing steps are unavoidable to yield good 3D models (see Figure 3).

FIGURE 3. Typical 3D model obtained with Flying Triangulation. It consists of dense 3D data which may show some outliers (dashed circles) caused by wrong indexing of the observed lines.

First, for some applications the amount of final 3D data is too large, e.g. for storage: A typical 3D model obtained with Flying Triangulation consists of some million 3D points. For this case, a homogeneous data distribution of reduced size is desired. Second, outliers caused by wrong line labeling ought to be eliminated. Outliers occur if object parts are captured outside the measurement volume of the sensor. The corresponding observed line segments are then incorrectly labeled and result in wrong 3D data, or outliers. We will now present methods to optimize our 3D data concerning these issues.

OPTIMIZED 3D DATA PROCESSING METHOD

Because of the appearance of the artifacts mentioned above, it is needed to remove points which appear comparably far from the true 3D surface (see Fig. 3). It is possible to find such points by calculating distances between each pair of points of the initial data, but such direct calculations are too time consuming (N^2 computational complexity). We suggest an algorithm, which allows decreasing the computational complexity.

Let us consider two arbitrary points $P = (P_x, P_y, P_z)$ and $Q = (Q_x, Q_y, Q_z)$ and suppose that the point P introduces so-called “3D space density” at the point Q with weighting function (see Fig. 4, a)

$$g(P, Q, r_a) = w(r(P, Q), r_a) = \begin{cases} 0.5 \cdot \left(1 + \cos\left(\frac{\pi \cdot r(P, Q)}{r_a}\right) \right), & r(P, Q) \leq r_a, \\ 0, & r(P, Q) > r_a, \end{cases} \quad (1)$$

where $r(P, Q) = \sqrt{(P_x - Q_x)^2 + (P_y - Q_y)^2 + (P_z - Q_z)^2}$, and r_a is a distance, which defines the “area portion” around each point.

Using Eq. (1), it is possible to calculate the “point density” (PD) at the point Q ,

$$\rho(\mathbf{P}, Q, r_a) = \sum_{n=0}^{N-1} g(P_n, Q, r_a), \quad (2)$$

introduced by a set $\mathbf{P}$ of N points $P_n \in \mathbf{P}$, $n = 0, \dots, N-1$. Then a fixed threshold value ρ_0 is introduced, and the points, which do not meet the criterion

$$\rho(\mathbf{P}, Q, r_a) > \rho_0 \quad (3)$$

are removed.

To illustrate the essence of the suggested approach, let us consider an example of a model object that presents simply a square part of a plane parallel to the horizontal axes XY with a border dimension equal to 6 mm (see Fig. 5 a).

FIGURE 4. (a) Cross-section of the weighting function and (b) an example of the 3D representation of the weighting function around a single point ($x = 1.5$, $y = 1.5$, $z = 1.5$).

Let the measurement results contain a small number of points with height random errors (along the Z-axis) up to 1 mm (Fig. 5, *b*). It is seen in Fig. 5, *c* that the PD clouds do not allow defining borders of this object surely. But if the number of points is large enough (Fig. 5, *d*) then the borders can be recognized from the calculated PD (Fig. 5, *e*).

FIGURE 5. (a) Model plane object of square shape evaluated with (b) 15 points, (d) 150 points and (c, e) corresponding visual representations of the PD (the distances at axes indicated in millimeters).

Thus, the suggested method provides “soft” separation of sparse points from dense points, it is why sparse points caused by artifacts and appeared comparably far from the surface can be separated and removed.

To increase the data processing speed, it is reasonable to apply downsampling and indexing of the data. The downsampling procedure is considered in detail below. The indexing consists in separating the entire 3D volume into cubic cells of side length r_a and in preserving the list of points belonging to each cell as well as their coordinates. Due to the fact that the maximal “influence” distance of two points is equal to r_a , in order to calculate the PD at any point Q_c belonging to a cell it is sufficient to take into account only the points inside the own cell and the 26 nearest neighbor cells. The computational complexity of such an indexing procedure increases linearly as $O(N)$ and hence requires much less computational time in comparison to the case of looking over all points.

The data processing method generally includes three main steps. In the first step, initial data sets are downsampled non-uniformly by removing redundant points (close to each other) and by preserving points which do not have close neighbor points. The second step is based on a comparison of vertical (V) and horizontal (H) multiline patterns (see Fig. 1) with subsequent removal of the points belonging to only one (V or H) pattern. In the third step, initial data sets are recovered without the removed artifact points. Let us consider these steps in detail.

Step 1.

In this step, the PD, Eq. (2), is calculated for multiline patterns (see Fig. 1) to find the closest points to a line center (with typical value of r_a selected in the range of 0.1 – 0.3 mm that is a little bit wider than the line width). For this purpose, the point with highest PD is found and this point is placed in a new data set of lines. Other points belonging to the sphere with radius r_a around this point are then removed from the initial data set. This procedure is repeated until the initial data set is empty.

The procedure described above allows removing points of the initial data set non-uniformly: We remove more points, where many points are placed close to each other and do not remove anything, if initial points are far from each other. In other words, it is an adaptive downsampling procedure, which provides a uniform spatial representation of the 3D surface by an essentially smaller number of points (see Fig. 6).

FIGURE 6. Downsampling results for a multiline data set using the PD value calculated for different values of r_a .

In the resulting data set, the minimal distance between points is equal to r_a . However, information losses are minimized (see Fig. 6, right) due to a uniform distribution of points along a line. It was found experimentally that when $r_a = 0.01$ (see Fig. 6, left) all points of the initial set remain in the new set. When $r_a = 0.1$, the new set consists of 26% of the initial points number; if $r_a = 0.3$ only 8.5% of the initial number remain in the new set.

An example of the downsampling of the initial data (Fig. 3) is shown in Fig. 7. It can be seen in Fig. 7 that the spatially non-uniform downsampling based on calculating the PD allows significantly decreasing the number of points without essential losses of useful information about the object.

FIGURE 7. Downsampling results for a multiline data set using the PD function.

Step 2.

It was found that artifacts appear mainly in one of the two vertical (V) or horizontal (H) line directions. “Bad” points appearing only in V or H direction can be found by calculating the PD for each point in the V set to all points in the H set and opposite. The PD is calculated using Eq. (2) for the joint data set ($H+V$) and then for each point of the set H introduced by the points of the data set V and opposite. Thus, each point is characterized by two values: PD_{H+V} and “orthogonal” PD_{HV} (or PD_{VH}). These values allow a removal of the points with the lowest PDs.

The result of the Step 2 is illustrated in Fig. 8.

FIGURE 8. Result of artifact points removal appearing in only one (V or H) pattern of lines.

Step 3.

In this step, the each point PD within the initial data set from the enhanced downsampled data set (see Fig. 8) are calculated. If the PD is higher than a fixed threshold (say, 5%), the initial point is interpreted as correct and placed in the resulting data set. In this step, we recover the initial data set, but without the removed artifact points. Fig. 9 illustrates the results (top view).

FIGURE 9. Enhanced initial data (left) and removed points (right).

In Fig. 10, the results of applying all the steps of processing are illustrated in 3-D representation.

FIGURE 10. Results of the processing steps in 3D representation.

CONCLUSION

The advantage of the suggested artifact removal method consists in providing processing speed without essential losses of useful information. Downsampling of 10 times yields an increase of the processing speed of approximately 100 times. Non-uniform removal of redundant points allows an accurate recovery of the 3D surface with removed outliers.

It is important to note that an indexing procedure was applied to the initial data sets which only calculated the index for distances up to r_a . This increased the processing speed about 20-50 times. The total processing speed increased by factor of some thousand with respect to the direct distance calculation between each pair of points.

Future research is directed to match 3D representations obtained from different observation angles in order to recover the entire 3D surface and to provide an effective representation and storage of the 3D data.

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