All Pixels Calibration for ToF Camera

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Abstract. ToF (Time of Flight) camera is a new three-dimensional measurement technology. ToF camera can acquire depth images at high frame rates. In this paper, the influence of different measurement parameters on the accuracy of camera depth data is studied, the result shows that Integration time and measurement distance have great influence on the accuracy of camera depth data. While the quality of the pixel's depth data is closely related to the pixel's amplitude data. Therefore an integration time auto adaptation method based on amplitude data is proposed, which makes each pixel obtain the depth information under the best conditions. The experimental results show that ToF camera can effectively capture depth data of the complex scenes with distant and close shots by applying the integration time adaptation method. Finally, Gaussian process regression (GPR) model is used to calibrate the range errors of ToF camera. Experimental results show that this method can effectively calibrate the whole pixel.

1. Introduction

Three-dimensional technology (3d) has broad application prospects and commercial value in the field of computer vision, robot target recognition, three-dimensional modeling [1]. ToF camera is a new three-dimensional measurement technology, unlike monocular and binocular vision, it can capture 3d data at high frame rates. At the same time, it has the problem of insufficient accuracy [2]. There have been several studies [3-6] to calibrate ToF cameras. In the above studies, a single integration time is used, however, this is not reasonable, because for foreground and background scenes, if the integration time is fixed, the high reflectivity of the foreground may be saturated and the low reflectivity of the background will be too high noise due to lack of integration time. In [7-8], the author selects the appropriate integration time based on the average amplitude data of a scene. The result of this approach is also not ideal for scenarios with foreground and background. In the paper, an integration time auto adaptation method based on amplitude data is proposed, which makes each pixel obtain the depth information under the best conditions.

Once each pixel gets its depth under optimal conditions, further calibration is required. In order to calibrate ToF camera, some suggestions such as look-up table [9], sine model [10] and polynomial model [11] have been proposed to improve the accuracy of the camera. These methods work well in a particular scenario, but the calculations are too complicated. In [12], the authors propose a method using Gaussian process regression (GPR) to improve camera accuracy. However, only the center pixel has been dealt with by the author, and the differences between pixels have not been considered. This paper...
presents a new Gaussian kernel, not only considering the distance factor, but also taking into account the pixel factors.

2. ToF Camera Principle

ToF cameras are based on the Time of Flight principle. According to the measurement principle, there are two types of Time of Flight principle, one is continuous wave modulation, the other is non-continuous wave modulation. ToF cameras are based on continuous wave modulation. Figure 1(a) is diagram of non-continuous wave modulation. The flight time of light pulse is measured directly by a single photon avalanche diode. If the accuracy of the depth data is to reach the millimeter level, the clock precision needs to reach the picosecond level [13]. Figure 1(b) is diagram of continuous wave modulation. Light source (usually LED) is modulated into a sinusoidal, and the light wavelength is generally in the 870mm level. Modulated infrared light shines on the object and is reflected by the object and received by the CMOS.

By measuring travel time of the modulated light, you can get the distance of each pixel:

\[ D = \frac{t}{2} \times c \]  

Where D is the distance between the sensor and the object; c is the speed of light, t is the time of the light from being emitted to being received.

Time of flight is measured indirectly, in fact, it is obtained by the phase difference between the emitted light and the received light [14]. As shown in Figure 2, the received modulated light is sampled 4 times in one cycle with the sampling interval kept at 1/4 cycle. Based on the four sample values a, b, c, and d, the amplitude A and the phase difference can be calculated:

\[ A = \sqrt{(b - d)^2 + (a - c)^2} \]  

\[ \varphi = \arctan\left(\frac{b - d}{a - c}\right) \]
The distance $D$ is then derived from phase difference:

$$D = \frac{c\phi}{4\pi f}$$

(4)

Where $f$ is the modulation frequency.

3. Methodology

3.1. Analysis of range image

In order to measure the system errors of the camera, the camera is mounted on a tripod, and a laser range finder is coaxially placed on the camera for measuring the true value of the depth information (Figure 3). The center pixel was measured 1000 times at 1271mm, 1986mm and 2721mm respectively using the same integration time. The measurement results are shown in Figure 4. It can be seen that the systematic errors are all subject to Gaussian distribution at different distances, and the average range measurement errors at different distances are different.
In order to explore the influence of integration time on the accuracy of camera depth information, the variation of range measurement errors with integration time was measured at different distances (436mm, 884mm, 1788mm). The measurement results are shown in Figure 5. The figure shows both the range measurement errors and the amplitude intensity as a function of the integration time. It can be seen that the integration time has a great influence on the depth information of the camera. The variation of the range measurement errors with the integration time can correspond to the variation of the amplitude intensity with the integration time. When the amplitude is very small, the range measurement errors is very large because the integration time is too small. When the integration time increases, the range measurement error decreases and the amplitude increases. And when the amplitude is not changing, then, an oversaturation phenomenon always happened, simultaneously, the range measurement errors becomes larger. In addition, for the same object, the closer the object is, the more likely it is to cause oversaturation phenomenon. The farther the object is, the more likely integration time is not enough.

The experiment illustrates the appropriate integration time can be chosen based on the amplitude data. Considering that in complex scenes, there are various objects which position is different, and the range measurement errors is stable with the change of amplitude over a high dynamic range. So define a signal-noise ratio function(SNR) to illustrate the current quality of the image:

$$y(x) = \begin{cases} \frac{(x-\mu)^2}{2\sigma_1^2}, & x \leq \mu \\ \frac{(x-\mu)^2}{2\sigma_2^2}, & x > \mu \end{cases}$$

(5)

Where x is the amplitude. In this case, $\mu = 400\text{LSB}$, $\sigma_1 = 400\text{LSB}$, $\sigma_2 = 1600\text{LSB}$. 

![Figure 4](image-url)  
**Figure 4.** Histogram of the 1000 distance measurements at different distance

![Figure 5](image-url)  
**Figure 5.** Range error and amplitude intensity at different integration time
3.2. Integration time auto adaptation
Because the integration time has a great effect on the ToF camera depth data, and the appropriate integration time can be chosen according to the amplitude data. Therefore an integration time auto adaptation method based on amplitude data is proposed to make the distance measurement of each pixel under the best conditions. The proposed adaptation algorithm for integration time can be summarized in the following lines:
   a. Set an initial integration time.
   b. Then get the amplitude data and the depth data simultaneously for each pixel, according to the signal-noise ratio function (13), writes the depth data with a signal-noise ratio greater than the threshold (0.85 here) to the output image. If all pixels of output image is high quality, save the output image to PC, otherwise proceed to step c.
   c. Change the integration time and go to step b.

3.3. Distance calibration with GPR
In last few years, many models have been proposed for processing the range measurement errors of ToF cameras, such as look-up table models, sinusoidal models and polynomial models. In contrast with [12], in this paper, a new Gaussian nuclear is used for ToF camera calibration. Gaussian Processes regression(GPR) is a machine learning method developed based on statistical learning theory and Bayesian theory [15] which is suitable for dealing with regression problems with high latitudes, small samples and is non-linear.

A GP is determined by its mean function $m(x)$ which is always assumed to be zero and a covariance function $k(x, x')$:

$$f(x) \sim GP(m(x), k(x, x'))$$  \hspace{2cm} (6)

Where

$$m(x) = E[f(x)]$$  \hspace{2cm} (7)
$$k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))]$$  \hspace{2cm} (8)

The core of the GPR is the Gaussian nucleus, which represents the correlation between samples. In order to explore the influence of range on the accuracy of camera depth information for different pixels, the 3d data of flat white walls were measured at different distances. The experimental results are shown in Figure 6.

![Figure 6. Range error of different pixels at different distance](image-url)
It can be seen that the measurement error of the same pixel changes with the measurement distance, and the measurement error of different pixels in the same measurement distance is different. Therefore, the Gaussian Kernel can be described as:

$$k(x, i, j) = \sigma_1 \exp\left(-\frac{(x - x')^2}{2l_1^2}\right) + \sigma_2 \exp\left(-\frac{(i - i_0)^2 + (j - j_0)^2}{2l_2^2}\right) + \text{whitenoise} \quad (9)$$

Where The first term illustrates the relation with the distance, the second is the difference of different pixels, the third is the systematic error.

4. Experiment result

4.1. Integration time adaptation
This experiment illustrates the performance of the integration time auto adaptation method. As shown in Figure 7 (a), a scene with a foreground and a background is taken.

Figure 7. experiment of integration time adaptation

Figure 7(b) is the 3D data with single integration time. We can see that the center of computer appears oversaturation phenomenon because the computer is too close, and the bookcase can not shoot because too far away. Figure 7 (c) is the 3D data with integration time adaptation method. After using the integration time adaptation method, the oversaturation phenomenon of the computer is disappered, and bookcase are ready for shooting.

4.2. GPR for calibration
This experiment illustrates the performance of GPR for calibration. Figure 8 (a) shows the raw 3D data of a flat white wall from 2493 mm using integration time adaption method. Figure 8(b) is the histogram distribution of pixel depth values, and the standard deviation is:

$$\text{std} = \sqrt{\frac{\sum_{i=1}^{n} (d_i - \mu)^2}{n}} = 50 \quad (10)$$

In the ideal case, the depth values of each pixel should be equal, but the acquired depth values of each pixel have large deviations. So it is proposed to use GPR for camera calibration with Gaussian Kernel (9).

Depth data of flat white wall were obtained from 850 mm to 3550 mm (100 mm apart). At each distance, pixels with abscissa interval $\Delta x = 6$ and vertical coordinate interval $\Delta y = 8$ from pixel (1,1) are selected as training samples. The results of calibration using GPR are shown in Figure 8 (c) and Figure 8 (d). It can be seen that the range measurement accuracy is greatly improved. The histogram distribution
of pixel depth values distributed in a Gaussian distribution with mean equal to true range, and the standard deviation is:

\[ std = \sqrt{\frac{\sum_{i=1}^{n}(d_i - \mu)^2}{n}} = 14 \]  

(11)

![Raw 3D data](image1)

(a) Raw 3D data

![Histogram of pixel depth values](image2)

(b) histogram of pixel depth values

![3D data after calibrate](image3)

(c) 3D data after calibrate

![Histogram after calibrate](image4)

(d) histogram after calibrate

**Figure 8.** Range data and histogram at 2493mm

5. Conclusions

ToF cameras can provide both range images and amplitude images at frame rates without scanning. But, it also has the problem of insufficient accuracy. In order to solve the problem of accuracy, this paper has made three contributions: First, the influence of integration time and measurement distance on the accuracy of camera depth data is studied, and it is proposed that appropriate integration time can be chosen based on the amplitude data. Second, based on the above conclusion, integration time auto adaptation method based on amplitude data is proposed, which makes each pixel obtain the depth information under the best conditions. The experimental results show that ToF camera can effectively capture depth data of the complex scenes with distant and close shots using integration time adaptation. Finally, a new Gaussian kernel is proposed for TOF camera calibration. Experimental results show that this method can effectively calibrate the whole pixel with standard deviation from 50mm down to 14mm. Besides that, further studies is needed to further improve the accuracy of TOF cameras.

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