Classifying Transverse Motion in Time-of-Flight Range Imaging

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Abstract: Classification of step motion in time-of-flight imaging using the stochastic oscillator and autocorrelation is proposed. Machine learning algorithms correctly identify the step location in 65–75% of trials, with apparent good noise robustness.

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1. Introduction

Optical time-of-flight (ToF) full-field range imaging is a leading method for full-field distance measurement [1], however ToF imaging is a multi-frame technique that assumes a static scene. Any object motion in the scene causes error. Here we are most concerned with the motion of an edge over a pixel, which causes a step change. Explicit modelling of the step change can lead to error free imaging [2], provided that the point in time that the step change occurred is correctly identified.

In this work we use machine learning to identify the step in time. Taking inspiration from stochastic modelling of ToF imaging [3], we investigate the financial modelling method of the stochastic oscillator [4], as well as auto correlation, to normalize unwanted parameters from the ToF data.

2. Methods

In ToF range imaging the scene is actively illuminated with amplitude modulated light of radio frequency modulation frequency, f. A phase shift, ϕ, given by,

$$\phi = \frac{4\pi d f}{c}, \tag{1}$$

is induced by the ToF of the light, where d is the distance and c is the speed of light. The light return is demodulated by the sensor (in CMOS) in homodyne with the illumination. The integrated intensity, I_n, (of phase step n for $n \in 1,\ldots,N$ and N is the number of frames acquired) is the so called correlated waveform, namely,

$$I_n = \alpha \cos(\phi + \theta_n) + \beta, \tag{2}$$

where α is the amplitude, β is the background light and θ_n is a programmable phase shift between the light source and sensor that is adjusted for each phase step n so that Fourier analysis of the I_n recovers ϕ.

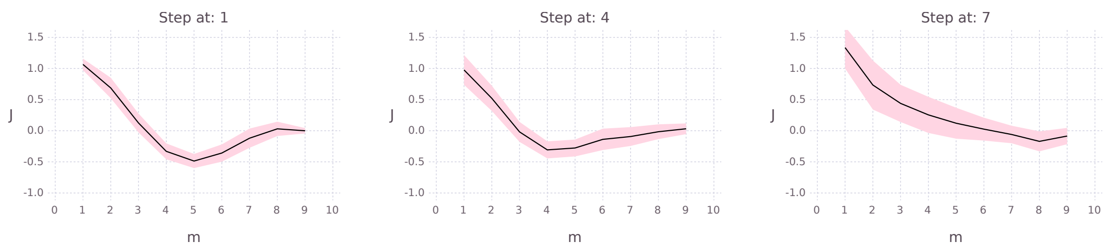
When the edge of an object in transverse motion passes over the pixel field of view, α, β, and ϕ can change [2]. Explicit modelling and system inversion can determine the range, provided that the step change at the pixel is both detected and localized to the correct phase step. Analysis of the second Fourier bin reveals the presence of a step change [2] but does not localize it. In this work we show how to localize the step change to phase step n.

The proposed method is the stochastic oscillator (SO) [4], and the autocorrelation of the result,

$$J_m = \sum_n S_n S_{n+m} \qquad \text{with} \qquad S_n = \frac{\max(I_n) - I_n}{\max(I_n) - \min(I_n)} - \frac{1}{2}, \tag{3}$$

where the maximum and minimum operations are taken over all n. (The subtraction of 1/2 is an innovation on our part to center S_n about zero.) Computing S_n eliminates constant α and β. The auto correlation, J_m, normalizes for ϕ.

We simulated plausible I_n and J_m. Nine even phase steps were used, i.e. $\theta_n = 2\pi(n-1)/N$ with $N = 9$. For step change at each n, 1001 simulations were taken, with random ϕ, α, and β and with random step values of ϕ and α (β is assumed constant [2]). The simulation was repeated for additive zero mean Gaussian noise with standard deviation of 0%, 0.5%, 5% and 10% of the average value of α.



(a) (b) (c)

Fig. 1: Autocorrelation of the SO at various phase step points. The solid line is the mean and the shaded region is one standard deviation.

The simulated data were imported into the WEKA machine learning package [5] to test logistic regression, C4.5 decision trees, random trees and random forests. First, ten-fold cross validation was used. Second, each of the machine learning algorithms trained on the 10% noise data and tested on the 5% noise data.

3. Results and Discussion

The correlation of the stochastic oscillator, J_m, is shown in Figure 1 for steps at the first, fourth, and seventh phase steps. The shape clearly changes with the step change location. In Table 1 we list the results of the classification.

Table 1: Rate of correct step change localization by cross validation and separate test set.

	Logistic	C4.5	Random Tree	Random Forest
0%	0.71	0.72	0.72	0.79
0.5%	0.71	0.73	0.71	0.77
5%	0.69	0.71	0.69	0.75
10%	0.68	0.72	0.71	0.77
Test Set	0.66	0.66	0.65	0.74

Random class assignment is 1 in 8 (0.125); perfect classification is 1.0. Logistic, C4.5 and random tree classifiers all performed around 0.70. Random forest performed better in the range 0.75–0.80, but at the cost of a very large tree. The interesting feature is that the proposed method appears robust to noise, an advantage over previous work [2] which rapidly declined in performance with noise level. Testing on the independent set saw a small a drop in performance, indicating the possibility of over fitting in cross validation.

4. Conclusion

Step identification using the stochastic oscillator improved robustness to noise. Tree based classifier algorithms and logistic regression correctly identified the step location in 65–75% of trials. In future work we will extend classification to two steps, and consider data over a local region around each pixel.

References

1. D. Lefloch, R. Nair, F. Lenzen, H. Schäfer, L. Streeter, M. J. Cree, R. Koch, and A. Kolb, *Technical Foundation and Calibration Methods for Time-of-Flight Cameras* (Springer Berlin Heidelberg, Berlin, Heidelberg, 2013), pp. 3–24.
2. L. Streeter, "Towards generalised time-of-flight range imaging at the edge of moving objects," in "Image and Vision Computing New Zealand (IVCNZ'17)," (Christchurch, New Zealand, 2017), pp. 1–6.
3. L. Streeter, "Stochastic calculus analysis of optical time-of-flight range imaging and estimation of radial motion." Journal of the Optical Society of America A **34**, 1063–1072 (2017).
4. Y. Ni, Y.-C. Liao, and P. Huang, "Momentum in the Chinese stock market: Evidence from stochastic oscillator indicators," Emerging Markets Finance & Trade **51**, S99–S110 (2015).
5. I. H. Witten, E. Frank, and M. A. Hall, *Data Mining: Practical Machine Learning Tools and Techniques* (Elsevier Science, Amsterdam, Netherlands, 2011), 3rd ed.