Fuzzy Calibration for Pulsed Time-of-Flight Laser Rangefinder

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Abstract

A fuzzy approach to real-time calibration of mobile laser rangefinder is presented as an alternative to the methods based on adaptive algorithms. The main error source in such a measurement system is drift error due to the changes of ambient temperature. It may be compensated using repeatedly performed calibration based on the time-of-flight measurement of laser pulse propagating through the constant section of optical fiber. To minimize calibration rate we designed fuzzy calibrator that traces actual changes of drift error and calculates the optimum rate of calibration. This method has been tested using mobile laser rangefinder with 3 cm single-shot accuracy.

1. Introduction

The accuracy of laser ranging system (LRS) is limited by many error sources including the quantization error of time-to-digital converters (TDCs), drift error and other factors that contribute to the overall measurement error as systematic or random errors [1]. Random errors typical for in-field operation of mobile laser rangefinders are caused e.g. by false returns from moving obstacles or by strong sunlight. Ranging over relatively long distances, especially to the noncooperative targets, when reflected laser beam detected by the receiver is very weak, may also be disturbed by the noise within the detector, receiver and discriminator. These errors may be reduced by averaging of multiple measurement results or/and by more complicated robust estimation methods that reject outliers from a sample of measurement results [2], [3]. Obviously, some error sources of LRS cannot be compensated by statistical data processing and appropriate calibration is needed to identify and correct these errors. According to our experience, the most important source of long time error (LTE) in LRS is due to the temperature drift that changes actual parameters of the receiver and pulse discriminator.

2. Automatic calibration of laser rangefinder

Figures 1 and 2 show an experimental setup of LRS and its simplified block diagram. The LRS consists of optics with pulsed laser diode, receivers/discriminators, and time-interval counter designed as a portable unit with integrated single-chip time counter [4].

Fig. 1. Experimental setup of pulsed LRS

Fig. 2. Simplified block diagram of pulsed LRS

The laser module ML100H15 (Power Technology Inc.) is a complete block with an embedded
power supply and features 15 ns pulse width, 100 W output power (peak), maximum pulse repetition rate of 5 kHz and the wavelength equal to 905 nm.

The laser beam is transmitted to the target and received as the Stop pulse. Simultaneously, a small part of the beam is sent to the receiving telescope directly via the optical fiber for calibration purposes. It means, that each Start pulse is accompanied by two Stop pulses coming from the target and from the calibration feedback. Since the integrated TDCs can operate only in a single-stop mode, one of the Stop pulses is rejected by the programmable gate at the TDC’s input. Therefore, the LRS can perform either the user measurement or calibration measurement, but not both of them at the same laser shot. Stop pulses are fed by the optical fibers to the opto-electric converters with avalanche photodiodes, amplifiers, constant-fraction discriminators and ECL/TTL converters. Then, the time interval between the Start and Stop pulses is measured by the precision time counter with 200 ps resolution based on the integrated FPGA chip. Relevant data processing is performed using embedded 16-bit processor (XA from Philips).

Figure 3 shows the typical long-term behavior of LRS’s drift error obtained by continuously repeated measurements of constant distance while calibration is disabled. It may be seen that the warm-up process of LRS after cold start (power-on) is observed as a dramatic change of the measurement result and the maximum difference \( r \) approaches 400 mm.

![Fig. 3. Illustration of the drift error (calibration disabled, constant ambient temperature)](image)

When ambient temperature is stable, the drift error becomes much smaller. In practice, during in-field operation such stable thermal conditions are not met and even after warm-up the drift error randomly varies within the bounds of few hundreds millimeters. Of course, this is unacceptable in precise measurements, when subcentimeter accuracy is needed (in averaging mode).

In order to improve the long-term accuracy of distance measurements one can calibrate the LRS using a sample of measurements (typically 100-1000 shots) with activated calibration feedback. The simplest real-time calibration strategy repeats the calibration at any given constant rate (say each 1 minute) but is far from optimum, because the constant calibration rate could be too small (e.g. after power-on) or too high, when thermal conditions are stable.

It should be noted, that a complete calibration consisting of 1000 measurements and relevant calculations needs about 3 s of LRS operation. Thus, the high calibration rate increases so called dead time of the instrument when LRS cannot perform user measurements. In other words, the calibration rate should be chosen by compromise between the calibration accuracy and dead time.

To overcome this drawback of constant calibration rate we used real-time self-calibration algorithm based on adaptive adjustment of calibration rate according to the current value of drift error. This method has been proposed in [5] and tested in LRS applications as described in [6] and [7]. We also tested that method using the LRS from figures 1 and 2. Experimental results are satisfactory [2], but not as good as one can expect considering results published before in [5]-[7]. Main reason for this are different environmental conditions that are more unstable in a case of a new mobile LRS comparing to the stationary LRSs tested before. Tailoring the adaptive self-calibration for a new LRS we met some difficulties with proper selection of algorithm’s parameters. This process has a heuristic nature and involves many field tests at different environmental conditions. Even after a careful adjustment of parameters the uncertainty of calibration may exceed few tens of millimeters when rapid changes of ambient temperature occur. These experiences led us to the fuzzy calibrator.

### 3. Fuzzy calibration of LRS

According to the general rules of fuzzy logic control [8], our fuzzy logic calibrator (FLC) may be regarded as a system shown in fig. 4. The controller determines consecutive moments of calibrations that are nonuniformly spaced in time, according to the current value of drift error.

The following five variables are used to exchange data between the process and fuzzy inference mechanism: \( \text{delta_time} \), \( \text{delta_ilte} \), \( \text{delta_mes} \), \( \text{start_ilte} \), \( \text{beta_time} \). First three of them are input variables for FLC and the last two are outputs of FLC. The variable \( \text{delta_time} \) is time interval between the current time \( \text{time_current} \) obtained from a real-time clock (RTC) and the moment \( \text{time_last_ilte} \) of last calibration (ILTE – identification of LTE) performed by LRS, normalized versus adaptively adjusted parameter \( \text{delta_time_set} \):

\[
\text{delta_time} = \frac{\text{time_current} - \text{time_last_ilte} - \text{delta_time_set}}{\text{delta_time_set}}.
\]
The parameter \( \text{delta\_time\_set} \) is a reference time period between two successive calibration, and its initial value \( \text{delta\_time\_init} \) is chosen experimentally (say equal to 8 s). After each calibration (ILTE) the variable \( \text{delta\_time\_set} \) is modified according to the rule:

\[
\text{delta\_time\_set} = \text{delta\_time\_set} \times \text{beta\_time},
\]

where \( \text{beta\_time} \) denotes an adaptive factor obtained from FLC. When \( \text{beta\_time} \) is less than 1, the calibration rate decreases, Otherwise the calibration rate is increased.

The variable \( \text{delta\_meas} \) is an absolute value of difference between the actual (\( \text{meas\_actual} \)) and last (\( \text{meas\_last} \)) result of user measurement:

\[
\text{delta\_meas} = |\text{meas\_actual} - \text{meas\_last}|.
\]

The variable \( \text{delta\_ilte} \) denotes an absolute value of difference between the actual (\( \text{ilte\_actual} \)) and last (\( \text{ilte\_last} \)) result of calibration:

\[
\text{delta\_ilte} = |\text{ilte\_actual} - \text{ilte\_last}|.
\]

Finally, the variable \( \text{start\_ilte} \) is used to switch the LRS operating mode:

\[
\text{if} \ (\text{start\_ilte} > 0.9) \ \text{then ILTE} \\
\text{else Measurement.}
\]

\[
\begin{array}{cccccc}
\text{delta\_time} & \text{delta\_meas} & \text{start\_ilte} \\
\text{beta\_time} & \text{delta\_ilte} & \text{ILTE}
\end{array}
\]

Fig. 5. The FLC in fuzzyTECH environment

Figure 5 shows a block diagram of FLC developed with the use of fuzzyTECH IDE. The FLC uses five variables described before and one block of fuzzy rules (RB1). The membership functions have been determined by a number of experiments followed by appropriate optimization using the fuzzyTECH interactive simulator (fig. 6 and 7).

\[
\begin{array}{cccccc}
\text{delta\_time} & \text{delta\_meas} \\
-1.2 & -0.5 & 0.4
\end{array}
\]

Fig. 6. Membership functions of input variables

It should be noted, that the membership function \( m_3 \) of the variable \( \text{beta\_time} \) having an asymmetric trapezoidal form is of special importance. When the drift error of LRS changes rapidly its value, this function provides an adequate increase of calibration rate (by factor of about 10).

The FLC has been developed using the fuzzyTECH software (ver. 5.54e) from Inform Software Corp. [9]. This integrated development environment (IDE) features fast and easy design, simulation and optimization of fuzzy logic controllers. It also generates complete output C code that may be directly implemented in a real system.
Table 1 shows the complete rule base of the FLC. Each membership function of the output variables beta_time and start_iltie is accompanied by DoS (degree of support).

Table 1. Rule base for the FLC

<table>
<thead>
<tr>
<th>If</th>
<th>Then</th>
<th>Then</th>
<th>DoS</th>
<th>beta_time</th>
<th>DoS</th>
<th>start_iltie</th>
</tr>
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<tr>
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<tr>
<td>m3</td>
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<tr>
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</table>

4. Tests and optimization of FLC

Figure 8 shows an experimental setup used for optimization of FLC. The fuzzy inference as well as the fuzzification and defuzzification blocks are implemented in the fuzzyTECH IDE, while other functions including hardware control, data exchange and GUI (Graphical User Interface) are developed using the MATLAB environment. Control signals for LRS and measurement results are transmitted via standard RS-232C interface. In order to connect the FLC part with MATLAB procedures we used a typical DDE technique (Dynamic Data Exchange).

An important feature of the experimental setup is a versatile toolbox for collecting and archiving the measurement data. Using this toolbox we were able to check different versions of FLCs for the same pre-recorded data from LRS. In this way, after several experiments we obtained the final form of membership functions and rule base presented in figs 6, 7 and table 1.

5. Experimental results

To verify the FLC we made many field experiments using portable data processing unit with embedded microcontroller instead of PC. Some tests have been performed at extremely difficult conditions (snow, heavy rain, fog, sun light, unstable ambient temperature).

Fig. 9 shows a typical measurement session for “good” environmental conditions (E1), when ambient temperature is stable. An example of measurement data for unstable temperature (E2) is illustrated in fig. 10.
a strong growth of drift, the maximum error has been decreased from 473 mm (calibration disabled) to about 35 mm (calibration enabled).

Looking closely to the solid lines in figs 9 and 10 we can see repetitive “teeth” resulting from FLC action. As we could expect, the calibration rate is high when drift error increases, and is respectively lower when drift error decreases.

![Graph showing experimental results for unstable environment (E2)](image)

**Fig. 10. Experimental results for unstable environment (E2)**

Table 2 shows a brief comparison of results obtained for conditions E1 and E2. The column ‘Adaptive method’ refers to the data obtained using the adaptive calibration method described in [5]. The symbol \( l \) denotes the total number of calibration points during the measurement session.

<table>
<thead>
<tr>
<th>Meas. envirom.</th>
<th>Calibration disabled</th>
<th>Calibration enabled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>FL method</td>
</tr>
<tr>
<td>( r ) [mm]</td>
<td>( l )</td>
<td>( r ) [mm]</td>
</tr>
<tr>
<td>E1</td>
<td>400</td>
<td>-</td>
</tr>
<tr>
<td>E2</td>
<td>473</td>
<td>119</td>
</tr>
</tbody>
</table>

6. Conclusion

The FLC presented in this paper performs better than adaptive calibration method used in our laboratory before, especially when thermal conditions are very unstable. An important advantage of the fuzzy approach to the LRS’s calibration is easier and faster optimization of the calibrator.

Acknowledgment

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References