Variability of Sounder Measurements in Manufacturing Facilities

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Abstract—Uncertainties in the linear regression fit of Path Loss are derived from variability in position. These uncertainties are used to determine the required positional accuracy for channel sounder measurements.

Keywords—Channel Sounders, Microwave Measurement, Uncertainty Analysis, Wireless System

I. INTRODUCTION

The National Institute of Standards and Technology (NIST) is characterizing manufacturing environments through measurements of the channel impulse response of representative production facilities. Using a pseudo-noise channel probe signal [1], a band-limited noise-like signal is transmitted over the channel. Since the signal’s autocorrelation function approximates an impulse, the channel impulse response (CIR) can be measured by correlating the received signal with the transmitted pseudo-noise code. This measured impulse response can be used to derive the path loss.

Relating measured path loss and other channel parameters to positioning a physical manufacturing environment can be done with differing levels of accuracy. A robot, which provides location information while measuring the channel, is highly accurate but costly. A human, pushing a cart during a measurement run, is more cost effective but less accurate. While cost is an important parameter, accuracy in physical location like check points is highly prized by system engineers deploying wireless networks using estimated path loss. Therefore, metrics that provide insight into the required accuracy between a single check point and path loss are useful when choosing between a robot or human walking approach. In this contribution, uncertainties are derived from a linear regression fit of measured path loss from statistical analysis.

II. TECHNICAL DISCUSSION

A. Variability in Path Loss Linear Regression

The linear regression used to find path loss provides channel information through the calculation of the slope. The slope of the linear regression provides insight into the type and path loss severity of the channel. The linear regression model with one independent variable for path loss is shown in (1):

\[ \rho = A + Br, \]

where \( \rho \) is the path loss in dB, \( r \) is the check point true values in meters, and \( A \) and \( B \) are sampled least-square estimators; \( r \) is not observed directly. Instead, the distance between the channel sounder’s transmitter and receiver, \( r \), is observed. Equation (1) becomes

\[ r = r_t + \sigma_{PE}, \]

where \( r_{PE} \) is the range position error which includes random perturbations. We assume that \( r_{PE} \) is distributed as a normal random variable with mean zero and a standard deviation of \( \sigma_{r_{PE}} \). The sampled least-square estimators, \( A \) and \( B \), for the linear regression model can be determined with a known \( \sigma_{r_{PE}} \) [2].

B. Range Position Error, \( r_{PE} \)

We simulated a range position error using a Monte Carlo simulation for small \( x_{PE} \) and \( y_{PE} \) surrounding a single \( r_t \). We use the standard deviation \( \sigma_{r_{PE}} \) of the normal distribution to quantify the error in \( r_{PE} \) for different check point true values \( r_t \) in a factory environment. A variety of standard deviation values were calculated with a Monte Carlo Position Uncertainty algorithm. An example of this algorithm for perturbation in Cartesian \( x_{PE} \) and \( y_{PE} \) is shown in (4), (5), and (6):

\[ x_{PE} = \pm v \cdot t \cdot \xi + \frac{1}{2} a \cdot t^2 \cdot \xi, \]  
\[ y_{PE} = \pm v \cdot t \cdot \xi + \frac{1}{2} a \cdot t^2 \cdot \xi, \]

\[ \xi \sim U(0,1). \]
where $\varsigma$ is a pseudorandom value from a uniform distribution with the open interval of $(0,1)$, $v$ is velocity, $t$ is time, and $a$ is acceleration.

The standard deviation $\sigma_{rPE} = \sqrt{\sigma_{PE}^2}$ is found with (7):

$$\sigma_{rPE}^2 = \frac{\bar{x}_{PE}^2 - \sigma_{PE}^2 + \bar{y}_{PE}^2 - \sigma_{PE}^2 + 2\bar{x}_{PE}\bar{y}_{PE}\sigma_{xyPE}}{\bar{x}_{PE}^2 + \bar{y}_{PE}^2},$$  \hspace{1cm} (7)

where $\bar{x}_{PE}$ is the mean of the $x_{PE}$, $\sigma_{PE}^2$ is the variance of $x_{PE}$, $\bar{y}_{PE}$ is the mean of the $y_{PE}$, $\sigma_{PE}^2$ is the variance of $y$, and $\sigma_{xyPE}$ is the covariance of $x_{PE}$ and $y_{PE}$. Fig. 1 shows our simulated $\sigma_{rPE}$ versus independent values of $r_t$ for 500 Monte Carlo simulations per $r_t$ with $t = 3$ s, $v = 1.4$ m/s, $a = 0.75$ m/s$^2$.

Fig. 1. Simulated Position Error for $t = 3$ s, $v = 1.4$ m/s, and $a = 0.75$ m/s$^2$.

Table 1 contains different simulated $\sigma_{rPE}$ values based upon time, velocity, and acceleration.

<table>
<thead>
<tr>
<th>$t$ (s)</th>
<th>$v$ (m/s)</th>
<th>$a$ (m/s$^2$)</th>
<th>$\sigma_{rPE}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stationary</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Robot</td>
<td>3</td>
<td>0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>Human Walking</td>
<td>3</td>
<td>1.4</td>
<td>0.75</td>
</tr>
<tr>
<td>Human Running</td>
<td>5</td>
<td>10</td>
<td>1</td>
</tr>
</tbody>
</table>

C. Calculation of Uncertainty in $A$ and $B$

With the assumption that the error in $r_{PE}$ is quantified by $\sigma_{rPE}$, $B$, and $A$ and their uncertainties can be computed with (8) – (13):

$$B = \frac{\sigma_{pr}}{\sigma_{rPE} - \sigma_{PE}}$$ \hspace{1cm} (8)

$$A = \bar{\rho} \cdot B \bar{r}$$ \hspace{1cm} (9)

$$B_{Uncert} = \frac{1}{(M-1)(\sigma_{rPE}^2 - \sigma_{PE}^2)} \left( \sigma_{rPE}^2 s_{vv} + B^2 \sigma_{PE}^2 \right),$$ \hspace{1cm} (10)

$$A_{Uncert} = (\bar{r})^2 B_{Uncert} + \frac{s_{vv}}{M},$$ \hspace{1cm} (11)

$$s_{vv} = \frac{1}{M-2} \sum_{m=1}^{M} [(\rho_m - \bar{\rho}) - (r_m - \bar{r})] B]^2,$$ \hspace{1cm} (12)

where $\sigma_{pr}$ is the covariance between the path loss $\rho$ and the range $r$, $\sigma_{PE}^2$ is the variance of $r$, $\bar{\rho}$ is the mean of $\rho$, $\bar{r}$ is the mean of the range, and $M$ is the number of samples.

In Table 2, the uncertainties for $A$ and $B$ were determined for different $\sigma_{rPE}$. From Table 1, when $\sigma_{rPE}$ equals 2.6 m, which corresponds to a human walking, the uncertainty of $B$ was 0.054. Based upon these values, the channel sounder platform of a human walking lies within the two sigma bounds of the bounds of the Stationary case. Fig. 2 shows the standard path loss versus range with the uncertainties introduced by $\sigma_{rPE}$ for a human walking as compared to path loss data collected for the Stationary case.

$$TABLE 2: B, and UNCERTAINTY $B$, A and UNCERTAINTY $A$$$

| Stationary | 3 | 0.0036 | 21 | 0.62 |
| Robot | 4.9 | 0.026 | -3 | 4.4 |
| Human Walking | 4.9 | 0.054 | -3 | 9.2 |
| Human Running | 4.9 | 130 | -3 | 2300 |

Fig. 2: Path loss versus range with uncertainties for a human walking.

III. CONCLUSION

$B$, $A$ and their uncertainties provide insight into the required accuracy between physical location and path loss, when choosing between a robot or the human walking approach for different levels of accuracy in check point position.

REFERENCES


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