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Blind Identification of occurrence of multi-modality in laser feedback based self-mixing sensor

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Self-mixing interferometry (SMI) is an attractive sensing scheme which typically relies on mono-modal operation of employed laser diode. However, change in laser modality can occur due to change in operating conditions. So, detection of occurrence of multi-modality in SMI signals is necessary to avoid erroneous metric measurements. Typically, processing of multi-modal SMI signals is a difficult task due to the diverse and complex nature of such signals. However, the proposed techniques can significantly ease this task by identifying the modal state of SMI signals with 100% success rate, so that interferometric fringes can be correctly interpreted for metric sensing applications.

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SELF-MIXING (SM) or optical feedback (OF) interferometry [1,2] is actively researched for vibration, angle [3], frequency [4], size [5], range-finding [6], topographical [7], and seismic applications [8] due to the simple, low-cost, and miniaturized nature of SM sensors. In order to design low-cost SM sensors, usually commercial off the shelf (COTS) laser diodes (LD) are preferred. However, due to OF inside the active laser cavity, such low-cost mono-modal LDs are prone to mode switching (as a function of operating conditions) and/or laser modality switching can occur due to change in operating conditions. So, detection of occurrence of multi-modal LDs is necessary to avoid erroneous metric measurements. Typically, processing of multi-modal SMI signals is a difficult task due to the diverse and complex nature of such signals. However, the proposed techniques can significantly ease this task by identifying the modal state of SMI signals with 100% success rate, so that interferometric fringes can be correctly interpreted for metric sensing applications.

Various mono- and multi-modal SM signals were acquired by using two different LDs, L637P5 by Oclaro® and HL6501MG by Hitachi®, one at a time. A polished metallic ring (mounted on a mechanical shaker, SF-9324 by PASCO®) was used as the remote vibrating target. L637P5 LD has operating wavelength $\lambda_0$ of 637 nm and threshold current $I_{th}$ of 20 mA, emitting 5 mW optical power. HL6501MG LD has $\lambda_0$ of 650 nm and $I_{th}$ of 45 mA, providing 35 mW optical power. Each LD has a built-in photodiode through which SM signals were obtained. Different mono- and multi-modal SM signals were acquired under varying optical feedback and LD operating current ($I_{op}$) conditions. Multi-modal SM signals were observed to occur when both the optical feedback coupling (by using the focusing lens) and $I_{op}$ were exceeded unity. Fig. 1(a-b) presents two multi-modal SM signals based on HL6501MG LD with $I_{op}/I_{th}$ ratio of 78mA/45mA=1.73, and 82mA/45mA=1.82 respectively under high optical feedback coupling. However, as optical feedback coupling was reduced (by de-focusing the lens) then mono-modal signal occurred even when $I_{op}/I_{th}$ was

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1.73 (see Fig. 1 (c)). A dataset of 60 SM signals (30 mono- and 30 multi-modal SM signals) is used to verify the performance of the proposed techniques using SM signal statistical parameters.

Each of the proposed four different techniques for identification of SM multi-modality is detailed below.

Variance based technique (VBT) is based on the parameter var_{p-diff}, which is a measure of peak to peak dynamic variation of an SM signal. Clearly, var_{p-diff} should be generally greater for a multi-modal SM signal due to composition of different modes producing dissimilar multi-modal fringes, as opposed to a mono-modal signal in which similar fringes occur (see Fig. 1). Consequently, larger variation in amplitude occurs in multi-modal signals as compared to mono-modal signals.

However, to perform VBT on normalized SM signal, two main phases are required: (1) customized local maxima detection and (2) estimation and analysis of var_{p-diff}. Customized local maxima detection is done by the following steps, which are also presented in Fig. 2.

1) First, inter-maxima separation (SM_{sep}) is computed by using auto-correlation of SM signal. SM_{sep} is indicative of the distance in between two consecutive maxima.

2) Then, the mean value of input SM signal, denoted by SM̅, is computed.

3) Input SM signal (having N number of samples) is divided into ‘n’ intervals by using n = round(N/SM_{sep}).

4) Then, local maxima of each interval is determined.

5) Valleys (SM signal portions with lower amplitude around local maxima) on left (lv) and right (rv) is determined, for each local maximum of every interval.

6) Valley-less maxima are discarded and maxima with

![Flowchart of customized maxima detection technique](http://dx.doi.org/10.3788/COL202018.011201)

Fig. 3. Flowchart of variance based technique (VBT).

both valleys are retained.

7) Finally, amplitude values of maxima (having both valleys) are compared with SM̅, and maxima with greater amplitude values are retained and considered as genuine maxima, while those with lower amplitude values are removed.

VBT second phase steps (see Fig. 3) are detailed below:

1) Differentiation of amplitude values of detected maxima (mx_{diff}) is taken to determine peak to peak dynamic variations (var_{p-diff}).

2) var_{p-diff} is determined by taking variance of mx_{diff} values.

3) A threshold value (th_{kur}) of var_{p-diff} is employed and is compared with var_{p-diff} value of under-process SM signal to determine the modality of input signal. If th_{kur} < var_{p-diff}, then input SM signal is considered a multimodal signal else it is considered a mono-modal signal. Note that this threshold (as well as subsequent thresholds in other techniques) is set in the light of various simulation results obtained under varying optical feedback coupling, amplitude of target vibration, and noise conditions as detailed ahead.

Kurtosis based technique (KBT) is based on the statistical parameter of kurtosis which is indicative of a signal’s irregularity. Usually, amplitude of multi-modal SM signals is more irregular as compared to that of mono-modal SM signals. Thus, kurtosis value of a SM signal, denoted by SM_{kur}, can be used to extract information about its modality, where

\[ SM_{kur} = \frac{\sum_{i=1}^{N} (SM_i - \bar{SM})^4}{s^4} \]  \hspace{1cm} (1)

Here s denotes the standard deviation value of the input SM signal. A threshold value (th_{kur}) is set (by using simulation results) and is compared with SM_{kur}. If SM_{kur} > th_{kur} then input SM signal is considered multi-modal, else it is considered a mono-modal SM signal. Steps of KBT are shown in Fig (4).

Skewness based Technique (SBT) uses the statistical parameter of skewness which is a measure of asymmetry of the SM data around the sample mean. Conventionally, mono-modal SM signals are evenly distributed around the mean value. However, most commonly encountered multi-modal signals are not even around the mean value. Thus, skewness parameter of a SM signal (denoted by SM_{skw}) can also be useful in classifying the modality of a SM signal.
Skewness-kurtosis based technique (SKBT) is based on the ratio \( SM_{skw} = SM_{skw}/SM_{skw} \) of above-mentioned SM signal parameters. As both \( SM_{skw} \) and \( SM_{skw} \) detailed above are good indicators of multi-modality, so their ratio \( SM_{skw} \) is also investigated for identifying multi-modality. Note that to avoid division by values of \( SM_{skw} \) approaching 0, all values of \( SM_{skw} \text{ < 0.02} \) were set to 0.02 to plot \( SM_{skw} \text{ in Fig. 5(d)}. \) Absolute value of \( SM_{skw} \) is compared with employed threshold value \( (th_{skw}). \) If \( SM_{skw} \text{ < th}_{skw} \) then under-process SM signal is considered multi-modal else it is considered mono-modal. Steps of SKBT are also shown in Fig 4.

Let us now discuss how the various threshold values, used in each of the four presented techniques, were set by performing simulations for a representative sample of SM signals, by using SM model\([1,2]\) under different optical feedback coupling (such as frequently encountered weak- and moderate-optical feedback regime \([1,2]\)), amplitude of target vibration in terms of \( \lambda \text{, and additive noise (resulting in different signal to noise ratio (SNR) of SM signals)} \text{ conditions. Evolution of different parameters with respect to C, and amplitude of target vibration in the absence of noise for mono-modal operation can be observed from Fig. 5. It can be observed from Fig. 5(a) that varp-diff is always lower than 0.017 for mono-modal noiseless SM signals. In Fig. 5(b) SMvar increases with C which is expected since the more C increases the more asymmetric the SM fringes become. Regarding SMskw (see Fig. 5(c)), for low C values (close to one), SMskw is close to zero as positive and negative fringes are similar. Then, as C increases, \(|SMskw|\text{ value tends to increase due to the increasing asymmetry between the positive and negative fringes of SM signal.}

Furthermore, to ascertain impact of additive noise on chosen parameters, simulations for weak feedback regime (\( C = 0.1 \)) and moderate feedback regime (\( C = 4 \)) are also performed (see Table 1 and Table 2 respectively). Two weak- and moderate feedback regime SM signals under different noise conditions (SNR = 10 dB and SNR = 40 dB) are graphically shown in Fig. 6 as well. Value of \( C = 4 \text{ is specifically chosen to perform noise analysis as it generally corresponds to the worst-case statistical parameter values. It can be observed from Table 1 and Fig. 6 that value of parameters such as varp-diff is decreasing significantly as SNR improves. Higher SNR values result in fewer local maxima generated by noise (and thus not genuine fringes) to be wrongly considered as fringe. Therefore, the calculation of varp-diff will not take them into account and hence varp-diff value will decrease. Conduct of these simulations under different levels of noise, amplitude of target vibration, and OF coupling provides information about the expected range and worst-case value of proposed parameters, resulting in extraction of different threshold values (see Table 3).
Table 1. Values of statistical parameters of simulated normalized mono-modal SM signals for varying SNR under weak-feedback regime for $C=0.1$, and amplitude = 5A_e.

<table>
<thead>
<tr>
<th>Techs.</th>
<th>Feats.</th>
<th>SNR (10 dB)</th>
<th>SNR (20 dB)</th>
<th>SNR (30 dB)</th>
<th>SNR (40 dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VBT</td>
<td>var-diff</td>
<td>0.015</td>
<td>0.012</td>
<td>0.012</td>
<td>0.008</td>
</tr>
<tr>
<td>KBT</td>
<td>SM_eve</td>
<td>1.718</td>
<td>1.452</td>
<td>1.433</td>
<td>1.429</td>
</tr>
<tr>
<td>SBT</td>
<td>SM_eve</td>
<td>0.149</td>
<td>0.144</td>
<td>0.142</td>
<td>0.141</td>
</tr>
</tbody>
</table>

Table 2. Statistical parameters’ values for simulated normalized mono-modal SM signals for varying SNR under moderate-feedback regime ($C=4$), and amplitude = 5A_e (a).

<table>
<thead>
<tr>
<th>Techs.</th>
<th>Feats.</th>
<th>SNR (10 dB)</th>
<th>SNR (20 dB)</th>
<th>SNR (30 dB)</th>
<th>SNR (40 dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VBT</td>
<td>var-diff</td>
<td>0.016</td>
<td>0.011</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>KBT</td>
<td>SM_eve</td>
<td>2.287</td>
<td>2.253</td>
<td>2.099</td>
<td>2.007</td>
</tr>
<tr>
<td>SBT</td>
<td>SM_eve</td>
<td>-0.345</td>
<td>-0.340</td>
<td>-0.326</td>
<td>-0.320</td>
</tr>
<tr>
<td>SKBT</td>
<td></td>
<td>6.777</td>
<td>6.627</td>
<td>6.162</td>
<td>6.103</td>
</tr>
</tbody>
</table>

Table 3. Extracted threshold values of proposed statistical parameters based on simulations on mono-modal SM signals under varying optical feedback, vibration amplitude, and signal to noise ratio.

<table>
<thead>
<tr>
<th>Features</th>
<th>VBT</th>
<th>KBT</th>
<th>SBT</th>
<th>SKBT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold values</td>
<td>0.017</td>
<td>2.7</td>
<td>0.2</td>
<td>5</td>
</tr>
</tbody>
</table>

In order to determine the performance of proposed techniques, experimental dataset was tested to identify the modality of these SM signals by using threshold values of Table 3. Results are presented in Table 4, where $N_{mon}$ and $N_{mul}$ indicates number of tested mono- and multi-modal SM signals respectively. Likewise, $N_{mon,Ti}$ and $N_{mul,Ti}$ indicates number of truly identified mono- and multi-modal SM signals respectively. Furthermore, $N_{mon,Fi}$ and $N_{mul,Fi}$ are the number of SM signals which are falsely identified as mono-, and multi-modal SM signals respectively. $N_{err}$ represents the total number of truly identified SM signals. In the last column, $R_e$ represents the overall success rate of proposed techniques.

Table 4 Performance of proposed techniques by testing experimentally acquired dataset of 60 SM signals.

<table>
<thead>
<tr>
<th>Techs.</th>
<th>$N_{mon}$</th>
<th>$N_{mon,Ti}$</th>
<th>$N_{mul}$</th>
<th>$N_{mul,Ti}$</th>
<th>$N_{mon,Fi}$</th>
<th>$N_{mul,Fi}$</th>
<th>$N_{err}$</th>
<th>$R_e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>VBT</td>
<td>30/30</td>
<td>21/21</td>
<td>9/9</td>
<td>0/0</td>
<td>51/51</td>
<td>85/85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KBT</td>
<td>30/30</td>
<td>24/21</td>
<td>9/9</td>
<td>6/6</td>
<td>45/45</td>
<td>75/75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SBT</td>
<td>30/30</td>
<td>29/24</td>
<td>6/6</td>
<td>4/4</td>
<td>55/55</td>
<td>91/91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SKBT</td>
<td>30/30</td>
<td>26/29</td>
<td>30/30</td>
<td>4/4</td>
<td>56/56</td>
<td>93/93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MV</td>
<td>30/30</td>
<td>30/30</td>
<td>0/0</td>
<td>0/0</td>
<td>100/100</td>
<td>100/100</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

An analysis of misidentified signals led to the observation that misidentification by the proposed techniques occurred for different SM signals. So, majority voting (MV) based on results of the four techniques was undertaken (for each tested signal) resulting in 100% success rate. If lower number of parameters is used for the sake of reducing the complexity of the blind identification then $R_e = 95\%$ if VBT is not used while $R_e = 92\%$ if only VBT and SBT are used, inclusive of MV in both the cases. Some correctly identified mono- and multi-modal experimental SM signals are graphically presented in Fig. 7, and Fig. 8, respectively.

To conclude, an OF based LD can provide multi-modal SM signal in place of usually encountered mono-modal SM signal because of mode-hopping caused by change in operating conditions such as LD-to-target distance. This can cause misinterpretation of SM fringe-count, resulting in drastic increase in metric measurement error. To avoid this error, a continuous monitoring of SM signal is necessary, so that, as SM signal becomes multi-modal, it could be detected immediately and possibly reverted back to mono-modal behavior (e.g. by changing LD current or OF strength). In this Letter, different techniques, based on SM signal statistics, are evaluated for future continuous monitoring of emission modality of low-cost LD based SM sensor. These proposed techniques have been successfully tested on experimentally acquired mono-, and multi-modal SM signals with success rate of 85% (VBT), 75% (KBT), 91% (SBT), and 93% (SKBT). Importantly, use of majority voting among the four proposed techniques has provided 100% success rate of SM modality identification.

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