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A Novel Approach to Signal Detection of Sensor Array Units Using 5-3-1 Rule Based Matched Filter Algorithm with Intelligent Identifiers

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Abstract: A novel approach to signal detection and identification was developed and tested. The new algorithm was based on provision of tagging a Matched Filter (MF) with identifiers to recognize the source signal with and without noise, so that classification can be carried out. The algorithm was applied successfully to chemical Sensor Array Units (SAU). **Problem statement:** Signals obtained from chemical sensors were sometimes contaminated with noise. Detection of known signals from noisy surroundings was critical in the field of sensors and their applications. **Approach:** Six chemical sensor array units were tested at different gas concentrations. The testing was carried out under normal conditions and with the presence of noise. The developed algorithm was then applied to detect, identify and classify the results. **Results:** The 5-3-1 algorithm produced symmetrical arrays with the source signal identifiers at the corners. The symmetry allowed the use of one-third of the produced data for identification, saving processing time and memory storage. **Conclusion:** The obtained data also proved that gap separation between conducting electrodes to inversely affect device conductance, with different gap widths affected similarly with temperature change per constant deposited film thickness. Also, each device conductance increased in response to increase in applied gas concentration.

Key words: Signal detection, arrays, sensors, matched filtering, software, algorithm, intelligence, identifiers

INTRODUCTION

Noise reduction and elimination is a typical problem in signal processing as well as many applications in the real world. Known linear system adaptive filtering techniques have been widely used in noise reduction problems. However, because of the linearity of the operation, such filters are unable to change the inherent property of the original noised signal (Khairnar *et al*., 2008; Bocchi *et al*., 2004; Abella *et al*., 2009; Knipp *et al*., 2006; Zurk *et al*., 2003; Soaresa and Jesusb, 2003).

Matched filtering is very useful in testing and processing an array of N-sensors so as to constantly check detection conditions of any of the sensors and obtain a numerical and graphical data certifying if that sensor or others are working properly. It operates on the principle of correlating an input array (known valued array) and another array surrounded by noise or interference (unknown valued array).The closest match can be found by allocating the output with the largest correlated value.

Matched Filtering algorithms are one of the adaptive systems that are widely used in signal applications because of their remarkable ability to extract patterns from surrounding noise, hence, can be applied to many real world problems such as pattern recognition, signal processing, optimization, control and others. The objective of MF design and application is to find the optimum response that can deliver a decision regarding the presence of a required signal taking into consideration, time, speed, reliability and possible future modifications.

To address the noise problem over long observation times, data-based, time-varying noise filtering using matched filters is proposed. The idea is to filter noise, which is not effectively cancelled by normal adaptive processing (Shi *et al*., 2007; Imam and Barhen, 2009; Zeng *et al*., 2010; Ricci *et al*., 2008; Fan *et al*., 2004; Tandra and Sahai, 2008).

There are at least two aspects that emerge by their relevance to the success of MF based techniques: one is the ability of an MF algorithm to accurately select the source while rejecting side lobes and the other is discrimination through highlighting any mismatch (Dorronsoro *et al*., 2003; Chen *et al*., 2006; 2009; Mohamed *et al*., 2008; Pados, 2001; Sheriff, 2010).

Thus the presented novel 5-3-1 matched filtering algorithm is designed to improve the detection, classification of the Matched Filter (MF) and adds the property of prediction to the overall signal processing system with its intelligent identifiers.

In this study, a novel approach to using Matched Filter algorithm is implemented. The resulted Filter is applied to detect and process signals obtained from a chemical sensors array units.

MATERIALS AND METHODS

An array of chemical sensors having different gap widths with vacuum sublimed PbPC films on a sapphire (α-Al_2O_3) substrates are produced as shown in Fig. 1.

Testing of the devices response to donor gases in particular NO_2 is carried out under computer control in a specifically designed temperature controlled stainless steel testing cells. Each testing cell formed an array of three multi-gap (three gaps) chemical sensors making an overall array of nine sensing elements per testing cell. Figure 2 and 3 show the transient response for normal and noisy sensors as a function of gas concentration.

A known time-limited signal representing sensors response to applied gas concentration denoted by f (t) is applied to the matched filter part of the system.

This is achieved by incorporating the provided average ratios obtained through repeated measurements of conductance changes of the tested three sensor array units comprising nine gaps. By using the ratios technique the following is achieved:

- Testing each individual gap for good or bad detection output signal
- Testing the relative gas detection between different gap sizes and film thicknesses
- Integrated large number of sensors or sensor array units, each with different properties

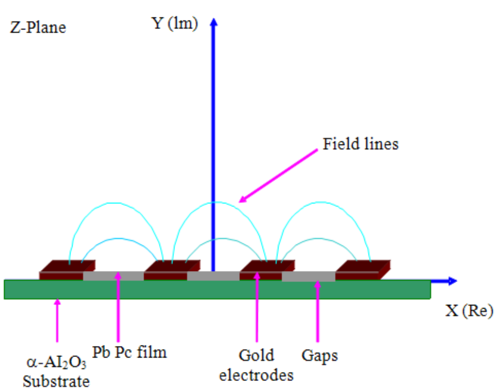

Fig. 1: SAU layout

The input matching array consists of gaps conductance ratios as shown in Table 1 and 2 with noisy average conductance ratios shown in Table 3. As a ratio is a dimensionless number+, then conductance gap ratio should in theory be the same at all temperatures as shown in Eq. 1:

$$\left(\frac{G_n}{G_m}\right)\Bigg|_{T=T_1} \cong \left(\frac{G_n}{G_m}\right)\Bigg|_{T=T_2} \left(\frac{G_n}{G_m}\right)\Bigg|_{T=T_2} \qquad (1)$$

Equation 1 assumes that all gaps are affected almost equally by temperature providing no phase transformation occurs within the used temperature range as it is the case shown in Table 1 and 2 for temperatures up to 160°C. This eliminates temperature as a variable of concern, when it comes to signal detection and gas discrimination and reduces significantly the number of necessary data inputs.

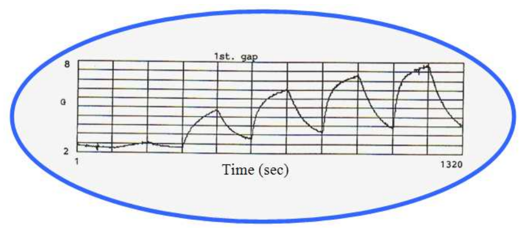

Fig. 2: Transient response for SAU

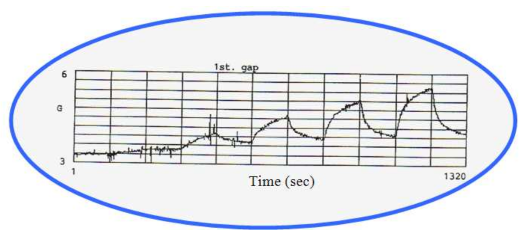

Fig. 3: Transient response for noisy SAU

Table 1: Average conductance ratios (Avg. G_r) for sensor unit arrays: X_1, X_2, X_3

Gas concentration	G_r (T = 130°C)	G_r (T = 160°C)	Avg. G_r
Gap1:Gap2 (10 µm: 33 µm)			
1	1.5532	1.5152	1.5342
3	1.4978	1.4552	1.4765
5	1.4673	1.4079	1.4376
7	1.4492	1.4104	1.4298
9	1.4342	1.3879	1.4111
Gap1:Gap3 (10 µm: 100 µm)			
1	2.9428	2.9004	2.9216
3	2.3125	2.2531	2.2828
5	2.1812	2.1179	2.1496
7	2.1083	2.0862	2.0973
9	2.0688	2.0360	2.0524
Gap2:Gap3 (33 µm: 100 µm)			
1	1.8886	1.9151	1.9019
3	1.5406	1.5491	1.5449
5	1.4836	1.5062	1.4949
7	1.4510	1.4806	1.4658
9	1.4389	1.4688	1.4539

Table 2: Average conductance ratios (Avg. G_r) for sensor unit arrays: X_4, X_5, X_6

Gas concentration	G_r (T=130°C)	G_r (T=160°C)	Avg. G_r
Gap1: Gap2 (5 μm: 10 μm)			
1	1.2954	1.2619	1.2787
3	1.2099	1.1768	1.1934
5	1.1641	1.1119	1.1380
7	1.1408	1.1014	1.1211
9	1.1139	1.0735	1.0937
Gap1: Gap3 (5 μm: 15 μm)			
1	1.7051	1.6525	1.6788
3	1.5683	1.5110	1.5397
5	1.4970	1.4279	1.4625
7	1.4656	1.4025	1.4295
9	1.4247	1.3621	1.3934
Gap2: Gap3 (10 μm: 15 μm)			
1	1.3175	1.3094	1.3135
3	1.2971	1.2837	1.2904
5	1.2858	1.2837	1.2848
7	1.2851	1.2726	1.2789
9	1.2784	1.2572	1.2678

Table 3: Average conductance ratios for noisy SAU

Gas concentration	Avg. G_r
X_1, X_2, X_3 Gap_1: Gap_2 (10 μm: 33 μm)	
1	0.192
3	0.187
5	0.183
7	0.181
9	0.179
X_4 X_5, X_6 Gap_1:Gap_3 (5 μm: 15 μm)	
1	0.406
3	0.378
5	0.364
7	0.357
9	0.349

RESULTS

The following matrices show the response of the 5-3-1 rule based matched filter with intelligent identifiers at the top and bottom corners to the average conductance of six array units with and without noise.

$$\begin{bmatrix} 2.380 & 0.103 & 0.109 \\ 4.296 & 4.357 & -0.031 \\ 10.611 & 4.461 & 2.235 \\ 4.034 & 4.198 & 0.166 \\ 1.758 & 0.052 & -0.009 \end{bmatrix}$$

MF: Sensors (1, 2, 3): gap_1:gap_2

$$\begin{bmatrix} 0.481 & 0.103 & 0.109 \\ 0.529 & 0.533 & -0.031 \\ 1.093 & 0.672 & 0.315 \\ 0.267 & 0.377 & 0.166 \\ -0.142 & 0.052 & -0.009 \end{bmatrix}$$

MF: Sensors (1, 2, 3) gap_1:gap_2 (Noisy)

$$\begin{bmatrix} 6.078 & 0.243 & 0.224 \\ 11.246 & 12.837 & -0.104 \\ 31.125 & 12.678 & 6.955 \\ 10.765 & 12.323 & 0.321 \\ 5.007 & 0.061 & -0.044 \end{bmatrix}$$

MF: Sensors (1, 2, 3) gap_1:gap_3

$$\begin{bmatrix} 2.861 & 0.152 & 0.144 \\ 5.187 & 5.786 & -0.060 \\ 13.982 & 5.839 & 3.170 \\ 4.864 & 5.536 & 0.208 \\ 2.141 & 0.045 & -0.022 \end{bmatrix}$$

MF: Sensors (1, 2, 3): gap_2:gap_3

$$\begin{bmatrix} 1.510 & 0.089 & 0.090 \\ 2.663 & 2.735 & -0.030 \\ 6.606 & 2.814 & 1.423 \\ 2.448 & 2.602 & 0.135 \\ 1.016 & 0.038 & -0.010 \end{bmatrix}$$

MF: Sensors (4, 5, 6): gap_1:gap_2

$$\begin{bmatrix} 2.372 & 0.116 & 0.116 \\ 4.278 & 4.436 & -0.041 \\ 10.759 & 4.515 & 2.306 \\ 4.002 & 4.257 & 0.174 \\ 1.743 & 0.048 & -0.015 \end{bmatrix}$$

MF: Sensors (4, 5, 6): gap_1:gap_3

$$\begin{bmatrix} 0.750 & 0.116 & 0.116 \\ 1.065 & 1.099 & -0.041 \\ 2.486 & 1.220 & 0.608 \\ 0.789 & 0.935 & 0.174 \\ 0.121 & 0.048 & -0.015 \end{bmatrix}$$

MF: Sensors (4, 5, 6): gap_1:gap_3 (noisy)

$$\begin{bmatrix} 1.790 & 0.083 & 0.090 \\ 3.202 & 3.219 & -0.021 \\ 7.84 & 13.347 & 1.659 \\ 2.983 & 3.087 & 0.138 \\ 1.255 & 0.046 & -0.003 \end{bmatrix}$$

MF: Sensors (4, 5, 6): gap_2:gap_3

DISCUSSION

Figure 4 shows matched filter response to the normal detected SAU signals after computing conductance averages at 130 and 160°C and their ratios, while Fig. 5 shows the same SAU delivering noisy signal to the MF. Figure 6 illustrates effect of gap width on SAU conductance and in turn the response of the MF to the output signals from the sensors.

The developed 5-3-1 algorithm provides intelligent identifiers per matched filter response with symmetrical data difference array, which reduces the amount of processed data and achieve excellent identification. The 5-3-1 algorithm is as follows:

- The detected sensor array unit signals are processed and stored into data matrices, each matrix has six identifiers at upper and lower corners as shown in Eq. 2:

$$S = \begin{bmatrix} a_{11} & id_1 & id_2 \\ a_{21} & a_{22} & id_3 \\ a_{31} & a_{32} & a_{33} \\ a_{41} & a_{42} & id_4 \\ a_{51} & id_5 & id_6 \end{bmatrix} \quad (2)$$

- Using tagged identifiers, the detected signals are identified then compared with reference ones and the result is stored in a new matrix as in Eq. 3:

$$S_{identified} = \begin{bmatrix} a_{11}-b_{11} & 0 & 0 \\ a_{21}-b_{21} & a_{22}-b_{22} & 0 \\ a_{31}-b_{31} & a_{32}-b_{32} & a_{33}-b_{33} \\ a_{41}-b_{41} & a_{42}-b_{42} & 0 \\ a_{51}-b_{51} & 0 & 0 \end{bmatrix} \quad (3)$$

- The identifiers are reinstated and data is rounded up in the new matrix to the nearest integer
- The resulting matrix is Folded and respective data values are compared, knowing that:

$$(a_{11}-b_{11}) = (a_{51}-b_{51})$$
$$(a_{21}-b_{21}) = (a_{41}-b_{41})$$
$$(a_{22}-b_{22}) = (a_{42}-b_{42})$$

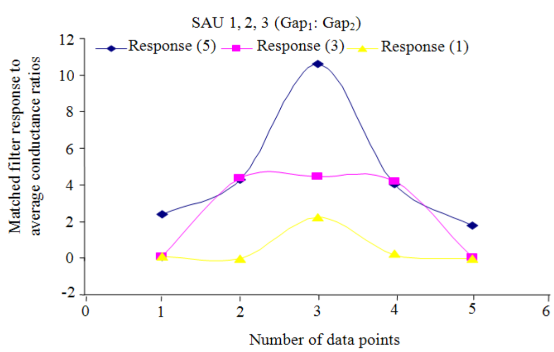

Fig. 4: MF response to SAU normal signals

The symmetry of the matrix allows us to use either half for identification and decision making. If the received signals are noisy, the output array would have large but decrementing data values; otherwise it will contain only zeros. Hence two cases are possible:

Normal signal:

$$S_{Normal} = \begin{bmatrix} 0 & id_1 & id_2 \\ 0 & 0 & id_3 \\ 0 & 0 & 0 \\ 0 & 0 & id_4 \\ 0 & id_5 & id_6 \end{bmatrix} \quad (4)$$

$$S_{Normal\_Upper} = \begin{bmatrix} 0 & id_1 & id_2 \\ 0 & 0 & id_3 \\ 0 & 0 & 0 \end{bmatrix} \quad (4a)$$

$$S_{Normal\_Lower} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & id_4 \\ 0 & id_5 & id_6 \end{bmatrix} \quad (4b)$$

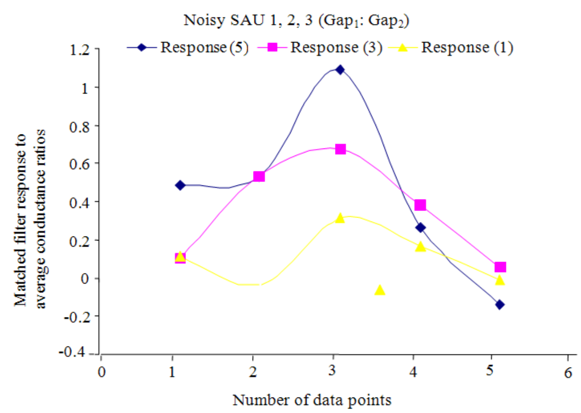

Fig. 5: MF response to SAU noisy signals

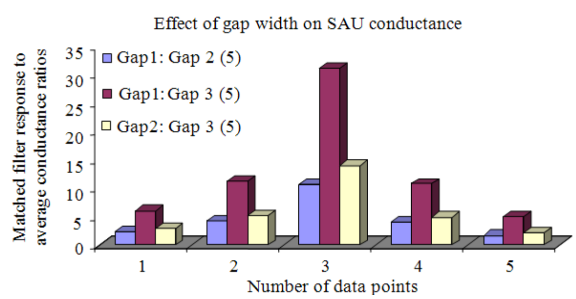

Fig. 6: Effect of gap width on MF response to SAU signals

Noisy signal:

$$S_{Noisy} = \begin{bmatrix} 0 & id_1 & id_2 \\ 0 & 0 & id_3 \\ a_{31}-b_{31} & a_{32}-b_{32} & a_{33}-b_{33} \\ 0 & 0 & id_4 \\ 0 & id_5 & id_6 \end{bmatrix} \quad (5)$$

$$S_{Noisy\_Upper} = \begin{bmatrix} 0 & id_1 & id_2 \\ 0 & 0 & id_3 \\ a_{31}-b_{31} & a_{32}-b_{32} & a_{33}-b_{33} \end{bmatrix} \quad (5a)$$

$$S_{Noisy\_Lower} = \begin{bmatrix} a_{31}-b_{31} & a_{32}-b_{32} & a_{33}-b_{33} \\ 0 & 0 & id_4 \\ 0 & id_5 & id_6 \end{bmatrix} \quad (5b)$$

Data identifiers are rearranged to produce a 3by 3 matrix:

$$S_{Final} = \begin{bmatrix} id_1 & id_2 & id_3 \\ D_1 & D_2 & D_3 \\ id_6 & id_5 & id_4 \end{bmatrix} \quad (6)$$

where, $D_1 \quad D_2 \quad D_3$ are interlarded as follows:

$$\begin{aligned}(a_{31}-b_{31}) &= D_1 = 2.5\,(a_{32}-b_{32}) \\ &= D_2 = 5\,(a_{33}-b_{33}) = D_3\end{aligned} \quad (7)$$

Hence:

$$S_{Final\_Noisy} = \begin{bmatrix} id_1 & id_2 & id_3 \\ D_1 & \frac{D_1}{2.5} & \frac{D_1}{5} \\ id_6 & id_5 & id_4 \end{bmatrix} \quad (8)$$

$$S_{Final\_Normal} = \begin{bmatrix} id_1 & id_2 & id_3 \\ 0 & 0 & 0 \\ id_6 & id_5 & id_4 \end{bmatrix} \quad (9)$$

Now as the identifiers are unique for each sensor array unit and there is a relationship between data values (D_1, D_2, D_3), then the final output can be sorted in any of the line arrays as follows as each one is unique to the sensor array unit and provides valuable indication to the quality of data obtained, with preference to line array A as it has maximum data value. Also, each line array has two guarding identifiers to mark start and stop of data values:

$$S_{Final\_NoisyA} = \begin{bmatrix} id_1 & D_1 & id_6 \end{bmatrix} \quad (10a)$$

$$S_{Final\_NoisyB} = \begin{bmatrix} id_2 & \frac{D_1}{2.5} & id_5 \end{bmatrix} \quad (10b)$$

$$S_{Final\_NoisyC} = \begin{bmatrix} id_3 & \frac{D_1}{5} & id_4 \end{bmatrix} \quad (10c)$$

Applying the previous to prove validity to SAU (1, 2, 3) Gap1: Gap2, we obtain:

From Eq. 3:

$$\begin{bmatrix} 1.899 & 0.000 & 0.00 \\ 3.767 & 3.824 & 0.00 \\ 9.518 & 3.789 & 1.92 \\ 3.767 & 3.821 & 0.00 \\ 1.900 & 0.000 & 0.00 \end{bmatrix}$$

From Eq. 5:

$$\begin{bmatrix} 1.9 & 0.103 & 0.109 \\ 3.8 & 3.8 & -0.031 \\ 9.5 & 3.8 & 1.900 \\ 3.8 & 3.8 & 0.166 \\ 1.9 & 0.052 & -0.009 \end{bmatrix}$$

From Eq. 6-8:

$$\begin{bmatrix} 0 & 0.103 & 0.109 \\ 0 & 0.000 & -0.031 \\ 10 & 4.000 & 2.000 \\ 0 & 0.000 & 0.166 \\ 0 & 0.052 & -0.009 \end{bmatrix}$$

From (10a), (10b) and (10c):

$$\begin{bmatrix} 0.103 & 0.109 & -0.031 \\ 10 & 4.000 & 2.000 \\ 0.052 & -0.009 & 0.166 \end{bmatrix}$$

The final intelligently guarded sequences that are used for identification and signal testing of an SAU are given by:

$$S_{Final\_NoisyA} = [0.103 \quad 10 \quad 0.052]$$

$$S_{Final\_NoisyB} = [0.109 \quad 4 \quad -0.009]$$

$$S_{Final\_NoisyC} = [-0.031 \quad 2 \quad 0.166]$$

CONCLUSION

The 5-3-1 system is used to correlate all SAU parameters with MF parameters. Correlation in the algorithm involves deduction from presented data whether the target data is valid or not. The designed and tested algorithm proved its validity with the novel feature of intelligent identifiers that regardless of the noise corrupting or interfering with the signal can identify the source and recalls the correct. The tested SAU devices proved to be stable over temperature variations for the detection of acceptor gases such as NO_2 with inter-electrode gap separation per fixed deposited film thickness playing an important role in conductivity level per applied gas concentration. For a fixed gap, it is shown that device conductance increased as the gas concentration increased.

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