BRIEF PAPER

A Novel Failure Detection Circuit for SUMPLE Using Variability Index

Leiou WANG[†a)], ***Member***, **Donghui WANG**[†], ***and*** **Chengpeng HAO**[†], ***Nonmembers***

SUMMARY SUMPLE, one of important signal combining approaches, its combining loss increases when a sensor in an array fails. A novel failure detection circuit for SUMPLE is proposed by using variability index. This circuit can effectively judge whether a sensor fails or not. Simulation results validate its effectiveness with respect to the existing algorithms.

key words: *SUMPLE, signal combining, failure detection, variability index*

1. Introduction

A sensor array is a collection of sensors spreading out over a field in some geometrical configurations, transmitting and receiving signals. Its primary use is to enhance the detection of signals with weak signal-to-noise ratio (SNR). With a good signal processing method, undesired signals such as environmental noise and receiver's internally generated noise can be suppressed and the combining output SNR can be amplified by several folds. One of the well-known approaches is called signal combining, whose main idea is to find a set of combining weights, so that the maximum output SNR can be achieved. Until now, there have been two main approaches employed to attain the combining weights. One of them, eigen-based method, is proposed by Cheung in [1], and a fundamental framework of the eigen-based theory is established. And then, several improved methods are proposed [2]–[6]. The major problem for all above eigen-based methods is the high computational cost especially for large sensor arrays [5], [6]. The other one, SUMPLE [7], [8] obtains the combining weights by cross correlation of each sensor with a weighted sum of all the other sensors' output as the reference. SUMPLE can significantly reduce the computational cost while at the same time providing a comparable performance. However, the combining loss of SUMPLE will increase if a sensor in an array fails. To circumvent the drawback, a modified α coefficient SUMPLE (α-SUMPLE) method is proposed by Shen in [9]. Although the α coefficient can quickly reduce the weight amplitude of the failure sensor, the α coefficient may incur extra combining loss for an array without failure sensor.

In this paper, a failure detection circuit for SUMPLE is presented. First, a mathematical model and related methods for a failure sensor in an array are introduced. Then, based on the above discussions, variability index (VI) is used as the failure detection criterion, and VI-SUMPLE circuit is proposed. In this method, the weight amplitude of the failure sensor can be compensated, and no extra combining loss is incurred for an array without failure sensor.

The rest of this paper is organized as follows. In Sect. 2, a related background is introduced. The proposed method is presented in Sect. 3. Finally, simulation results and conclusions are included in Sect. 4 and Sect. 5, respectively.

2. Related Backgrounds

2.1 Basic Definition

The received signal from the ith sensor can be represented by

$$\hat{S}_{i,k} = \hat{s}_{i,k} + \hat{n}^s_{i,k}, \tag{1}$$

where the subscript k is time index, $\hat{s}_{i,k}$ is the source signal, and $\hat{n}^s_{i,k}$ is the noise. The hat notation over the various quantities indicates complex. The weights used to obtain a weighted sum of the various sensors is represented by

$$\hat{W}_{i,K} = \hat{w}_{i,K} + \hat{\eta}_{i,K}, \tag{2}$$

where K is the time index in units of the correlation averaging interval, *ncor*. In addition, $\hat{w}_{i,K}$ is the signal weight, and $\hat{\eta}_{i,K}$ is the noise weight. Accordingly, the combining output of the sensor array is

$$\hat{C}_k = \sum_{i=1}^{N} \hat{S}_{i,k} \hat{W}^*_{i,K}, \tag{3}$$

where N is the total number of sensors, and superscript $*$ represents complex conjugation.

Let the individual sensor signal SNR be $\rho_{si} = \left|\hat{s}_{i,k}\right|^2 / \left|\hat{n}^s_{i,k}\right|^2$ and the weight SNR be $\rho_{wi} = \left|\hat{w}_{i,K}\right|^2 / \left|\hat{\eta}_{i,K}\right|^2$, the combining SNR becomes [7]

$$SNR = N\rho_{si}\left[\frac{\rho_{wi}\rho + \frac{1}{N}}{\rho_{wi} + 1}\right] = N\rho_{si}\Delta SNR, \tag{4}$$

where the ratio $\rho \approx 1$ [7], and ΔSNR represents the combining loss. When $\rho_{wi} \gg 1$, the combining SNR becomes, as expected,

$$SNR_{opt} = N\rho_{si}. \tag{5}$$

Manuscript received August 23, 2017.
Manuscript revised October 17, 2017.
[†]The authors are with the Key Laboratory of Information Technology for Autonomous Underwater Vehicles and the Institute of Acoustics, Chinese Academy of Science, Beijing, 100190, China.
a) E-mail: wangleiou@mail.ioa.ac.cn
DOI: 10.1587/transele.E101.C.139

2.2 Related Methods

The weights for SUMPLE in the next time interval [7]

$$\hat{W}_{i,K+1} = R_{K+1}\frac{1}{ncor}\sum_{k=Kncor}^{(K+1)ncor-1}\left[\hat{S}_{i,k}\sum_{j=1,j\neq i}^{N}\hat{S}^{*}_{j,k}\hat{W}_{j,K}\right]. \quad (6)$$

The outer sum over *ncor* corresponds to the correlation averaging interval, and the inner sum corresponds to the reference signal. The R_{K+1} is a normalization factor.

The combining loss of SUMPLE will increase if a sensor in an array fails. Reference [9] indicates that the greater the weight amplitude of the failure sensor, the worse the combining SNR. Therefore, α-SUMPLE is proposed and the weight of α-SUMPLE can be expressed as [9]

$$\hat{W}_{i,K+1} = \hat{W}_{i,K+1}\left|\hat{W}_{i,K}\right|^{\alpha}, \quad (7)$$

where $\left|\hat{W}_{i,K}\right|^{\alpha}$ is a weight correcting coefficient, and α is a variable real number with ranging from 0 to 1. When a sensor in an array fails, the weight amplitude of the failure sensor is usually smaller than 1. Therefore, $\left|\hat{W}_{i,K}\right|^{\alpha}$ can further reduce the weight amplitude of the failure sensor. However, this unconditional correcting coefficient also results in an extra combining loss for an array without failure sensor.

3. Proposed Method

The above discussions demonstrate that we need to judge whether a sensor fails or not in an array. Variability index is a second order statistic which is a function of the estimated population mean and the estimated population variance. VI can be calculated for each combining weight power using

$$VI = 1 + \frac{1}{N-1}\sum_{i=1}^{N}\left(\left|\hat{W}_{i,K}\right|^{2} - \left|\bar{W}_{K}\right|^{2}\right)^{2}/\left(\left|\bar{W}_{K}\right|^{2}\right)^{2}, \quad (8)$$

where $\left|\bar{W}_{K}\right|^{2}$ is the arithmetic mean of the combining weight power for N sensors. From Eq. (8), we can find that if a sensor in an array fails, the weight amplitude of the failure sensor will decrease, which results in VI increases. Consequently, we consider using VI to be the failure detection criterion.

For implementation purposes, it is possible to reduce the computational costs associated with calculating VI using alternative definition. In this manner, a simplified VI^{*} [10] is obtained by using the biased, maximum likelihood estimate of the population variance rather than the unbiased estimate used in Eq. (8)

$$VI^{*} = N\sum_{i=1}^{N}\left(\left|\hat{W}_{i,K}\right|^{2}\right)^{2}/\left(\sum_{i=1}^{N}\left|\hat{W}_{i,K}\right|^{2}\right)^{2}. \quad (9)$$

The simplified VI^{*} requires fewer arithmetic operations than the original VI.

In order to detect a failure sensor, VI^{*} is compared with a threshold T_{VI}. We can use the following hypothesis test:

$$\begin{array}{l} VI^{*} \leq T_{VI} \Rightarrow without\ failure\ sensor \\ VI^{*} > T_{VI} \Rightarrow with\ failure\ sensor \end{array}. \quad (10)$$

The use of the above hypothesis test requires the value of the corresponding threshold T_{VI}, such that a low probability of the hypothesis test error is achieved. For an array without failure sensor, we define this probability as

$$\beta = \Pr ob\left(VI^{*} > T_{VI}\,|without\ failure\ sensor\right). \quad (11)$$

In an analogous fashion, for an array with failure sensor, we define another probability as

$$\gamma = \Pr ob\left(VI^{*} \leq T_{VI}\,|with\ failure\ sensor\right). \quad (12)$$

Because an analytic expression for β and γ is difficult, we use Monte Carlo simulation to estimate β and γ. The probabilities of error β and γ as a function of threshold T_{VI} in different signal SNRs are shown in Fig. 1 and Fig. 2, respectively. The simulation results are the statistics of 1000 independent tests. From Fig. 1 and Fig. 2, it can be observed that increasing T_{VI} can reduce β, but results in a higher γ. Therefore, we need to carefully choose T_{VI} for both β and γ. Precisely, T_{VI} can be determined as

$$\hat{T}_{VI} = \underset{T_{VI}}{argmin}\left(\beta \times \gamma\right), \quad (13)$$

where $\hat{T}_{VI}$ is the threshold corresponding to the minimum value of $\beta \times \gamma$.

According to above analysis, we propose a failure detection circuit, which uses VI^{*} as the failure detection criterion. The block diagram of VI-SUMPLE is shown in Fig. 3. A set of weight correcting coefficients and a VI module are added in this architecture. The input signals of the VI module are the combining weight of each sensor. The VI module calculates the value of VI^{*} based on Eq. (9), and outputs a set of control signals according to the comparison result between VI^{*} and $\hat{T}_{VI}$ in Eq. (13). If VI^{*} is smaller than $\hat{T}_{VI}$, $\alpha = 0$ and VI-SUMPLE is identical to SUMPLE. Otherwise, the performance of VI-SUMPLE approaches that of

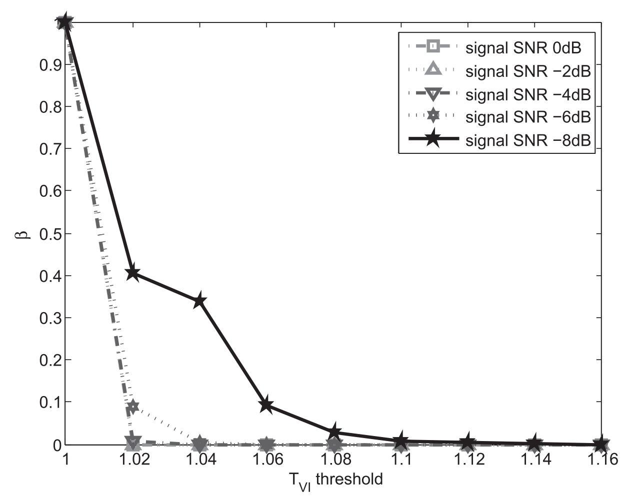

Fig. 1 Probabilities of the hypothesis test error β for a $N = 4$, and $ncor = 1024$ without failure sensor.

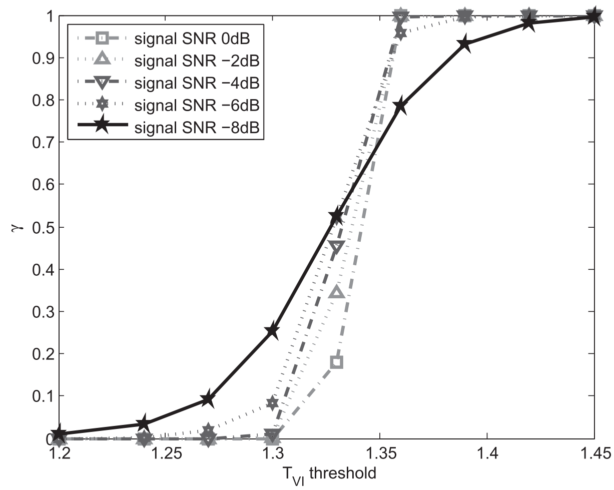

Fig. 2 Probabilities of the hypothesis test error γ for a $N = 4$, and $ncor = 1024$ with a single failure sensor.

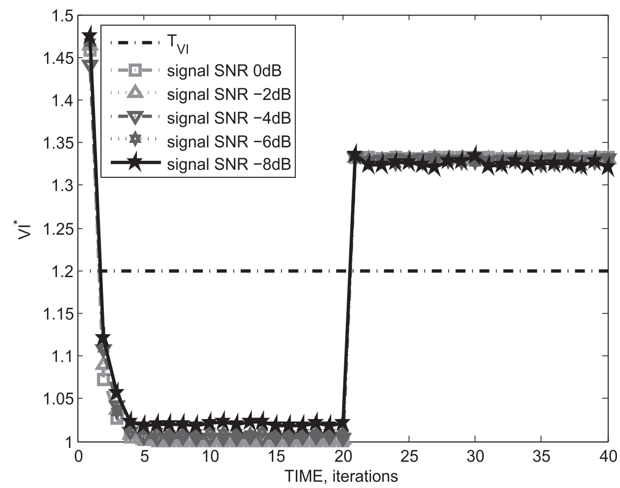

Fig. 4 VI^* for a $N = 4$, and $ncor = 1024$ as a single sensor drops out.

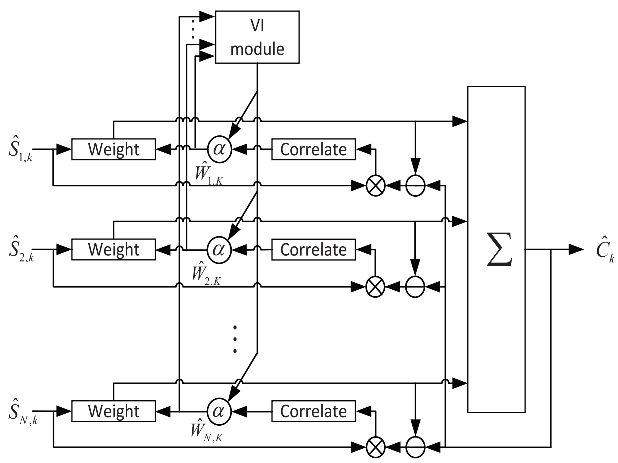

Fig. 3 Block diagram of VI-SUMPLE.

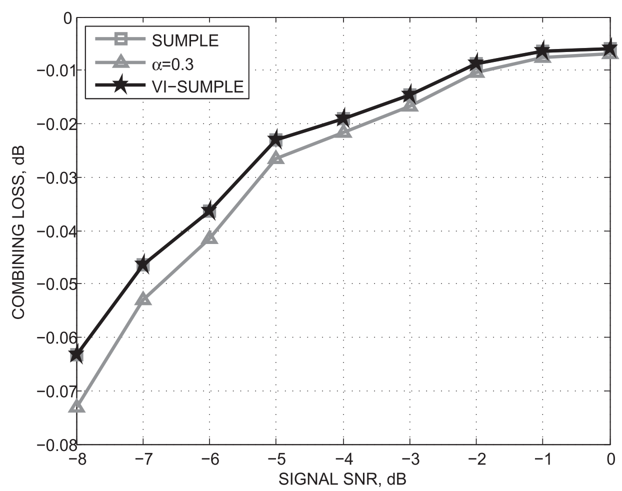

Fig. 5 Array combining loss in different signal SNRs without failure sensor.

α-SUMPLE with a certain α value.

The computational complexity of SUMPLE is order $(NKncor)$ [5], [6], [8]. Nevertheless, the extra computational costs of VI-SUMPLE only has several addition and multiplication operations in each iteration.

4. Simulation Results

Simulations are conducted to compare the performance of SUMPLE, α-SUMPLE, and VI-SUMPLE for signal combining. The source is a QPSK signal, and $\hat{n}_{i,k}^{s}$ is independent white Gaussian noises.

Test 1: The aim of the test is to investigate VI^* for an array when a sensor suddenly drops out. To this end, we set $N = 4$, $ncor = 1024$, $K = 40$, and $\hat{T}_{VI} = 1.2$. The 1th sensor in the array drops out at $K = 20$. The simulation results are the statistics of 100 independent tests. From Fig. 4, as expected, VI^* increases about 0.35 when the sensor drops out. At the same time, we can observe that is lower than T_{VI} before $K = 20$, but it immediately exceeds T_{VI} after $K = 20$. The failure sensor detection is the primary motivation in this paper. From above simulation results, it can be seen that VI^* is an easily used indicator which can effectively judge whether a sensor fails or not in an array.

Test 2: Simulations are made to compare these methods combining loss in different signal SNRs, and the simulation results are the statistics of 2000 independent tests for a $N = 4$, $ncor = 1024$, and $\hat{T}_{VI} = 1.2$. For the array without failure sensor, based on above simulation results, VI^* is lower than T_{VI}. The VI module outputs the control signals to make $\alpha = 0$, so VI-SUMPLE is identical to SUMPLE. Fig. 5 shows that SUMPLE and VI-SUMPLE have a better combining performance than α-SUMPLE. Although the theoretically weight amplitude $\left|\hat{W}_{i,K}\right| = 1$, the practical weight amplitude deviates from the theoretical value due to noise [7] and $\left|\hat{W}_{i,K}\right|^{\alpha}$ makes the deviation even worse. As a result, α-SUMPLE incurs more extra combining loss.

For the array with a single failure sensor, the combining loss for different methods is presented in Fig. 6. At this

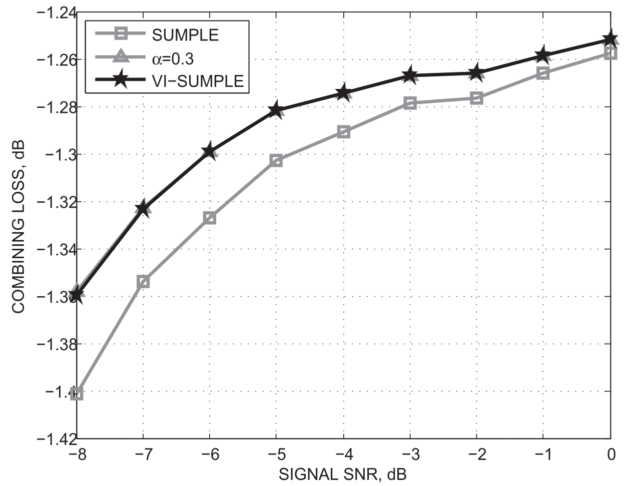

Fig. 6 Array combining loss in different signal SNRs with a single failure sensor.

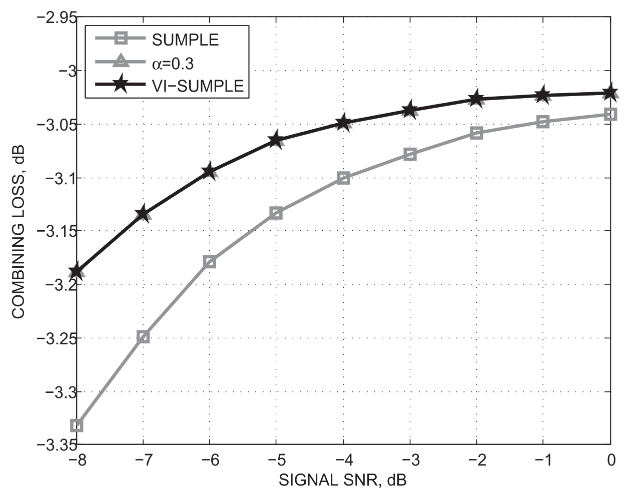

Fig. 7 Array combining loss in different signal SNRs with three failure sensors.

time, VI^* is higher than T_{VI}, and the performance of VI-SUMPLE approaches that of α-SUMPLE with $\alpha = 0.3$. It can be seen that α-SUMPLE and VI-SUMPLE are superior to SUMPLE.

In order to investigate the combining loss for an array with multiple failure sensors, the previous test is repeated for a $N = 6$, $ncor = 1024$, and $\hat{T}_{VI} = 1.1$. The simulation result is shown in Fig. 7. It can be seen that the improvements of VI-SUMPLE becomes more significant.

5. Conclusions

In this paper, a failure detection circuit for SUMPLE is presented. we first discussed the mathematical model and the performance analysis when a sensor in an array fails. Based on this discussion, VI is used as the failure detection criterion, and VI-SUMPLE is proposed. This circuit can effectively judge whether one or more sensors fail or not in an array. Moreover, the weight amplitude of failure sensor can be compensated to reduce the combining loss. Simulation results indicate that this failure detection circuit performs better than the traditional state-of-the-art counterparts.

Acknowledgments

This work was supported by the Young Talent Program of Institute of Acoustics, Chinese Academy of Science under Grant Y654831511 and the National Natural Science Foundation of China under Grant 61571434. The authors are grateful to the anonymous reviewers for their constructive comments.

References

[1] K.M. Cheung, "Eigen theory for optimal signal combining: A unified approach," TDA Progress Report, vol.42, no.126C, pp.1–9, Aug. 1996.

[2] H.H. Tan, "Optimum combining of residual carrier array signals in correlated noises," TDA Progress Report, vol.42, no.124, pp.33–52, February, 1996.

[3] S. Doclo and M. Moonen, "Robust time-delay estimation in highly adverse acoustic environments," IEEE Workshop on Applications of Signal Process. to Audio and Acoustics 2001, New York, pp.59–62, Oct. 2001.

[4] C.H. Lee, V.A. Vilnrotter, E. Satorius, Z. Ye, D. Fort, and K.M. Cheung, "Large-array signal processing for deep space applications," IPN Progress Report, vol.42, no.150, pp.1–28, Aug. 2002.

[5] C.H. Lee, K.M. Cheung, and V.A. Vilnrotter, "Fast eigen-based signal combining algorithms for large antenna arrays," IEEE Aerospace Conference, Montana, pp.1123–1129, March 2003.

[6] B. Luo, H. Yu, X. Zhang, and Q. Li, "On eigen-based signal combining using the autocorrelation coefficient," IET Communications, vol.6, no.18, pp.3091–3097, Sept. 2012, (DOI: 10.1049/iet-com.20120141)

[7] D.H. Rogstad, "The SUMPLE algorithm for aligning arrays of receiving radio antennas: Coherence achieved with less hardware and lower combining loss," IPN Progress Report, vol.42, no.162, pp.1–29, Aug. 2005.

[8] Y. Shang and X.T. Feng, "MLC-SUMPLE algorithm for aligning antenna arrays in deep space communication," IEEE Trans. Aerospace and Electronic Systems, vol.49, no.4, pp.2828–2834, Oct. 2013.

[9] C. Shen, Y. Hu, and H. Yu, "Analysis on failed antenna based on SUMPLE algorithm in antenna array," J. Astronautics, vol.32, no.11, pp.2445–2450, Nov. 2011, (DOI: 10.3873/j.issn.1000.1328.2012.11.021).

[10] M.E. Smith and P.K. Varshney: "Inteligent CFAR processor based on data variability," IEEE Trans. Aerospace and Electronic Systems, vol.36, no.3, pp.837–847, July, 2000.