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Fluctuation Enhanced Sensing with Zero Crossing Analysis for High Speed and Low Power Applications

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***Abstract*— A new method to generate fingerprints of agents has been introduced. The method is based on using the zero crossing statistics at fluctuation-enhanced sensing. It is a new version of Ben Kedem's original method based on low-pass filters. To improve computation time and energy efficiency, high-pass filtering is used and in doing that in the simplest possible way, local zero levels for short-time sub-windows are defined and a zero crossing counting by the use of such windows is carried out. The method turns out to be an effective tool to identify noise processes with different spectra or amplitude distribution, with at least 1000 times less calculation and correspondingly lower energy need than that of the Kedem or the FFT methods. We demonstrate the usability of the method by the analysis and recognition of different stochastic processes with similar and different spectra.**

***Index Terms*— zero crossing, high speed, low power, fluctuation enhanced sensing**

I. Introduction

FLUCTUATION-ENHANCED sensing methods generate a fluctuation-fingerprint of the stochastic component of sensor signals which can be identified by pattern recognizers [1,2]. Typical FFT and bispectrum methods involved a large amount of data processing steps and therefore significant processing time and energy requirements [1]. For wireless, palmtop, and similar low-power and low-processor-speed systems there is consequently a need for analysis in a more time and energy efficient way. In this paper we modify Ben Kedem's method of combining low-pass filtering and zero crossing analysis to determine spectra of Gaussian noise. Kedem's method needs practically the same amount of data processing as the standard FFT analysis for spectral estimation. Our goal is to achieve fluctuation-fingerprinting with data processing needs being much smaller than in the Kedem or the FFT methods in order to achieve high speed and low power dissipation.

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II. The new method

The Rice formula for stationary Gaussian stochastic processes provides the mean zero crossing frequency as [3]

$$F_0 = 2\frac{\sqrt{\int_0^\infty f^2 S(f)df}}{\sqrt{\int_0^\infty S(f)df}}, \tag{1}$$

where F_0 is the mean zero crossing frequency, and $S(f)$ is the power density spectrum of the process, $U(t)$. The new method to generate a fingerprint determined by $S(f)$ is described below. It should be noted that in the new method, the Gaussian nature of the process is not required because the methods test the empirical zero crossing frequency.

The measurement window is divided into short sub-windows with identical length (digital sampling step number) N_j and a local averaging is done within each window to define a local, short-term, zero value $U_0(N_j)$:

$$U_0(N_j) = \frac{1}{N_j}\sum_{i=1}^{N_j} U(t_i) \quad . \tag{2}$$

Then the average local zero crossing frequency is determined for each sub-window and the local values are averaged over the whole measurement window. In this way, frequencies below the reciprocal of the sub-window length are removed from the obtained zero-crossing frequency value $F_0(N_j)$. This is a very computationally and energetically efficient high-pass filtering, and the resulting zero crossing frequency depends on the power density spectrum.

Subsequently the whole process is repeated with different sub-window sizes over the achievable range of sub-window sizes and the zero crossing frequency fingerprint $F_0(N_j)$ is found for all sub-window sizes N_j. This is a computationally and energetically efficient stochastic fingerprinting technique.

The method turns out to be an effective tool to identify noise processes with different spectra or amplitude distribution with (practically) at least 1000 times less calculation and correspondingly lower energy need than the FFT method.

III. Computer-Simulated Data and Pattern Generation for Classification

Four computer-simulated stochastic processes, each of which interpreted to be a different agent, have been used to demonstrate the efficiency of the new method. These processes are:

- A is a Gaussian Lorentzian noise. It is generated by a first order digital filtering of white noise. This represents a macroscopic adsorption-desorption noise or can be thought of as sensor/amplifier background noise.
- B is a Random Telegraph signal and represents a single molecule adsorption-desorption noise in a nano-sensor.
- C is a single molecule diffusion noise in a nano sensor. Diffusion noise is generated on the basis of a one-dimensional random walk.
- D is a single molecule diffusion noise in a nano sensor with 25 times greater diffusion coefficient than that of C. Diffusion noise is generated on the basis of a one-dimensional random walk.

Ten mixture cases have been formed that contain the four stochastic processes. These are: A + A (the sum of two independent A processes), B + B (the sum of two independent B processes), C + C (the sum of two independent C processes), D + D (the sum of two independent D processes). The other mixture cases that contain the above agents are as follows: A+B, A+A+B, A+B+B, C+D, C+C+D, C+D+D.

Fig. 1-Fig. 6 show the computed zero-crossing patterns obtained by the new method and the power spectrum density (PSD) patterns for the 4 single and 10 mixture cases. In computing the PSD spectrum patterns, Welch spectrum method is applied with a window size of 8192 and using Hamming window. A visual comparison of the zero-crossing and PSD patterns in Fig. 1-Fig. 6 indicate that zero-crossing patterns yield more distinct signatures with respect to each other, while PSD patterns look similar in waveform shape.

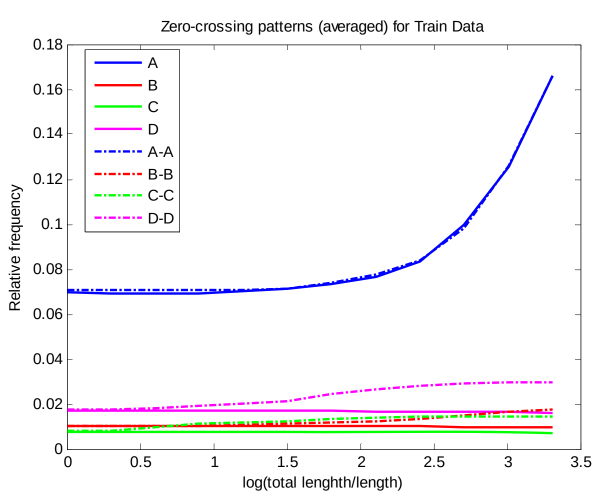

Fig. 1 Zero-crossing patterns (averaged) for stochastic signals (A, B, C, D, A-A, B-B, C-C, D-D)

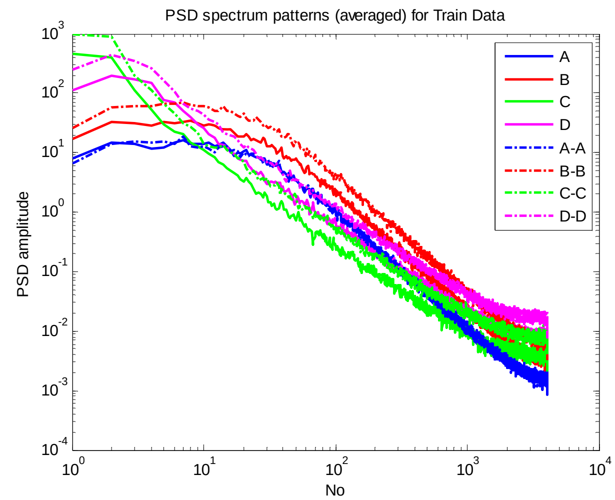

Fig. 2 PSD patterns for the same stochastic signals as in Fig. 1

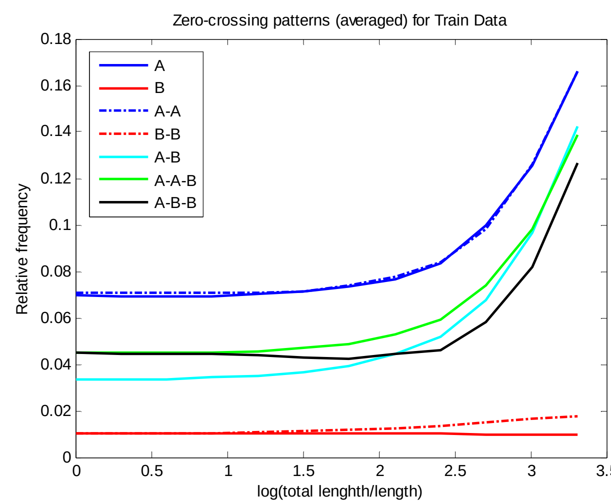

Fig. 3 Zero-crossing patterns (averaged) for stochastic signals (A, B, A-A, B-B, A-B, A-A-B, A-B-B).

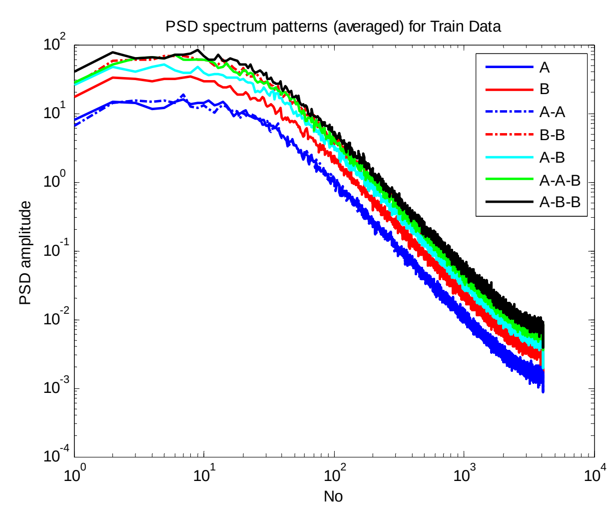

Fig. 4 PSD patterns for the same stochastic signals as in Fig. 2.

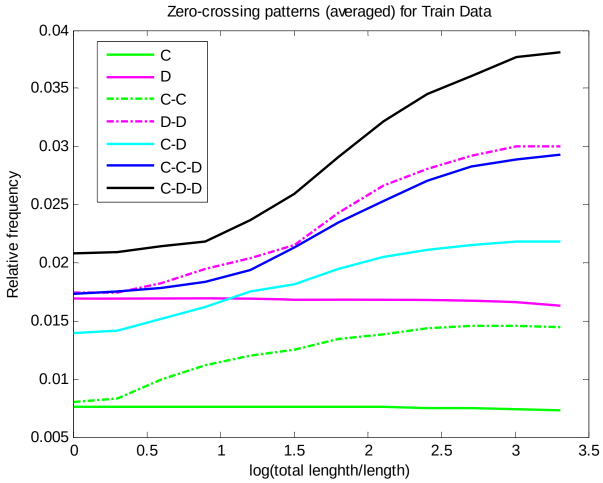

Fig. 5 Zero-crossing patterns (averaged) for stochastic signals (C, D, C-C, D-D, C-D, C-C-D, C-D-D).

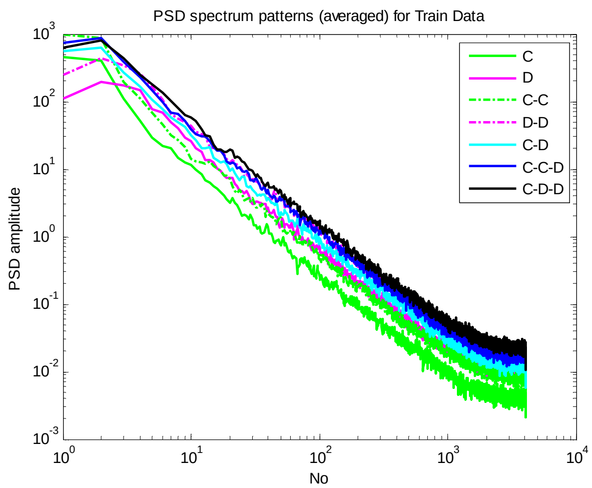

Fig. 6 PSD patterns for the same stochastic signals as in Fig. 3.

IV. Classification

A. Training and testing data set generation

A classification study has been performed to evaluate the efficiency of the zero-crossing patterns of the new method with respect to using classical PSD patterns. It should be recalled that there is a total of 14 different cases (A, B, C, D, A+A, B+B, C+C, D+D, A+B, A+A+B, A+B+B, C+D, C+C+D, C+C+D), which can be thought of as 14 classes. Time domain data in each of the 14 cases consist of 1,048,576 points. The data for each case is partitioned into 121 overlapping data segments. Each of these overlapping data segments consists of 65,536 data points. The number of non-overlapping data points in a data segment is 8,192 (number of overlapping data points between two consecutive data segments is thus equal to 57,344). Among the 121 partitioned data segments, the first 60 data segments is used for training (classifier model generation) and the last 61 is used for testing. That is, for 14 cases, there are 840 training data files and 854 testing data files.

B. Pattern recognizers

Two pattern recognizers have been used in the classification study. The first one is a minimum-distance classifier. Suppose $\mathbf{a}_i$ is the zero-crossing pattern for class i (which is obtained by averaging of zero-crossing patterns of train data), where $i=1,\ldots,14$, and $\mathbf{b}_j$ is the test data zero-crossing pattern which belongs to class j (where $j=1,\ldots,14$). The minimum-distance classifier computes the Euclidian distance between $\mathbf{b}_j$ and $\mathbf{a}_i$ ($i=1,\ldots,14$), $\mathrm{Dist}(\mathbf{b}_j,\mathbf{a}_i)$, and assigns the class label to the test data, $\mathbf{b}_j$, that yields the minimum value. That is, the decision class label for $\mathbf{b}_j$ is equal to $\underset{i}{\mathrm{argmin}}\left(\mathrm{Dist}(\mathbf{b}_j,\mathbf{a}_i)\right)$.

As a second pattern recognizer, Support Vector Machine (SVM) is used. SVMs have been extensively used as a highly effective tool for pattern recognition and regression tasks [4]. One important attribute of SVM is that it uses the Structural Risk Minimization (SRM) principle in its formulation. SRM has been shown to be superior to traditional Empirical Risk Minimization (ERM) principle, which has been used by conventional neural networks [5]. For a detailed theoretical explanation of SVM, one should see [4], but in summary, SVM uses an optimal hyperplane to separate clouds of data in the feature space. A nonlinear mapping from inner products of the pattern space to a higher dimensional feature space is conducted via the use of kernel functions. Mapping from pattern space to a higher dimensional feature space results in linear separation of the clouds of data. Only the data points near the optimal hyperplane are used as a basis for the model and these are called support vectors. SVMs have been used in a number of applications such as: isolated handwritten digit recognition [6], [7], object recognition [8], speaker identification [9], and face detection in images [10].

C. Classification results

The minimum-distance classifier when using zero-crossing patterns as features yielded a correct classification rate of 78.22% for the test data (correct classification rate was 85.48% when case A and case “A + A” are considered as one same class; it should be noted that since A corresponds to a Gaussian Lorentzian process, the mixture of A with itself, A+A, shows the same stochastic characteristics as case A). The confusion matrix for the min-distance classifier using zero-crossing patterns is shown in Table 1.

The same minimum distance classifier has been applied but this time with the PSD patterns used as the features. With this configuration, a correct classification rate of 72.01% has been observed (correct classification rate was 78.81% when case A and case “A + A” are considered as one class). It can be recognized that the use of zero-crossing patterns provided better correct classification performance when compared to the use of PSD patterns in the same classifier. The confusion matrix for the min-distance classifier with PSD patterns is shown in Table 2.

Finally, a nonlinear SVM Classifier with a radial basis kernel function has been applied using the zero-crossing patterns as the features (the two parameters in the SVM classifier are set as: gamma = 2, C= 0.5). The correct classification rate with the SVM classifier was 80.91 % (correct classification rate was 87.47% when case A and case “A + A” are considered as one class). Table 3 shows the corresponding confusion matrix.

The classification results indicated that the zero-crossing patterns of the new method are highly promising for generating distinct fingerprints of chemical agents, and their performance exceeded the PSD patterns.

Table 1 Confusion Matrix for Test Data using the Minimum-Euclidian-Distance Pattern Classifier with Zero-Crossing Patterns

	A	B	C	D	A+A	B+B	C+C	D+D	A+B	A+A+B	A+B+B	C+D	C+C+D	C+D+D
A	0.49	0.00	0.00	0.00	0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	0.00	0.28	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D	0.00	0.00	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00
A+A	0.51	0.00	0.00	0.00	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B+B	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C+C	0.00	0.21	0.00	0.00	0.00	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.74	0.00	0.00	0.00	0.00	0.18	0.08
A+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
A+A+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
A+B+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
C+D	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.38	0.00
C+C+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.25	0.36	0.05
C+D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.87

Table 2 Confusion Matrix for Test Data using the Minimum-Euclidian-Distance Classifier with PSD Spectrum Patterns

	A	B	C	D	A+A	B+B	C+C	D+D	A+B	A+A+B	A+B+B	C+D	C+C+D	C+D+D
A	0.62	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A+A	0.57	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B+B	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.36	0.02	0.00	0.00	0.00
C+C	0.00	0.00	0.02	0.00	0.00	0.00	0.74	0.02	0.00	0.00	0.00	0.21	0.02	0.00
D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	0.00	0.00	0.00	0.11	0.00	0.00
A+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
A+A+B	0.00	0.00	0.00	0.00	0.00	0.56	0.00	0.00	0.00	0.30	0.15	0.00	0.00	0.00
A+B+B	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00
C+D	0.00	0.00	0.00	0.07	0.00	0.00	0.03	0.31	0.00	0.00	0.00	0.34	0.20	0.05
C+C+D	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.03	0.00	0.00	0.00	0.02	0.46	0.28
C+D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.26	0.70

Table 3 Confusion Matrix for Test Data using SVM classifier with Zero-Crossing Patterns

	A	B	C	D	A+A	B+B	C+C	D+D	A+B	A+A+B	A+B+B	C+D	C+C+D	C+D+D
A	0.66	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	0.00	0.30	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A+A	0.57	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B+B	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C+C	0.00	0.15	0.00	0.00	0.00	0.00	0.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.00	0.00	0.00	0.00	0.18	0.07
A+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
A+A+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
A+B+B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
C+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.67	0.15	0.00
C+C+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.20	0.39	0.07
C+D+D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.03	0.87

V. CONCLUSION

In this paper, we introduced and tested zero-crossing analysis as a new method for generating fingerprints from stochastic signals. The tests were carried out by use of practical types of sensor signals and pattern recognition techniques are applied to the generated fingerprints. Pattern recognition tests indicated that the zero-crossing patterns yield more distinct signatures with respect to each other. By using more advanced classifiers such as "SVM (Support Vector Machines)", the accuracy of the pattern recognition could be even further improved, which we have observed in our results. Therefore our method turned out to be an effective tool to identify noise processes with different spectra or amplitude distribution with at least 1000 times less calculation and correspondingly lower energy need than that of the Kedem or the FFT methods.

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