NOISE SEPARATION IN ANALOG INTEGRATED CIRCUITS USING EMD-PCA-ICA

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ABSTRACT

The idea of applying blind source separation (BSS) algorithms has recently been introduced for noise separation in integrated circuits. Until now, the introduced methods were based on multi-channel BSS. But in many real applications only one mixture is available. Therefore, multi-channel BSS methods are not helpful. In this paper, we propose a new approach to separate individual noise and source signals from an observed mixture in analog integrated circuits. This method is based on one-channel BSS and includes empirical mode decomposition (EMD), principle component analysis (PCA) and independent component analysis (ICA). By using this method, we are able to separate noise and estimate desired source signals from only a single observed mixture. Experimental results substantiate the strong potential of the proposed method for noise separation in analog integrated circuits.

1. INTRODUCTION

Noise limits the minimum signal level that a circuit can process with acceptable quality. Integrated circuits are becoming increasingly vulnerable to different types of noise sources, such as, capacitive and inductive crosstalk, charge sharing, leakages, power supply noise, substrate coupling, ground bounce etc. Compared with digital integrated circuits, analog devices are inherently much more susceptible to noise disturbance.

The idea of applying blind source separation (BSS) algorithms for noise suppression in integrated circuits is a new concept introduced in [1]. In that paper, a digital signal processing algorithm known as blind source separation (BSS) technique is utilized to separate individual noise sources from a compound noise measurement in digital integrated circuits. In [2] similar technique has been proposed to address compound noise separation problem in analog integrated circuits using FastICA algorithm. FastICA [3] is well-known algorithm that is based on independent component analysis (ICA). Independent component analysis is a powerful tool giving good separation under the hypotheses of linear mixture, statistical independence of the sources and number of observed mixtures being no less than that of contributing sources. The application of ICA to separate individual noise sources from a compound noise can be helpful in selected problems when the departure from the above hypotheses is moderate. In fact methods which employ only ICA algorithm in separation process can not be applicable in one-channel source separation e.g. in real integrated circuits where only one mixture is available.

Recently some one-channel methods [4, 5, 6] for signal denoising scheme are introduced that are based on empirical mode decomposition (EMD) [7]. In these methods, noisy signal is decomposed adaptively into intrinsic oscillatory components called intrinsic mode functions (IMFs). The basic principle of them is to reconstruct the signal with IMFs previously filtered or thresholded and in some methods this reconstruction is partial and in some other it is complete.

In this paper, we propose a new approach to separate individual noise and source signals of analog integrated circuits from a single observed mixture. This approach utilizes EMD but it is not based on reconstruction of filtered or thresholded IMFs as done in [4, 5, 6]. Our method consists of three stages. In the first stage we use EMD to decompose the observed mixed signal into a collection of IMFs. EMD can be applied to any nonlinear and non-stationary signal. Furthermore, it uses only a single mixture to extract IMF components. We consider these components as mixture observations. In the second stage, principal component analysis (PCA) [8] is applied to these observations to produce some uncorrelated and dominant basis components. The basis components obtained by PCA are only uncorrelated but not statistically independent. To derive the independent basis components a further procedure called independent component analysis must be carried out. Therefore, in the third stage, we apply FastICA. The most important advantages of our separation method are: 1) It is not necessary that the circuit components be purely linear. 2) A single mixture is only necessary.

2. EMPIRICAL MODE DECOMPOSITION

The empirical mode decomposition [7] is a signal processing technique to decompose any non-stationary and nonlinear signal into oscillating components with some basic properties. The key benefit of using EMD is that it is automatic and fully data adaptive.

EMD decomposes a time series $x(t)$ into a sum of band-limited functions $f_m(t)$ by empirically identifying the physical time scales intrinsic to the data. Each extracted mode $f_m(t)$ named intrinsic mode function (IMF) contains two basic conditions. First, in the whole data set, the number of extrema (maxima and minima) and the number of zero crossings must be the same or differ at most by one. Second, at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The first condition is similar to the narrow-band requirement for a stationary Gaussian process, and the second condition is a local requirement induced from the global one and, is necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by asymmetric waveforms. There exist many approaches for computing EMD. The following algorithm follows the procedure given in [9].

1. Identification of all maxima and minima of the time series $x(t)$.

2. Generate the upper and lower envelopes $u(t)$ and $l(t)$, respectively, by connecting the maxima and minima separately with cubic spline interpolation.

3. Determine the local mean as $\mu_1(t) = [u(t) + l(t)]/2$.

4. IMF should have zero local mean thus we subtract $\mu_1(t)$ from the original signal $x(t)$ as $e_1(t) = x(t) - \mu_1(t)$.

5. Check whether $e_1(t)$ is an IMF or not by checking the two basic conditions as described above.

6. Repeat steps 1–5 and stop when an IMF $e_1(t)$ is obtained. Once the first IMF is obtained, define $f_1(t) = e_1(t)$, which is the smallest temporal scale in $x(t)$. To find the rest of the IMFs, generate the residue $r_1(t)$ of the data by subtracting $e_1(t)$ from the signal $x(t)$ as $r_1(t) = x(t) - f_1(t)$.

The sifting process will be continued until the final residue is a constant, a monotonic function, or a function with only one maxima and one minima from which no more IMF can be obtained.

The subsequent IMFs and the residues are computed as:

$$r_1(t) - f_2(t) = r_2(t)...r_{M-1}(t) - f_M(t) = r_M(t) \quad (1)$$

where $r_M(t)$ is the final residue. At the end of the decomposition, the signal $x(t)$ is represented as

$$x(t) = \sum_{m=1}^{M} f_M(t) + r_M(t) \quad (2)$$

where M is the number of IMFs, and $r_M(t)$ is the final residue.

The IMFs are the foundations for representing the time series data. Being data adaptive, the basis usually offers a physically meaningful representation of the underlying processes. There is no need of considering the signal as a stack of harmonics and, therefore, EMD is ideal for analyzing non-stationary and nonlinear data [10]. EMD uses only a single mixture (obtained from one sensor) to extract IMFs.

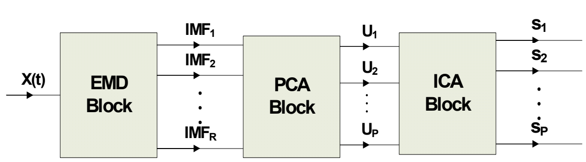

Figure 1 – Proposed model for noise separation.

In this paper we use the EMD method to extract IMFs from a single mixed signal which is a combination of a source signal and compound noises.

3. PROPOSED SEPARATION METHOD

In our proposed method we use a separation model of three stages shown in figure 1.

Stage 1: in this stage we apply EMD algorithm to the mixed signal $X(t)$ and obtain R IMF components. The IMFs are vectors of size $1 \times L$ where L is length of data. Then we form an observation matrix $Y_{R\times L}$ as:

$$Y_{R\times L} = \begin{bmatrix} IMF_1 & IMF_2 & \dots & IMF_R \end{bmatrix}^T \quad (3)$$

where R is number of IMFs and T stands here as transpose operator.

Stage 2: in this stage, in order to find uncorrelated dominant basis components, PCA algorithm is used. PCA is implemented by employing SVD. The SVD of $Y_{L\times R}$ ($Y_{L\times R} = Y_{R\times L}^T$) is a factorization of the form $Y_{L\times R} = U_{L\times L} D_{L\times R} V_{R\times R}^T$ where U and V are orthogonal matrices (with orthogonal columns) and D is a matrix of R singular values $\sigma_r = \sigma_{r\times r}$, where $\sigma_1 \geq \sigma 2 \geq ... \geq \sigma_R \geq 0$. Matrix U is referred to as a row basis representing the principal components of $Y_{L\times R}$. The singular values represent the standard deviations proportional to the amount of information contained in the corresponding principal components. A reduced set of P basis vectors are selected from U (i.e. $U_{L\times P}$) using P first singular values.

Stage 3: after applying PCA, we obtain uncorrelated basis vectors. These basis vectors are not statistically independent. To derive the independent basis vectors a further procedure i.e. ICA must be carried out. The ICA expresses the observation vector $U_{P\times L} = U_{L\times P}{}^T$ as the product of mixing matrix A and the statistically independent vector S:

$$U_{P\times L} = A_{P\times P}\, S_{P\times L} \quad (4)$$

FastICA algorithm is used here to estimate the demixing matrix W such that

$$\hat{S}_{P\times L} = W_{P\times P}\, U_{P\times L} \quad (5)$$

where $\hat{S} = [\hat{s}_{1\times L}, \hat{s}_{2\times L}, ..., \hat{s}_{P\times L}]^T$ is the collection of independents vectors that form our estimated sources and W is the demixing matrix.

In the next section we use our separation model to separate individual noise and source signals from only a single observed mixed signal (a combination of noise signals and the original source signal) in two analog integrated circuits.

4. EXPERIMENTAL RESULTS

In this section, the proposed method is applied to the observed mixture of noise and source signals as simulated in analog integrated circuits. The simulations are performed by Hspice and Matlab softwares. The first example is differential cascode topology (figure 2(a)). Differential cascode topologies also called "Telescopic" cascode op-amps. Telescopic cascode op-amps can be used to achieve a high gain (in our simulation gain is around 1000) [11]. This circuit is not composed of linear components because transistors M1-

M8 work in saturation region and we assume that only one output is available. The input of the simulated circuit is a sine wave and a compound noise, including power supply noise and ground noise. These signals are shown in figure 3. The measured mixed signal at the output node is depicted in figure 3(d). The mixed signal is a nonlinear combination of the input signal and the power supply and ground noises. At the first stage of the separation process we apply the EMD algorithm on the measured mixture at the output node of the Telescopic op-amp. As a result we obtained 8 IMFs and a residue (as shown in figure 4). To obtain uncorrelated basis components, we apply the principle component analysis on the obtained IMF components to obtain three basis vectors shown in figure 5. These vectors are uncorrelated but not independent. In the last stage we apply FastICA algorithm. The estimated sources are shown in figure 6. Since we have employed EMD algorithm in our separation process the estimated signals are symmetric with respect to the horizontal axis with DC value equal to zero. Notice that we assume nothing about the original sources in order to estimate them. Generally ICA has two ambiguities [5]: First, the variances of the independent component can not be determined (i.e. scaling ambiguity) and second, they can appear at the output of the source-estimating network in any order (i.e. permutation ambiguity). In order to eliminate scaling ambiguity, we must multiply the separated output signals by scaling coefficients to ensure equality between separated and original signals. In order to obtain these coefficients, we need to solve an over determined linear system of equations in the simple case of an instantaneous mixture such as ours:

$$A.c = b \tag{6}$$

In the above equation c is a m-by-1 vector that indicates unknown coefficients, b is a L-by-1 vector (L is the length of data) and consists of the single observed mixture and A is a L-by-m matrix comprising m separated signals ($L > m$ i.e. an over determined system). The least square solution to this matrix equation is vector c that minimizes the Euclidean norm of the residual $r = b - Ac.$ We can utilize MATLAB built-in functions for this solution which can be computed using the following command $c = pinv(A) * b$.
Here $pinv$ stands for the pseudoinverse matrix. After finding the multiplying coefficients and applying them to the appropriate separated output signals, it is observed that the scaling ambiguity is eliminated.

If we compare the estimated source signal and separated noise signals of figure 6 with the original input source and noise signals of figure 3, it can be observed that the estimated results are acceptable and it is noticeable that by applying the above proposed procedure, original and separated signals are approximately in the same scale.

In the second example, we used "Crossed-Coupled Oscillator". The schematic of this circuit is shown in figure 2(b). This configuration does not latch up because its low-frequency gain is very small. Furthermore, at resonance, the total phase shift around the loop is zero because each state contributes zero frequency-dependent phase shifts. That is if $g_{m1}R_p g_{m2}R_p \geq 1$ then the loop oscillates [11]. The circuit generates a feedback sine wave and this time, a compound noise including power supply noise, ground noise and coupling noise (shown in figure 7) is injected in the circuit. Coupling noise is injected in node A. We measure again the mixed signal at output node and the same separation process is used. The measured mixed signal is given in figure 7(e). The estimated source signal and the separated noise signals are shown in figure 8. From this example we can see that the algorithm works adequately efficient in the compound noise environment. In order to measure the distortion between the original and the estimated sources we use the improvement of signal-to-noise ratio (ISNR) as the quantitative measure of separation performance [12].

The ISNR is the difference between input and output SNRs. The input SNR (SNR_I) is defined as

$$SNR_I = 10\log\frac{\sum_t |s(t)|^2}{\sum_t |x(t) - s(t)|^2} \tag{7}$$

where $x(t)$ is the observed mixture and $s(t)$ is the original input signal. If $\hat{S}(t)$ is the estimated source signal then the output SNR (SNR_O) is defined as:

$$SNR_O = 10\log\frac{\sum_t |s(t)|^2}{\sum_t |s(t) - \hat{s}(t)|^2}. \tag{8}$$

We consider $ISNR(dB) = SNR_O - SNR_I$ as the performance measure. Table.1 shows the ISNR obtained for the previous two examples. The ISNR represents the degree of suppression of the interfering signals. It is noticeable that although only two or three mixed sources of analog circuits are used here the proposed method is general.

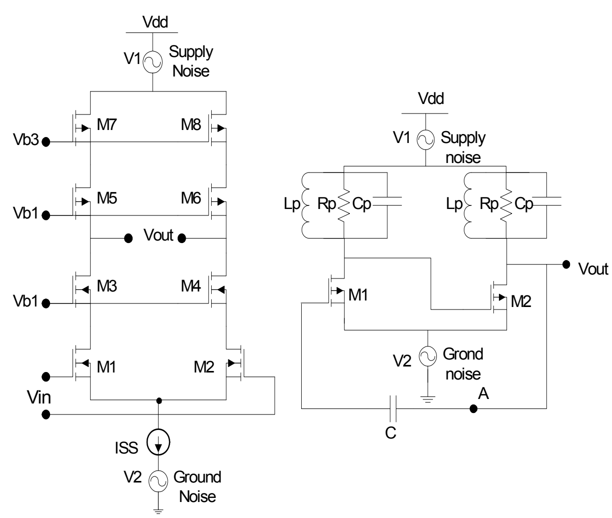

Figure 2 – Analog circuits: a) Telescopic op-amp. b) Cross-Coupled oscillator.

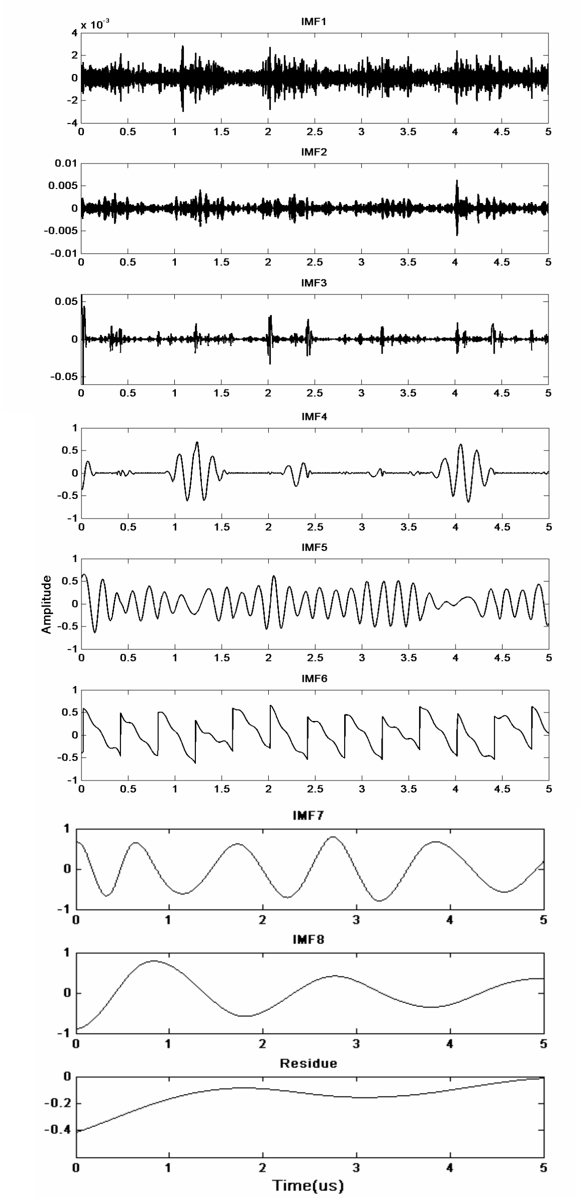

Figure 4- EMD of a single mixture (output node of Telescopic op-amp) showing 8 IMF components and residue.

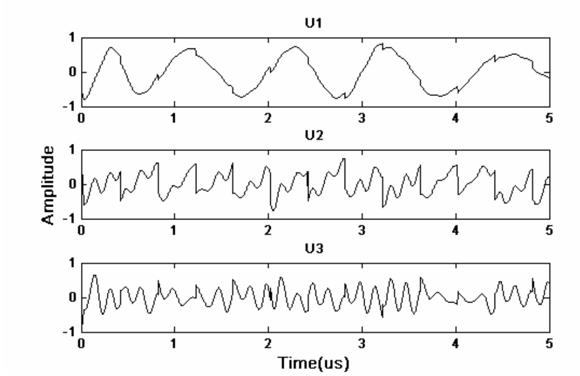

Figure 5 - The uncorrelated and dominant basis components.

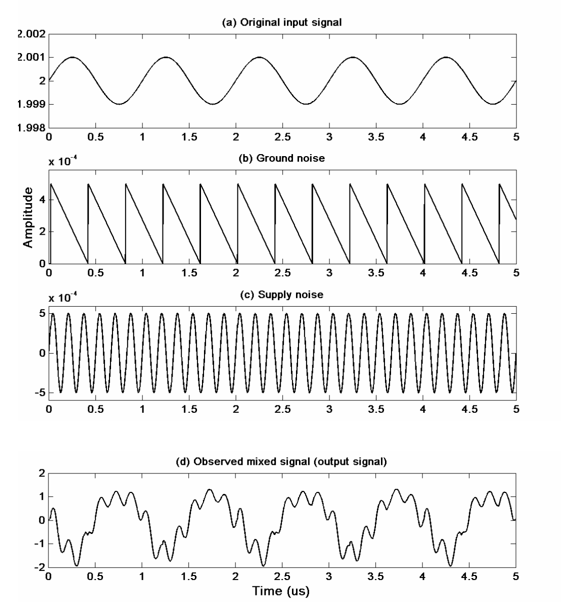

Figure 3- The original signals: (a) Original input signal; (b) Ground noise; (c) Supply noise; (d) Observed mixed signal that is output signal of Telescopic op-amp circuit.

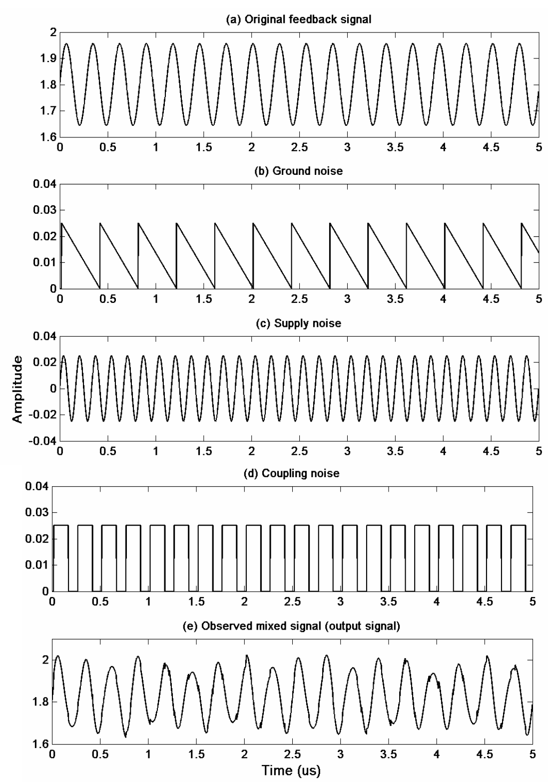

Figure 7 - The original signals: (a) Feedback signal; (b) Ground noise; (c) Supply noise; (d) Coupling noise (e) Observed mixed signal that is the output signal of Cross-Coupled oscillator circuit.

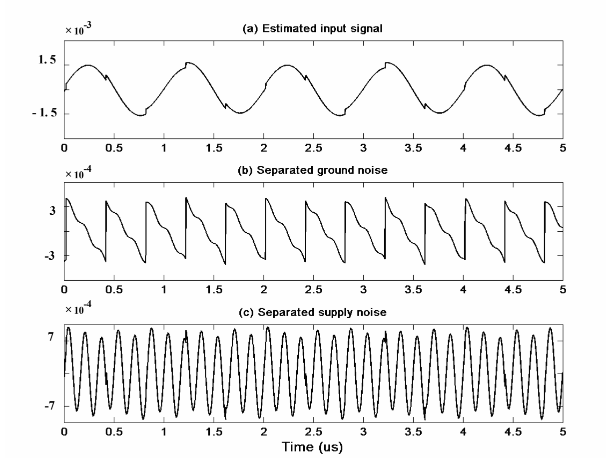

Figure 6 - The estimated signals: (a) Estimated input signal; (b) Separated ground noise; (c) Separated supply noise.

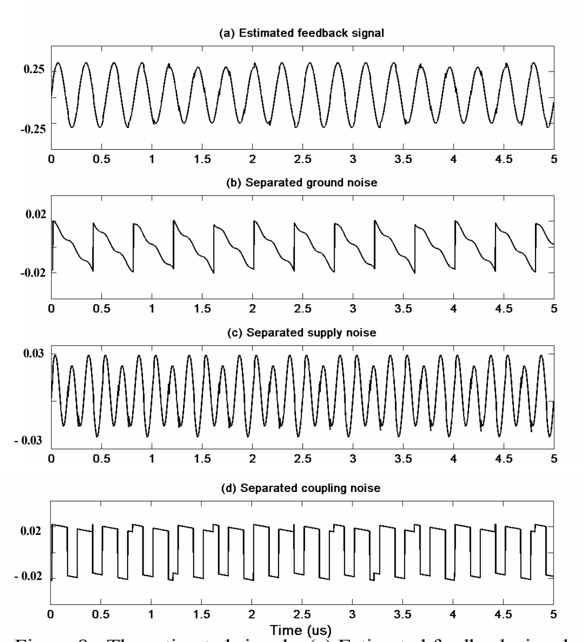

Figure 8 - The estimated signals: (a) Estimated feedback signal; (b) Separated ground noise; (c) Separated supply noise; (d) Separated coupling noise.

Table 1 - The experimental separation results (in terms of ISNR) of the proposed method.

Mixed signal	ISNR(dB)
Mix1 (output of Telescopic op-amp)	11.01
Mix2 (Cross-Coupled oscillator)	9.86

5. CONCLUSION

In this paper, we proposed a new approach to separate noise and source signals from a single observed mixture in the analog integrated circuits. Our method is based on one-channel blind source separation (BSS) and consists of three stages. In the first stage we used EMD to decompose the observed mixture as a collection of some oscillatory basis components termed IMFs. At the second stage, PCA is applied to these IMFs to produce uncorrelated and dominant basis components. The components obtained by PCA not statistically independent thus in the third stage, we applied ICA. The most important advantages of our method are 1) It is not necessary that the components in the circuit to be linear. 2) Separation process can be performed using only a single mixture. In this paper we employed the proposed separating model to separate individual noise and source signals in analog integrated circuits. Experimental results confirmed the strong potential of the proposed method for noise separation in analog integrated circuits.

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