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Letters

Sparse coding blind source separation through Powerline

Harold Szu*, Pornchai Chanyagorn, Ivica Kopriva

Digital Media RF Laboratory, Department of ECE, George Washington University, 725 23rd St., N.W., Lab# 308, Washington, DC 20037, USA

Abstract

Without multiplexing, Powerline (PL) can support the concept of smart sensor web broadcasting of an N-sensors-to-single-owner (N-to-1) for household/stadium/mall/metro/city surveillance. In order to make the single user scenario feasible, the underdetermined blind source separation (BSS) problem $x(k) = \langle \vec{a}, \vec{s}(k) \rangle + n(k)$ has to be solved so that only inner product time series signal $x(k)$ is known. Our contribution is based on the understanding that the finite alphabet property of the binary sources $\vec{s}(k)$ can resolve the underdetermined PL BSS case. For example, the alphabet of two binary sources consists of four states (1 1, 1 −1, −1 1, −1 −1), which mixing vector $\vec{a}$ and noise $n(k)$ will spread in the mixed signal $x(k)$, around the four centroids. We apply self-organizing maps to compute centroids from which the impulse response vector $\vec{a}$ is determined. Then, the source vector $\vec{s}(k)$ is recovered using the standard LMS method. Published by Elsevier Science B.V.

Keywords: Powerline communication; Smart sensor web; Under-determined blind source separation

1. Introduction

Powerline communication (PLC), [7], has become a new choice of communication media by using orthogonal frequency division multiplexing (OFDM), [10], in European Internet application and by using time division multiple access (TDMA) to read electric power meters and mimic the function of phone-line DSL in Japan. Several hundred homes sharing one power transformer make a value-added Internet application economically and technically feasible in Germany, Israel, and Japan. However in the

* Corresponding author.
E-mail address: harold_szu@onr.navy.mil (H. Szu).
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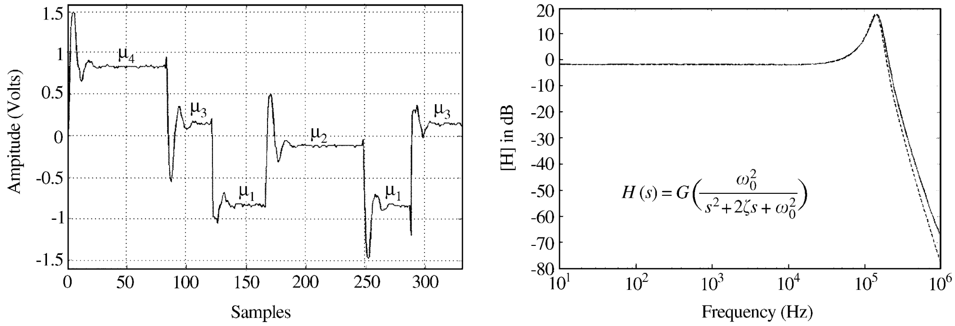

Fig. 1. Time response of the real PL on the two input square wave signals (left): The experiment had been done by generating data pulses from two sources, then sent them into a powerline network (NM-B AWG14-2 with ground and AWG12-2 with ground, indoor standard power cables), and the output of the mixing signal is obtained. Magnitude response of the isolation transformer (right): The isolation transformer is also placed in between the two sources and the receiver for a reality of the network. The figure also shows that the isolation transformer has a low-pass filter property with the resonance frequency at 141.81 kHz. The solid line represents a real magnitude response obtained from measurement, and the dash line represents a magnitude response from the model where the gain constant $G = 0.905$ and the resonance factor $\zeta = 0.189$.

USA, a dense power grid supplies 110 V of electrical power to only a few houses. The low-pass nature of the transformer limits the bandwidth to 0.1 MHz only, Fig. 1. Moreover, PLC has unpredictable Lenz induction noise, impedance-mismatch echoes, and fatal attenuation, allowing no address for signal switching. Thus, the US has so far neglected the PLC about which six IEEE International Symposiums have been held outside the North America. In this letter, we consider a special surveillance niche that, without using any kind of addressing and switching infrastructure, plugs N surveillance sensors into the same powerline that broadcasts to a single receiver, [4]. In such a niche, [3], this could be very suitable for homeland defense; PL is more cost effective than fiber optics and demands less maintenance. Once these surveillance sensors have found a local receiver or terminal, they will propagate through the existing Internet and other wireless networks.

Signal de-mixing in a single plug-out case is an under-determined BSS problem that cannot be solved by traditional ICA algorithms [1,8]. Instead, we extend the method given in [5] where we exploit the sparseness of the binary data representation (finite alphabet or finite realization phase space). The single measurement results in a scalar time series $x(k)$:

$$x(k) = \langle \vec{a}, \vec{s}(k) \rangle + n(k) \tag{1}$$

that is described by the inner product of the unknown column mixing vector $\vec{a} = [a_1, a_2, \ldots, a_N]^{\mathrm{T}}$, and unknown source vector $\vec{s}(k) = [s_1(k), \ldots, s_N(k)]^{\mathrm{T}}$ with an additive noise $n(k)$, where k represents the time sample index. Based on works in [2,11], we create a new powerline model that is suitable for a frequency range below 100 KHz. The new model shows that the powerline is a memoryless system in this particular frequency range and (1) can be applied.

2. Traditional statistical techniques

In a case of poor SNR, we could, but we do not, rely on the traditional statistical density estimation methods [6]. Rather because of robust binary signal mixture, we can use the simple centroid self-organizing maps (SOM) from the histogram of the measured data in order to count the number of independent binary sources existing in the received signal $x(k)$. Our contributions are: (1) we are the first to apply BSS on sparse binary representation in the PLC (US Patent Pending); (2) we reduce the explosive $O(N^2)$ broadcasting growth rate to the linear $O(N)$ law by broadcasting the N sensors-to-single owner (N-to-1); (3) each sensor contributes to the time series $x(k)$ through an unknown impulse response function that can be determined from the binary data by an unsupervised neural network using sparseness of the signal phased space that contains 2^N elements; (4) unlike the method described in [5], which assumes that a number of source signals is known, we use an unsupervised clustering algorithm to determine the number of source signals $s_i(k)$ in the mixture $x(k)$. It has been shown in [4,5] that probability distribution function of $x(k)$ can be modeled as a mixture of $M = 2^N$ Gaussians. Assuming that elements of $\vec{a}$ are ordered i.e. $a_1 > a_2 > \cdots > a_n > 0$, it has been shown in [5] that the mixing vector $\vec{a}$ can be computed uniquely once the centroids μ_i are estimated. We propose the use of two unsupervised nearest neighbor-like clustering algorithms to estimate centroids μ_i. If the distance between the incoming new data $x(k)$ and the ith class centroids μ_i is less than some predefined value ε, then the new data are labeled with the ith class label. However, if distances between $x(k)$ and all existing class centroids μ_i are greater than ε, then the new class is created. At the end of the clustering process, the algorithm returns the number of the classes $\hat{M}$, and the number of source signals $s_i(k)$ existing in the received signal $x(k)$ is estimated by $\hat{N} = \log_2 \hat{M}$. In Fig. 2, centroids μ_i can be sequentially extracted by using the described unsupervised clustering algorithm. We plot 1D and 2D histograms for one second of the mixed speech data $x(k)$ obtained with an 8 kHz sampling rate. From the 2D histogram, we can observe the clustering of four centroids $\mu_1, \mu_2, \mu_3, \mu_4$ that implies the presence of two binary sources; $\hat{N} = \log_2 4 = 2$ in the received signal $x(k)$. As shown on Fig. 2, by using only one receiver and computing the 1D histogram, some peak of the centroids is difficult to distinguish. The mean estimators for efficient electronic chip implementation at each sensor are Kohonen's SOM, which in a sequential mode is equivalent to a Kalman-like orthogonal update. Namely the difference between new data $x(k+1)$ and an old average is added with a learning rate known as Kalman gain ρ:

$$\hat{\mu}_i \cong \langle \mathrm{X} \rangle_{k+1} \equiv (x_1 + x_2 + \cdots + x_k + \mathrm{x}_{k+1})/(k+1) = \langle \mathrm{X} \rangle_k + \rho(x_{k+1} - \langle \mathrm{X} \rangle_k). \quad (2)$$

The Kohonen SOM learning rate for the new centroid is equivalent to the Kalman gain for uniform average, which is derived as $\rho = 1/(k+1)$, and $\hat{\mu}_i$ means that the ith centroid is selected according to the nearest-neighbor classifier.

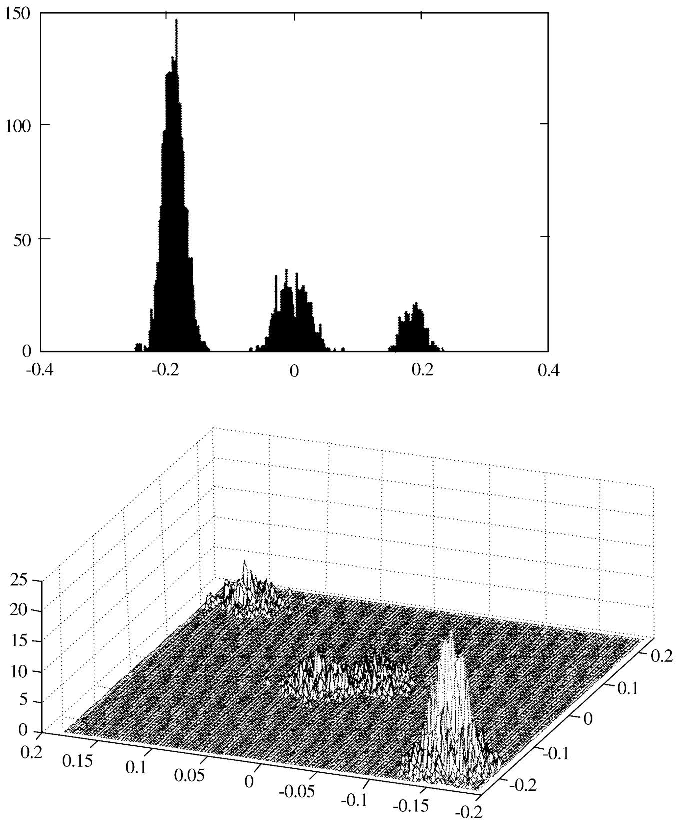

Fig. 2. 1D histogram of the received signal $x(k)$ (top); 2D of the same signal using two receivers (bottom). By representing mixing data in higher dimensional space, the centroids of the data can be extracted easier. Using the 2D histogram, the 1D histogram can be clearly extracted from a projection of the 2D histogram, and then the centroids can be estimated by PCA. Based on (5) and (6), not all of the centroids need to be estimated in order to estimate the mixing parameters, $\hat{a}$. This increases the robustness of signal separation.

3. Sparse phase space coding

After estimating the centroids $\hat{\mu}_i$, components of the mixing vector $\vec{a}$ are obtained as follows. The coding constraint imposed on the data signal is binary format i.e. $s_i(k) \in \{-1, 1\}$. If we apply an ensemble-averaging operator $E[x] = \int_{-\infty}^{+\infty} x\rho(x)\,\mathrm{d}x$ on Eq. (1), where the probability density function $\rho(x)$ is obtained from the measured normalized histogram, Fig. 2, we get:

$$E(x) = E(\langle \vec{a}, \vec{s} \rangle | \vec{s} = \vec{t}_i) + E(n) \cong \langle E(\vec{a}), E(\vec{t}_i) \rangle = \langle \vec{a}, \vec{t}_i \rangle = \mu_i \tag{3}$$

where $\vec{t}_i =$ the ith row of a finite alphabet matrix which in a case of two sources equals to:

$$T = \begin{bmatrix} -1 & -1 & +1 & +1 \\ -1 & +1 & -1 & +1 \end{bmatrix}^T .$$

Because the voltage of Lenz impulsive shot noise $n(k)$ has usually zero offset value, and taking into account that the impulse response function is independent of the input video signals: $E(\langle \vec{a}, \vec{t}_i \rangle) = \langle E(\vec{a}), E(\vec{t}_i) \rangle$, and that the expectation of the binary signal mixture is one of the four possible combinations in Eq. (4).

$$\begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \end{bmatrix} = \begin{bmatrix} -1 & -1 \\ -1 & +1 \\ +1 & -1 \\ +1 & +1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} . \tag{4}$$

Given centroid values $\vec{\mu}$ estimated by SOM, we did solve Eq. (4) component-wise as follows: $\mu_1 = -a_1 - a_2$, $\mu_2 = -a_1 + a_2$, $\mu_3 = a_1 - a_2$, $\mu_4 = a_1 + a_2$. If centroids μ_i are sorted in increasing order $\mu_1 < \mu_2 < \mu_3 < \mu_4$, and assuming components of $\vec{a}$ are ordered and positive, the algebraic solution for $\vec{a}$ is obtained as:

$$\hat{a}_1 = (\hat{\mu}_3 - \hat{\mu}_1)/2 = (\hat{\mu}_4 - \hat{\mu}_2)/2 = (\hat{\mu}_4 + \hat{\mu}_3)/2 = -(\hat{\mu}_1 + \hat{\mu}_2)/2, \tag{5}$$

$$\hat{a}_2 = (\hat{\mu}_2 - \hat{\mu}_1)/2 = (\hat{\mu}_4 + \hat{\mu}_2)/2 = (\hat{\mu}_4 - \hat{\mu}_3)/2 = -(\hat{\mu}_1 + \hat{\mu}_3)/2, \tag{6}$$

$$\hat{\mu}_2 + \hat{\mu}_3 = 0, \quad \hat{\mu}_1 + \hat{\mu}_4 = 0. \tag{7}$$

However, as already discussed, in the poor SNR by using 2D histogram shown in Fig. 2 we can determine the centroid values more accurately.

4. Source time series recovery

Once the mixing vector $\vec{a}$ has been obtained, it is no longer blind source separation (BSS) and the standard LMS methods, [9], can be used to estimate the binary source signals $\hat{s}_i(k)$. Then the benefit of using two receivers is an error correction capability that enables the algorithm to automatically select a final value, one that is closer to the corresponding measurement of two binary speech signals. Two original speech signals as well as two de-mixed signals recovered by using described algorithm are shown in Fig. 3.

5. Conclusions

The presented algorithm works well provided the source signals are binary. The performance of the whole de-mixing algorithm depends on the accuracy of the SOM for the estimation of the centroids μ_i, of which the quality of the self-organization-clustering

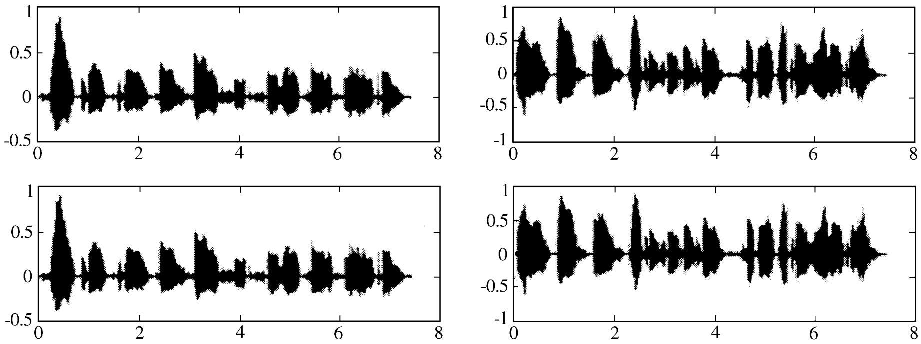

Fig. 3. First row are original two speech signals; second row are de-mixed speech signals by means of binary representation and one receiver only, so-called underdetermined sparse BSS.

algorithm is critical. Use of two receivers and a 2D histogram can improve accuracy of the centroids, μ_i, estimation process in the case of a noisy environment. The separation distance between the components of the mixing vector $\vec{a}$ that determines the minimal distance between the centroids μ_i can be adjusted. These adjustments are critical for the success of the clustering algorithm in the noisy scenario. Therefore, we conclude that the powerline N-to-1-user broadcasting communication without addressing for home security surveillance is feasible and experimentally verifiable. The bandwidth scaling law in terms of number of sensors remains to be demonstrated experimentally.

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