A BLIND SIGNAL LOCALIZATION AND SNR ESTIMATION METHOD

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ABSTRACT

Congested radio frequencies call for efficient and flexible spectrum use and, hence, spectrum sensing. As cognitive radios need channel information for achieving better use of radio frequencies, military systems require information about unknown signals. In this paper, a novel method for computing signal-to-noise ratios (SNR) of several unknown narrowband signals without a priori information is proposed. The presented frequency domain method is an extension of the localization algorithm based on double-thresholding (LAD). The main point is to produce fast and cost-efficient estimators with adequate accuracy. The proposed method is verified via computer simulations and tested also with real-life radio channel measurement data. The results verify that the proposed method gives sufficient approximations of SNR values with low overall computational complexity.

INTRODUCTION

Future cognitive radios [1], signal intelligence as well as the suppression of jamming signals [2] in both military and commercial applications require information about signals in specific frequency bands. When investigating radio channels, signal-to-noise ratio (SNR) is one of the key parameters of interest. In the applications described above, narrowband signals are usually unknown and that calls for blind SNR estimation.

Blind SNR estimation is a difficult problem, and several techniques have been reported in the literature. In [3], the SNR was computed from higher order averages of the envelope of a modulated signal. The SNR estimation in narrow-band channels based on correlation properties of the signal and noise was considered in [4]. In [5], higher-order moments were used to estimate the SNR of noisy data. Therein, the shape of the narrowband signal and noise power density spectrum (PDFs) were assumed to be known. Lately, several SNR estimation techniques have been compared in [6].

However, there are many problems and limitations in existing blind SNR estimation techniques. First, several methods are not actually blind because some kind of *a priori* information is required. Second, they are often useful only for some specific narrowband signals. Thirdly and lastly, the presence of several simultaneous narrowband signals may collapse the performance of the SNR estimator, and several methods are computationally demanding.

Versatility is one way to control the complexity of a system. In many applications it would be practical to use one method for several purposes, for example, to suppress jamming signals as well as estimate bandwidths (BWs) and SNR values. In this paper, a localization algorithm based on doublethresholding (LAD) [7,8] is extended to estimate the SNR values of several unknown narrowband signals in the frequency domain. Any a priori information about the narrowband signals is not required. LAD is a multipurpose tool, and the total complexity is reasonably low, since computations are shared by several applications - localization [7,8], interference suppression [8] and now, blind SNR estimation. The SNR estimation performance of the proposed extension is verified via computer simulations and tested also for reallife radio channel measurement data. Also, BW estimation accuracy of LAD is briefly considered.

SYSTEM MODEL

The received discrete-time signal samples are assumed to have the basic form

$$r(n) = \sum_{k=1}^{m} i_k(n) + w(n),$$
(1)

where m is the number of unknown narrowband signals, $i_k(n)$ is the kth narrowband signal, and w(n) is a zero-mean complex proper Gaussian random variable with total variance $2\sigma^2$. The considered narrowband signals are off-center sinusoids as well as binary phase shift keying (BPSK) communication signals in the simulations, and narrowband communication signals in the real-life radio channel measurement survey. The signals are assumed to be independent of each other.

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The SNR of the kth signal is defined to be

$$\gamma_k = \frac{P_k^i}{P_w},\tag{2}$$

where P_k^i is the power of the kth narrowband signal and P_w is the power of the noise.

THE LOCALIZATION ALGORITHM BASED ON DOUBLE-THRESHOLDING

LAD [7, 8] calculates two detection thresholds in order to separate the total set of samples into two or more sets: m' sets are from detected narrowband signals and one set contains the assumed noise samples. The threshold setting can be performed, for example, using the forward consecutive mean excision (FCME) algorithm [8,9].

The FCME algorithm is an automated, iterative method for setting a threshold. First, the desired clean sample rejection rate $P_{\text{FA,DES}}$ is selected [10] and threshold parameter T_{CME} is calculated. The threshold parameter depends on the assumed distribution of the noise. Here, complex Gaussian distributed samples are magnitude squared, so they will follow a scaled chi-squared distribution, and $T_{\text{CME}} =$ $-\ln(P_{\text{FA,DES}})$ [9]. For example if $P_{\text{FA,DES}} = 0.05$ which means that on the average about 5% of noise samples are classified to be signal samples in the case when there is only noise present, $T_{\text{CME}} = 2.99$. Samples are rearranged in an ascending order according to sample energy [11]. The total number of observations is N. Next, n (usually $n = 0.1 \cdot N$) smallest observations are selected to form the initial set. Let the size of this set be Q.

Step 1: Calculate threshold

$$T_{h} = \frac{1}{Q} \sum_{i=1}^{Q} |x_{i}|^{2} \cdot T_{\text{CME}}.$$
 (3)

Step 2: Add x_i , $i = Q+1, \dots, N$ to the set Q if $|x_i|^2 < T_h$. The algorithm continues until there are no new samples below the threshold. Finally, samples below the threshold are assumed to belong to the noise set. For two thresholds, the FCME algorithm is run twice with two different threshold parameters.

After the thresholds have been calculated, LAD groups the adjacent samples above the lower threshold into the same group, a *cluster*. According to LAD, the cluster is accepted to be a narrowband signal if at least the sample with the largest energy is also above the upper threshold [7, 8]. The



Figure 1. One realization of LAD, an RC-BPSK signal with a BW of 5%. Detected samples are the adjacent samples above the lower threshold T_{lo} . Because at least one of the samples is also over the upper threshold T_{up} , the cluster is accepted to be caused by a signal.

use of two thresholds avoids needless separation of the signal and falsely detected signals [8]. The principle of LAD is illustrated in Fig. 1.

BLIND SNR ESTIMATION

After LAD has been performed in the frequency domain, there are m' estimated sets of narrowband signals, and one noise set containing estimated noise. The SNR estimate for the *k*th estimated narrowband signal is

$$\hat{\gamma}_k = \frac{\frac{1}{N} \sum |I_k(n)|^2}{\frac{1}{K} \sum |W(n)|^2} = \frac{\hat{P}_k^i}{\hat{P}_w},\tag{4}$$

where $\{I_k\}, k = 1, \dots, m'$, denotes the received frequency domain samples belonging to the kth estimated narrowband signal set, N is the total number of samples, $\{W(n)\}$ denotes the received frequency domain samples belonging to the noise set and K is the size of the noise set. If the noise mean is known, \hat{P}_w is replaced by $2\sigma^2$. Because all the samples are already squared, the overall complexity is relatively low. Note that if the SNR is required only from the narrowband signal's BW, coefficient N/n_k is used, where n_k is the size of the kth narrowband signal set. Estimated SNR in dBs is $\hat{\gamma}_k[d\mathbf{B}] = 10 \log_{10} \hat{\gamma}_k$.

The bias and the normalized mean square error (NMSE) [12] are used to measure the correctness of the estimated SNR. The average bias of a SNR estimator is defined as $Bias(\hat{\gamma}_k) = E|\gamma_k - \hat{\gamma}_k|$, where E is the expected value and γ_k is the actual SNR for the *k*th signal. Note that

here we have assumed that the numbering of the estimated and actual narrowband signals correspond to each other. If $Bias(\hat{\gamma}_k) = 0$, the estimated SNR equals the real SNR, i.e., $\hat{\gamma}_k = \gamma_k$. The NMSE is $J = E|\gamma_k - \hat{\gamma}_k|^2/\gamma_k^2$. In the simulations, the sample bias was computed according to $Bias(\hat{\gamma}_k) = \frac{1}{N_i} \sum_{i=1}^{N_i} |\gamma_k - \hat{\gamma}_{ki}|$, where N_i is the number of iterations. Similarly, sample NMSE was $J = \frac{1}{N_i} \sum_{i=1}^{N_i} [(\gamma_k - \hat{\gamma}_{ki})^2/\gamma_k^2]$.

The performance of the method is strictly connected to the accuracy of LAD. For example, if LAD separates one signal into two or more signals, it results in two or more SNR values instead of one, respectively. Moreover, LAD can accidentally handle two closely spaced signals as one signal, thus giving only one SNR instead of two. The numerical study is made assuming that LAD finds the correct number of signals, i.e., m' = m. LAD has good performance in finding the correct number of BPSK signals, especially at low SNR [8]. However, this seems to be quite a common problem from which many blind SNR methods suffer.

NUMERICAL RESULTS

The method is tested both in simulations and using real-life radio channel measurement data.

SIMULATION RESULTS

Monte Carlo computer simulations consisted of a complex AWGN channel, several off-center sinusoids, and BPSK signals with BWs 2-10% of the system bandwidth. The BPSK signals were band-limited by a root raised cosine (RC) filter with a roll-of factor of 0.22. The noise mean was assumed to be unknown. The total number of samples N = 1024, and the FFT length was 1024. There was no temporal windowing before the FFT. The SNR values were defined separately for each signal. The threshold parameters were 13.81 ($P_{\text{FA,DES}} = 10^{-4}$, upper) and 2.66 ($P_{\text{FA,DES}} = 0.07$, lower) [8,9] which seems to be a good compromise. If the lower threshold parameter is too low, sidelobes will skew the BW estimation. Respectively, if the lower threshold parameter is too high, it may cause false separation of the signal (see Fig. 1).

Fig. 2 shows some BW and SNR estimation examples. For example, when there are two simultaneous BPSK signals with BWs of 5% and 5 dB SNR values (Fig. 2(a)), estimated BWs are 5.7% and 5.2%. Respectively, estimated SNR values are 4.8 dB and 4.78 dB. In these cases, both the BW and

	Estimated BWs							
	SNR [dB]							
	0	5	10	15	20	25		
BPSK, BW 5%	5.0	5.6	6.1	6.9	8.6	11.9		
BPSK, BW 10%	7.7	10.3	11.3	11.9	12.7	14.6		
BPSK #1, BW 5%	4.8	5.0	5.8	6.5	7.9	9.8		
BPSK #2, BW 5%	3.9	4.7	5.9	6.6	7.8	10.0		
BPSK #1, BW 10%	5.9	6.6	9.1	10.0	11.4	12.5		
BPSK #2, BW 10%	3.6	6.3	8.6	10.5	11.2	12.5		

SNR estimates correspond rather well the real ones. Note that these are only examples based on single realizations.

Numerical BW estimation results are shown in Table I. Results are based on about 10^5 Monte Carlo iterations. For example, when there are two simultaneous BPSK signals with BWs of 10% and 15dB SNR, estimated BWs are, on average, 10.0% and 10.5%.

In Figs. 3–6, the performance of the SNR estimation method is demonstrated through simulations, and also the bias and NMSE are considered. The BPSK signal was simulated with BWs of 2%, 5% and 10%. In Fig. 3, results are presented for one BPSK signal with a BW of 5%. At low SNR, the performance of the method is very good. At high SNR, say 25dB or more, the SNR estimate is about 2dB too small. The NMSE is at most 0.11 which is a good result. At low SNR, the NMSE is large. When considering a BPSK signal with a BW of 2% or 10%, or one sinusoid, the performance of the method was almost the same. Results for several signals are presented in Figs. 4–6. In that case, the signals are randomly spaced and, hence, may interfere each other. When there are two BPSK signals (Fig. 4) or two sinusoids (Fig. 5) with equal SNR values, the performance is almost equal to the situation when there is only one signal. However, the NMSE is somewhat larger: with low SNR it is at most 1.0 for BPSK signals. For sinusoids, the NMSE is at most 0.11. When the SNR is 6 dB or more, the NMSE is small. In Fig. 6, there are two BPSK signals, and the SNR of the second signal is 3 dB lower. The SNR estimation method performs well even though there is more bias and NMSE. However, when the SNR is 6 dB or larger, the NMSE is relatively small.

The SNR estimation method seems to be able to give satisfactory approximations about the SNR values. At low SNR, <6dB, noise causes large NMSE. The NMSE decreases as the SNR increases. With a large SNR, the amount of estimation error increases. That is because the rising sidelobes



(a) Two RC-BPSK signals. Actual BWs 5%, estimated BWs 5.7 and 5.2%. γ_k =5 dB, $\hat{\gamma}_k$ =4.8 and 4.78 dB.

(b) Two RC-BPSK signals. Actual BWs 8 and 2%, estimated BWs 8.5 and 3.2%. γ_k =10 and 7 dB, $\hat{\gamma}_k$ =9.7 and 6.4 dB.



(c) Five sinusoids. $\gamma_k=5$ dB, $\hat{\gamma}_k=4.7$, 4.8, 4.96, 4.96 and 4.7 dB.





Figure 3. Estimated SNR, Bias and NMSE vs. actual SNR. One RC-BPSK signal, actual BW 5%.

increase the noise level since it is difficult to identify if the sidelobes belong to the signal or to the noise. This problem is illustrated in Fig. 7, where NMSE of the estimated noise mean is presented for several signals. When the SNR is 15 dB, the noise estimation error starts to increase.

In the case when the noise mean is assumed to be known, the SNR estimation method yields very accurate results also for large SNR values. For example, in Fig. 8, there are simultaneously two sinusoids. In that case, the SNR estimation method gives very accurate results, and also the bias and NMSE are lower when compared to the situation where the noise level is not known (Fig. 5).

REAL-LIFE RADIO CHANNEL MEASUREMENT RE-SULTS

Multiple-input multiple-output (MIMO) real-life radio channel measurements have been performed using the Elektrobit PropSound multidimensional radio channel sounder [13] in the city of Oulu, Finland, in Autumn 2004 [14]. The investigated radio channel was measured at 2.45 GHz with 200 MHz receiver BW, and the number of total samples was 2046 (2 samples/chip). The measured *M*-sequence with a 100Mcps rate was corrupted by several wireless local area network (WLAN) signals (in Finland, 2.412-2.472 GHz) and other narrowband (ca. 10-20 MHz) signals [15, 16]. Be-



Figure 4. Estimated SNR, Bias and NMSE vs. actual SNR. Two RC-BPSK signals, actual BWs 5%.



Figure 5. Estimated SNR, Bias and NMSE vs. actual SNR. Two sinusoids.

cause we do not know what the narrowband signals were, we are not able to measure the correctness of the BW and SNR estimation. Nevertheless, some BW and SNR estimation results for some frequency domain 'snapshots' are presented in Fig. 9 and Table II, respectively. In these results, the SNR values were estimated in the narrowband signal's BW, so coefficient N/n_k was used in Eq. (4). At 2.45 GHz, there is DC component (Fig. 9). When comparing figures and numerical results from Table II it can be noticed that the BW and SNR estimation seems to be quite successful.

CONCLUSIONS

Blind SNR estimation was considered. The proposed SNR estimation method is an extension of the doublethresholding signal detection method called LAD. The proposed SNR estimation method was verified via computer simulations and was tested also for real-life radio channel measurement data. It can be concluded that the proposed method offers good approximations of SNR values when the number of narrowband signals has been estimated properly.

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Figure 6. Estimated SNR, Bias and NMSE vs. actual SNR. Two RC-BPSK signals with different SNR values, actual BWs 5%.



Figure 8. Estimated SNR, Bias and NMSE vs. actual SNR. Two sinusoids in the case when the noise mean is known.

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Figure 9. BW and SNR estimation examples for real-life radio channel measurement. Corresponding results are presented in Table II.

Table II BW AND SNR ESTIMATION EXAMPLE RESULTS.

	Fig. 9(a)			Figs 9(b)				
Detected signals		3			3			
center freqs [GHz]	2.45*	2.50	2.53	2.45*	2.50	2.53		
estimated BWs [MHz]	0.39	21.48	18.75	0.19	19.73	16.02		
$\hat{\gamma}_k$ [dB]	31.65	18.86	15.16	30.17	18.80	15.53		
		Fig. 9(c)			Fig. 9(d)			
Detected signals		3			3			
center freqs [GHz]	2.45*	2.48	2.50	2.45*	2.50	2.53		
estimated BWs [MHz]	0.98	11.52	13.281	0.19	15.04	9.77		
$\hat{\gamma}_k$ [dB]	20.66	8.99	12.23	30.74	18.39	15.97		
	Fig. 9(e)							
Detected signals	4							
center freqs [GHz]		2.45*	2.48	2.50	2.53			
estimated BWs [MHz]		0.19	6.45	21.88	15.82			
$\hat{\gamma}_k$ [dB]		34.04	8.64	20.96	17.89			
* DC component								



Figure 7. Estimated noise mean. NMSE vs. SNR

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