(iii) for very low supply voltage, the delay variations due to the voltage threshold voltages could be very large [7]. It can be shown that if the clock inverter delay at high voltage is generally smaller than the master latch delay, it could be the contrary at very low voltages (< 1 V) [7].
(iv) for the cell design itself, i.e. people designing, for instance, flip-flops for cell libraries, it is much more difficult to design cells containing a critical race. Obviously, it is necessary to control the race, so we must, for instance, keep an internal delay quite long. It could be at the price of a slower cell if this internal delay is on the critical path of the cell. Or if a fast cell is mandatory, it means that the input inverter must be faster, requiring very large transistors and a lot of power.

Speed-independence at gate level: Race-free or speed-independent circuits at the implementation levels can be designed using another design method [4 – 6] based on the properties of the negative gates. The method starts from a flow table (and not from a STG or SG). The basic idea is to modify the original flow table by adding supplementary internal variables to satisfy the properties of the negative gates. So, the final synthesis produces only negative gates without input inverters. The divider (by two) in [5] has no clock inverter (it is a static version of a TSPC true single phase clock [8]) and contains four gates and 24 transistors. The divider derived from a flip-flop with D = not(Q) in [4, 5] with five gates contains 24 transistors [7] and can be reduced to 22 transistors or less [[9], paper 2.2].

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Algorithm for the Wigner distribution of noisy signals realisation

LJ. Stanković

A simple robust algorithm which efficiently represents signals with a very high amount of noise is presented, according to the expressions for the mean, variance and the optimal window width of the Wigner distribution estimator. Its application in the time-varying filtering is illustrated.

Introduction: Time-frequency analysis provides a joint time-frequency representation of a signal and is an area of intensive research [1]. Among the quadratic energy distributions, the Wigner distribution (WD), along with its smoothed forms, plays the central role. Analysis of the noise influence on these distributions is an important research topic which has been reported in several papers; some of the most recent ones are [2 – 4]. A simple algorithm, which can significantly improve time-frequency representation in the case of signals heavily corrupted by the noise, is presented in this Letter. The algorithm is based on two Wigner distributions, with two very different window widths: one is such that the bias is always small; the other is such that the variance is always small. The idea for this algorithm originated from the method for nonparametric regression [5], and its version for the instantaneous frequency estimation [6, 7]. The conditions, results and conclusions are quite different from the case where the instantaneous frequency estimation was considered [6, 7].

The WD, in its pseudo-form, of a discrete-time noisy signal $x(n) = f(n) + \nu(n)$ is defined as [1, 3, 8]:

$$W_{xx}(n,\theta;N) = \sum_{k=-\infty}^{\infty} w(k)w(-k)x(n+k)x^*(n-k)e^{-jk2\theta} \tag{1}$$

where N is the window $w_e(k) = w(k)w(-k)$ length. We will consider the case when the signal $f(n)$ is deterministic and the noise $\nu(n)$ is white, Gaussian, and complex with independent real and imaginary parts, [2 – 4]. The variance of noise is assumed to be σ_ν^2. Estimator $W_{xx}(n, \theta; N)$ of $W_{ff}(n, \theta; N)$ has the bias [3]

$$bias(n,\theta;N) = \frac{1}{8}\frac{\partial^2 W_{ff}(n,\theta;N)}{\partial\theta^2}m_2 = \frac{1}{8}B_f(n,\theta)m_2 \tag{2}$$

where $m_2 = (1/2\pi)\int_{-\pi}^{\pi}\omega^2 F_w(\omega)d\omega$ is the amplitude moment and $F_w(0) = FT[w_e(k)]$ is the Fourier transform of $w_e(k)$. If $w_e(k)$ is a Hanning window, then $m_2 = 2(\pi/N)^2$. The variance of $W_{xx}(n, \theta; N)$ could be written as eqns. 2 and 3:

$$\sigma_{xx}^2 = \sigma_\nu^2 \sum_{k=-N/2}^{N/2-1} w_e^2(k)\left[|f(n+k)|^2 + |f(n-k)|^2 + \sigma_\nu^2\right] \tag{3}$$

For an FM signal $f(n) = A(n)\exp(j\phi(n))$ with slow-varying amplitude $\sigma_{xx}^2 = E_w\sigma_\nu^2(2A^2(n) + \sigma_\nu^2)$, where $E_w = \sum_{k=-N/2}^{N/2-1} w_e^2(k)$ is the energy of $w_e(k)$. For the Hanning window $w_e(k)$, we have $E_w = 3N/8$.

The optimal window length can be obtained by minimising the mean square error $e^2 = bias^2(n, \theta; N) + \sigma_{xx}^2$. For the FM signal with slow-varying amplitude and the Hanning window, the mean square error is (eqns. 2 and 3)

$$e^2(n,\theta;N) = B_f^2(n,\theta)\frac{\pi^4}{16N^4} + \frac{3}{8}N\sigma_\nu^2(2A^2(n) + \sigma_\nu^2) \tag{4}$$

From

$$\frac{\partial e^2(n,\theta;N)}{\partial N} = 0$$

the optimal window width N_{opt} follows [3]:

$$N_{opt} = \sqrt[5]{\frac{B_f^2(n,\theta)\pi^4}{3\sigma_\nu^2(2A^2(n)+\sigma_\nu^2)}} \tag{5}$$

For optimal window width $bias(n, \theta; N_{opt}) = \sigma_{xx}/2$. But eqn. 5 is not practically useful since it requires $B_f(n, \theta)$ which is not known and depends on the WD's derivatives. The main topic of this Letter is to present a very simple method that will significantly improve the time-frequency presentation, on the basis of time-frequency varying window width $N(n, \theta)$, obtained without using the bias parameter $B_f(n, \theta)$.

For the WD of signal $f(n)$, $W_{ff}(n, \theta; N)$, and its estimator $W_{xx}(n, \theta; N)$ as a random variable, we may write

$$|W_{xx}(n,\theta;N) - [W_{ff}(n,\theta;N) + bias(n,\theta;N)]| \le \kappa\sigma_{xx}(N) \tag{6}$$

where the inequality holds with a probability $P(\kappa)$ depending on parameter κ. For now assume that κ is such that $P(\kappa) \simeq 1$. In statistics that usually means taking $\kappa = 2$, known as a two-sigma role, when for the Gaussian distribution of error $P(\kappa) > 0.95$. According to eqn. 6, if the bias is small, i.e. such that $bias(n, \theta; N) \le \sigma_{xx}(N)/2$ for each considered N, all confidence intervals

$$D(n,\theta;N) = \left[W_{xx}(n,\theta;N) - \left(\kappa + \frac{1}{2}\right)\sigma_{xx}(N),\right.$$

$$W_{xx}(n,\theta;N) + \left(\kappa + \frac{1}{2}\right)\sigma_{xx}(N)\Big] \quad (7)$$

intersect, since $W_{ff}(n, \theta; N) \in D(n, \theta; N)$. Of course, if the bias is large compared with the variance then $D(n, \theta; N)$, for two different N, will not intersect.

Algorithm: A very simple algorithm, proposed here, is based on the following fact: for regions in the time-frequency plane where $W_{ff}(n, \theta; N) \equiv 0$ (or is very slow-varying with respect to θ, for a given instant n), we have $B_f(n, \theta) = 0$ and, consequently, the optimal window width (eqn. 5) is very small and theoretically tends to zero. For the points where the distribution $W_{ff}(n, \theta; N)$ is highly concentrated around the instantaneous frequency, the values of distribution derivatives are large and the bias parameter $B_f(n, \theta)$ is large. For those points, the optimal window width should be very large as well.

Now, we assume a set of only two window lengths $\mathbf{N} = \{N_1, N_2\}$, such that N_1 is small enough that the variance of distribution is small at any point (n, θ), and N_2 is large so that the bias is small at any point, i.e. $N_1 < N_2$. This choice is possible according to eqn. 4. If the bias at a point (n, θ) is very small, i.e. the factor bias$(n, \theta; N_s)$ is close to zero, then all confidence intervals (eqn. 7), including those for N_1 and N_2, will intersect. Thus, for this point, we will use a better choice with respect to variance, i.e. distribution $W_{xx}(n, \theta; N_1)$ calculated with N_1. Otherwise, for large bias we have that the confidence intervals (eqn. 7) do not intersect and, for that point, we will use the distribution calculated with N_2. According to the relation between the bias and variance for the optimal window length, if we take the bias to be 'small' if $bias(n, \theta; N) < \sigma_{xx}/2$ and 'large' otherwise, then according to eqn. 7, we obtain the adaptive distribution with time-frequency varying window length:

$$W_{xx}^{(a)}(n,\theta) = \begin{cases} W_{xx}(n,\theta;N_1) & \text{for } \Phi = \text{true} \\ W_{xx}(n,\theta;N_2) & \text{otherwise} \end{cases} \quad (8)$$

where, according to eqn. 7, the event Φ = true is $|W_{xx}(n, \theta; N_1) - W_{xx}(n, \theta; N_2)| \le (\kappa + \frac{1}{2})[\sigma_{xx}(N_1) + \sigma_{xx}(N_2)]$. Therefore, using only two distributions, we can expect a significant improvement in the time-frequency representation. A theoretical analysis, as in [7], with a large number of window lengths within interval (N_1, N_2) can prove that we may get the optimal window length (eqn. 5) within the accuracy of the window length discretisation. But, we have concluded that the multi-window approach, although theoretically more accurate, does not in practice produce significant improvement with respect to the very simple two-windows approach presented here.

The only parameter which is required in eqn. 8 is the variance $\sigma_{xx}(N)$. There are several ways to accurately estimate it. For high noise cases, $\sigma_\nu^2 > A^2$, as in this Letter, the estimation is very simple since $\sigma_{xx}^2(N)/E_w(N) = \sigma_\nu^2(2A^2(n) + \sigma_\nu^2) \simeq (\sigma_\nu^2 + A^2(n))^2 \simeq (\Sigma_{k=-N/2}^{N/2-1}$. Factor $E_w(N) \simeq N$ is a constant for the given window type. The variance $\sigma_{xx}(N_1)$ can be calculated from the better estimated $\sigma_{xx}(N_2)$ as $\sigma_{xx}^2(N_1) = \sigma_{xx}^2(N_2)N_1/N_2$. Since $\sigma_{xx}(N)$ is frequency independent, it can also be estimated, for a high noise cases and a given instant n, by calculating the variance of $W_{xx}(n, \theta; N_2)$ over frequency θ. Some other approaches for the precise variance estimation, including small noise cases are presented in [7].

Example: Consider a sum of three noisy chirp signals:

$$x(n) = A\Big(e^{-25(nT-0.25)^2}e^{j1200(nT)^2} + e^{-20(nT-0.65)^2}e^{j750(nT+0.75)^2} + 3.5e^{-22500(nT-0.96875)^2}e^{j1000nT}\Big) + \nu(n) \quad (9)$$

The sampling interval $T = 1/2048$, with $\mathbf{N} = \{64, 512\}$ samples within the Hanning window are used. The signal amplitude and variance of noise are such that $10\log(E_f/\sigma_\nu^2) = -5$ [dB]. The WDs with constant window widths and adaptive window width are presented in Fig. 1. The algorithm has chosen the distribution with $N_1 = 64$ and very low variance for all regions where the bias is small, including the third signal component. Distribution with $N_2 = 512$ is chosen by the algorithm only for the small regions where the first two signal components exist (Fig. 1). It is exactly what we wanted and expected. Note that the signals do not significantly overlap in time, so the lag-window was sufficient to reduce the cross-terms in the WD. To combine two WDs, the distribution with $N_1 = 64$ is interpolated (using zero padding prior to the FFT) up to $N_2 = 512$.

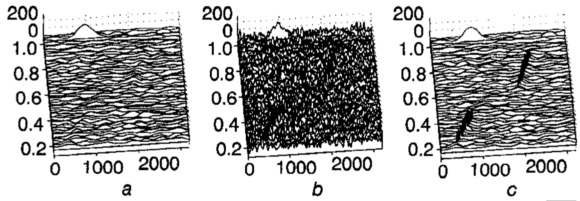

Fig. 1 *Wigner distribution of noisy signal*

a Constant window length $N_1 = 64$
b Constant window length $N_2 = 512$
c Adaptive time-frequency varying window length

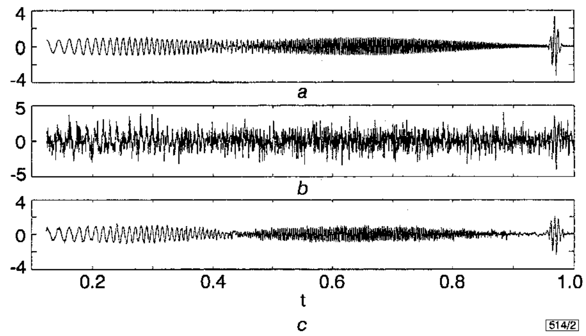

Fig. 2 *Time-varying filtering*

a Original signal without noise
b Noisy signal
c Signal filtered with time-varying filter

Time-varying filtering application: The distribution $W_{xx}^{(a)}(n, \theta)$, presented in Fig. 1*c*, is used as an estimate of $W_{ff}(n, \theta)$ in the time-varying Wiener filter definition, [9], $H(n, \theta) = W_{ff}(n, \theta)/W_{xx}(n, \theta)$. Using this transfer function, the signal $x(n) = f(n) + \nu(n)$ is filtered and the following equation is produced:

$$y(n) = \sum_{m=-\infty}^{\infty} h(n,m)x(m) = \frac{1}{2\pi}\int_{-\pi/2}^{\pi/2} H(n,\theta)X(\theta)d\theta$$

In this example, the simplified form of $H(n, \theta)$ is used: $H(n, \theta) = 1$, for a given time instant n, on θ where the maximum of $W_{xx}^{(a)}(n, \theta)$ is detected, and zero otherwise. The original signal, the noisy signal and the signal after time-varying filtering using $H(n, \theta)$ are shown in Fig. 2. The efficiency of the time-varying filter is evident, especially if we have in mind that the signal occupies a wide frequency range and the time-invariant filtering would not produce a significant noise reduction.

Conclusion: The presented algorithm may be used efficiently in the time-frequency representation of noisy signals, as well as being applied to time-varying filtering. The theory is quite general and may easily be extended to other time-frequency distributions.

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Analysis of ML and WSF in wireless channels

K.W. Cheung and S.W. Cheung

The performances of the WSF and deterministic ML methods are studied and compared when used without minimising techniques to super-resolve the coherent multipath components in simulated and experimental multipath channels. Studies have shown that, when all the sources are coherent, the WSF and the deterministic ML methods achieve the same results.

Introduction: It has been proven that with the use of minimising techniques the weighted subspace fitting (WSF) method always performs better than the deterministic maximum likelihood (ML) method for direction-of-arrival (DOA) estimation [1, 2]. In this Letter, the performances of the WSF and the deterministic ML methods without using minimising techniques are studied and compared when used to super-resolve coherent sources. It is assumed that the number of multipath components are known, and the WSF and deterministic ML methods are used to estimate the multipath arrival times in computer simulated wireless channels and experimental wireless channels generated inside an anechoic chamber. Studies have shown that, without using the minimising techniques and when all the sources are coherent, the WSF and the deterministic ML methods achieve the same results.

Problem formulation: A wireless channel can be expressed in complex equivalent lowpass representation as

$$h(t) = \sum_{i=1}^{K} h_i e^{j\theta_i} \delta(t - T_i) + n(t) \qquad (1)$$

where $\delta(.)$ is the Dirac delta function. h_i, θ_i and T_i are the scalar multipath gain, phase and arrival time, respectively, corresponding to the ith multipath component. $n(t)$ is AWGN and K is the number of the multipath. From eqn. 1, the channel frequency response, sampled at L equal frequency intervals Δf can be expressed as

$$S(f_l) = \sum_{i=1}^{K} h_i e^{j\theta_i} \exp(-j2\pi f_l T_i) + N_l \quad \text{for } 0 \le l \le L \qquad (2)$$

where $f_l = f_o + l\Delta f$, N_l is AWGN at frequency f_l and f_o is the smallest frequency component. eqn. 2 can be written as a matrix equation as

$$S = \mathbf{A}b + n \qquad (3)$$

where $S = [S(f_0)S(f_1)\cdots S(f_L)]^T$, $b = [h_1e^{j\theta_1}h_2e^{j\theta_2}\cdots h_Ke^{j\theta_K}]^T$ and $\mathbf{A}$ consists of the remaining exponential terms in eqn. 2. The output covariance matrix $\mathbf{R}$ is

$$\mathbf{R} = \langle SS^* \rangle \simeq \mathbf{A}\Lambda\mathbf{A} + \sigma^2\mathbf{I} \qquad (4)$$

where $\Lambda = \langle bb^* \rangle$, $\langle\cdot\rangle$ denotes the ensemble average, * denotes the complex conjugate transpose, $\mathbf{I}$ is the identity matrix and σ^2 is the power of AWGN.

If the channel frequency response at each frequency f_l is treated as the signals received by an uniform linear array (ULA) sensor element and the multipath arrival time as a source direction-of-arrival (DOA), then it can be realised that eqn. 3 has the same form as [1, 2] and, hence, the WSF and the deterministic ML methods can be used to super-resolve the multipath components in a wireless channel.

Super-resolution methods: In this Section, the super-resolution methods based on ML and WSF for resolving the coherent sources in the wireless channels are described. To compare their resolution performances, it is assumed that the number of sources is known.

(i) *Deterministic maximum likelihood (ML) method:* For the deterministic ML method, the desired sources are regarded as unknown deterministic data [1]. The optimal solution for eqn. 3 is then determined by nonlinear multidimensional searching for either of the two functions

$$\min_T |S - \mathbf{A}(\mathbf{T})b|^2 \qquad (5)$$

or

$$\max_T tr\{\mathbf{P}_A(\mathbf{T})\mathbf{R}\} \qquad (6)$$

over the multipath arrival time estimates $\mathbf{T} = \{\hat{T}_1, \hat{T}_2, ..., \hat{T}\}$ where $\mathbf{P}_A(\mathbf{T}) = \mathbf{A}(\mathbf{T})(\mathbf{A}^H(\mathbf{T})\mathbf{A}(\mathbf{T}))^{-1}\mathbf{A}^H(\mathbf{T})$ is the projection matrix, H denotes the Hermitian conjugate, $\mathrm{tr}\{\cdot\}$ is the trace of the bracketed matrix, $\min_T$ and $\max_T$ are the minimisation and maximisation of the problem, respectively.

(ii) *Weighted subspace fitting (WSF) method:* Theoretically, the output covariance matrix $\mathbf{R}$ in eqn. 4 can be eigendecomposited as

$$\mathbf{R} = \mathbf{E}_s\Lambda\mathbf{E}_s^* + \sigma^2\mathbf{E}_n\mathbf{E}_n^* \qquad (7)$$

where $\Lambda_s = \mathrm{diag}\{\lambda_1, \lambda_2, ..., \lambda_K\}$ is a diagonal matrix of real eigenvalues corresponding to the signal subspace vectors $\mathbf{E}_s$ such that $\lambda_1 > \lambda_2 > ... > \lambda_K > \sigma^2 > 0$, and $\mathbf{E}_n$ are the noise subspace vectors.

For WSF, the optimal solution is determined by minimising the function

$$\min_T tr\{\mathbf{P}_A(\mathbf{T})\hat{\mathbf{E}}_s\mathbf{W}\hat{\mathbf{E}}_s^*\} \qquad (8)$$

where

$$\mathbf{W} = \left(\hat{\Lambda}_s - \hat{\sigma}^2\mathbf{I}\right)^2 \hat{\Lambda}_s^{-1} \qquad (9)$$

with $\hat{\sigma}^2$ and $\hat{\Lambda}_s$ being the noise power and the eigenvalues of the signal subspace estimated from the output covariance matrix $\mathbf{R}$, respectively.

In practice, the eigenvalues from $\mathbf{R}$ are generally all different and so separating the eigenvectors into signal and noise subspaces becomes very difficult. However, when the sources are coherent, the first eigenvalue λ_1 is usually much larger than the rest of the eigenvalues (i.e. $\lambda_1 \gg \lambda_2 > ... > \lambda_L$). Hence, $\hat{\Lambda}_s$ is the largest eigenvalue λ_1, the signal subspace $\hat{\mathbf{E}}_s$ is its corresponding eigenvector and $\hat{\sigma}$ is simply the average of the remaining eigenvalues (λ_2, λ_3, ..., λ_L). Consequently, from eqn. 9, $\mathbf{W}$ becomes $(\lambda_1 - \hat{\sigma})^2\lambda_1^{-1} \simeq \lambda_1 = \Lambda_s$ because $\lambda_1 \gg \hat{\sigma}^2$ and so $\hat{\mathbf{E}}_s\Lambda_s\hat{\mathbf{E}}_s^* \simeq \mathbf{R}$. Therefore, the result obtained from the WSF method is $\min_T tr\{\mathbf{P}_A(\mathbf{T})\hat{\mathbf{E}}_s\mathbf{W}\hat{\mathbf{E}}_s^*\} \simeq \min_T tr\{\mathbf{P}_A(\mathbf{T})\mathbf{R}\}$ which is same as eqn. 6 obtained from the deterministic ML method.

Table 1: Multipath arrival times in nS obtained from ML and WSF in computer simulated channels at different SNRs

SNR [dB]	40	30	20	10	00
ML	10, 30	10, 30	12, 31	9, 27	15, 17
	10, 31	11, 31	12, 29	3, 29	6, 8
	16,46	16, 50	18, 50	26, 28	1, 13
WSF	10, 30	10, 30	12, 31	9, 27	15, 17
	10, 31	11, 31	12, 29	3, 29	6, 8
	16, 46	16, 50	18, 50	26, 28	1, 13

Upper, middle and lower entries are, respectively, BW = 2500, 1875 and 1250 kHz at different SNR

Simulation channels: Assuming that the number of the multipath components is known, the WSF and ML methods are used to estimate the multipath arrival times in computer simulated wireless channels. The channel frequency response data is simulated for bandwidths of 2500, 1875 and 1250kHz at 125kHz frequency