Available online at www.sciencedirect.com
ScienceDirect
Digital Signal Processing 16 (2006) 454–467
Digital Signal Processing
www.elsevier.com/locate/dsp

A time-frequency approach to the adjustable bandwidth concept

Lorenzo Galleani [a,1], Leon Cohen [a,*], Andrew Noga [b]

[a] City University of New York, New York, NY 10021, USA
[b] Air Force Research Laboratory, 525 Brooks Road, Rome, NY 13441, USA

Available online 26 August 2005

Abstract

The aim of the adjustable bandwidth concept (ABC) is to enhance nonstationary signals in noise by bringing out the main features so that they be effectively used in detection and classification algorithms. We show that the method transforms a time-frequency distribution by means of individual time-frequency transformations into a set of final time-frequency distributions. Each step of the procedure can be understood and formulated in terms of the kernel method. Explicit expressions are derived and examples are given. The formulation suggests further enhancements of the method.

Keywords: Adjustable bandwidth concept; Detection; Nonstationary signals; Time-frequency

1. Introduction

The adjustable bandwidth concept (ABC) is a method that enhances the performances of detection and estimation algorithms [1–3]. The aim is to enhance nonstationary signals in noise, that is, to bring out the main features of signals that may be buried in noise. This is essential for detection and classification and the method may be thought of as a "preprocessing algorithm" for classification applications and in particular for automatic signal recognition methods. In this article we show that the ABC approach is a time-frequency

* Corresponding author.
E-mail address: leon.cohen@hunter.cuny.edu (L. Cohen).
[1] Permanent address: Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy.

1051-2004/$ – see front matter
doi:10.1016/j.dsp.2005.08.001

method in that its basic idea is to treat time and frequency jointly. In particular we show that the algorithm transforms a time-frequency distribution by means of individual time-frequency transformations into a set of final time-frequency distributions. Each step of the procedure can be understood and formulated in terms of the kernel method, a technique that is standard in time-frequency analysis [4,5]. Once the procedure is formulated in terms of kernels, the ABC properties can be better studied and can suggest further enhancement and effectiveness of the method.

2. Time-frequency and the kernel method

A fundamental idea of time-frequency distributions is the concept of a kernel. The kernel characterizes the distribution and its properties and typically by examining the kernel one can ascertain the properties of the distribution. There have been many methods and distributions proposed over the years, among them the Wigner distribution, the spectrogram, the Choi–Williams, Margenau–Hill or Rihaczek, and the Zam distributions and several others. Among the many areas to which they have been applied are biomedical signal analysis (e.g., heart sounds, heart rate, the electroencephalogram (EEG), the electromyogram (EMG) and others), machine fault monitoring, radar and sonar signals, acoustic scattering, wave propagation, speech processing, analysis of marine mammal sounds, musical instruments, linear and nonlinear dynamical systems, among many others. The primary reason for the applicability of these methods to such a variety of fields is that in all the cases cited, the spectra of the signals of interest change with time and these changes are fundamental to understand as they reflect the source and/or propagation medium [6].

All time-frequency distributions may be generated from the general class that is given by [7]

$$C(t,\omega)=\frac{1}{4\pi^2}\iiint s^*\left(u-\frac{1}{2}\tau\right)s\left(u+\frac{1}{2}\tau\right)\phi(\theta,\tau)e^{-j\theta t-j\tau\omega+j\theta u}\,du\,d\tau\,d\theta, \tag{1}$$

where $\phi(\theta,\tau)$ is a two-dimensional function, the kernel. An alternative and useful formulation is to write

$$C(t,\omega)=\frac{1}{4\pi^2}\iint M(\theta,\tau)e^{-j\theta t-j\tau\omega}\,d\theta\,d\tau, \tag{2}$$

where

$$M(\theta,\tau)=\phi(\theta,\tau)\int s^*\left(u-\frac{1}{2}\tau\right)s\left(u+\frac{1}{2}\tau\right)e^{j\theta u}\,du \tag{3}$$

$$=\phi(\theta,\tau)A(\theta,\tau), \tag{4}$$

and where $A(\theta,\tau)$ is the standard ambiguity function commonly used in radar for the design of signals. The function $M(\theta,\tau)$ is called the characteristic function of the distribution.

We now briefly mention some kernels and their respective distributions. If the kernel is taken to be one then the Wigner distribution is obtained [8]. To avoid the cross term problems of the Wigner distribution a kernel methodology has been developed for kernel design and these ideas were initiated by Choi and Williams and Zhao, Atlas, and Marks [9]. The Choi–Williams kernel is given by $\phi(\theta,\tau)=\exp(-\theta^2\tau^2/\sigma)$ and the Zam kernel by $\phi(\theta,\tau)=g(\tau)|\tau|\frac{\sin a\theta\tau}{a\theta\tau}$. Williams and co-workers devised and crystallized the idea of kernel design [10,11]. They developed a methodology for the construction of distributions with desirable properties. Of particular interest is the spectrogram, given by

$$C_S(t,\omega)=\left|\frac{1}{\sqrt{2\pi}}\int w(t-t')s(t')e^{-i\omega t'}\,dt'\right|^2, \tag{5}$$

where $w(t)$ is the window. The kernel for the spectrogram is given by

$$\phi(\theta,\tau)=\int w^*\left(u-\frac{1}{2}\tau\right)w\left(u+\frac{1}{2}\tau\right)e^{j\theta u}\,du. \tag{6}$$

That is, the kernel of the spectrogram is the ambiguity function of the window. We point out that the squared magnitude of the wavelet transform can be used as a time-frequency distribution and formulated in the above terms [12,13]. Also, a number of fundamental results on the relation between the distribution and kernel have been developed, over the last ten years, the paper by Loughlin et al. being fundamental [14].

2.1. *The kernel as a transformation of distributions*

While the kernel method has generally been used to study, obtain, and characterize distributions, we discuss here the fact that it can also be used as a way of transforming distributions. The reason we emphasize this is that the ABC method is a sequence of time-frequency distribution transformations. Here we give some general properties of transformation. Suppose we have two distributions, C_1 and C_2, with corresponding kernels, ϕ_1 and ϕ_2. Their respective characteristic functions are related by

$$M_1(\theta,\tau)=\frac{\phi_1(\theta,\tau)}{\phi_2(\theta,\tau)}M_2(\theta,\tau). \tag{7}$$

This relationship connects the characteristic functions of any two distributions. To obtain the relationship between the distributions one uses Eq. (2) to obtain

$$C_1(t,\omega)=\iint g_{12}(t'-t,\omega'-\omega)C_2(t',\omega')\,dt'\,d\omega' \tag{8}$$

with

$$g_{12}(t,\omega)=\frac{1}{4\pi^2}\iint\frac{\phi_1(\theta,\tau)}{\phi_2(\theta,\tau)}e^{j\theta t+j\tau\omega}\,d\theta\,d\tau. \tag{9}$$

What this shows is that one distribution can be transformed into another by way of a two-dimensional convolution where the convolution function is given in terms of the kernels of each distribution.

3. The ABC method

The ABC approach is a multi-stage procedure that operates on a starting time-frequency distribution, $C_S(t,\omega)$, and generates N output distributions, $C_1(t,\omega), C_2(t,\omega), \ldots,$

$C_N(t,\omega)$. In this paper we show that the procedure at each stage is a time-frequency distribution transformation and that the end distribution can be characterized by a kernel which is a functional of the kernels at each stage.

3.1. Overall view

We first give an overall view of the basic algorithm and indeed we present two but equivalent views. The first formulates everything in the time-frequency plane and the second formulates some of the steps in the kernel or ambiguity function domain as discussed above. Each formulation has certain advantages, the first formulation allows a clearer mathematical view of the issues but the second formulation lends itself to more detailed discussion of the implementation issues. We present both formulations but in this paper we discuss in detail the second one. The first view is presented in detail in [15] where also an analytic example is given. The equivalence of the two formulations is given in [15].

In the first formulation the basic idea is to take a time-frequency distribution and from it obtain N new distributions. The new distributions have progressively different perspectives or resolutions of the original distribution. For the starting distribution we use $C_S(t,\omega)$, and the N resulting distributions are $C_1(t,\omega)$, $C_2(t,\omega),\ldots,C_N(t,\omega)$. However the actual iterative process is done on N intermediate distributions that we call $A_1(t,\omega)$, $A_2(t,\omega),\ldots,A_N(t,\omega)$. The iterative process is

$$A_m(t,\omega)=A_{m-1}(t,\omega)-\int h_{m-1}(t-t',\ \omega-\omega')A_{m-1}(t',\omega')\,dt'\,d\omega' \tag{10}$$

and to start one takes $A_1(t,\omega)=C_S(t,\omega)$. The $h_m(t,\omega)$ are fixed functions. We note that at each stage one removes from the distribution the effect that the second term of Eq. (10) produces. The iterative scheme, Eq. (10), is self-contained and produces distributions with certain properties that are achieved by the judicious choice of the $h_m(t,\omega)$ so chosen to achieve required results, such as frequency smoothing. Now, to further manipulate and enhance the result we obtain $C_m(t,\omega)$ from $A_m(t,\omega)$ by

$$C_m(t,\omega)=\int g_m(t-t',\omega-\omega')A_m(t',\ \omega')\,dt'\,d\omega', \tag{11}$$

where again $g_1(t,\omega), g_2(t,\omega),\ldots,g_N(t,\omega)$ are fixed filter functions prechosen to achieve desired characteristics. Of course one can just stick with the As and from a mathematical point of view that can be achieved by taking delta functions for the gs, in which case the result would be that $C_m(t,\omega)=A_m(t,\omega)$. Also, one can combine Eqs. (11) and (10) but we have found it clearer to write the procedure in the above form. We note that both transformations in Eqs. (11) and (10) are of the form as given by Eq. (8).

In the second formulation, at each stage of the algorithm there is an input distribution $A_m(t,\omega)$, an intermediate distribution $B_m(t,\omega)$, and an output distribution $C_m(t,\omega)$. The input distribution at the stage 1 is $A_1(t,\omega)\equiv C_S(t,\omega)$. The distributions $A_m(t,\omega)$ and $B_m(t,\omega)$ are needed to calculate the output *and* to go on to the next stage. In particular we tabulate here the overall steps:

$$A_m(t,\omega)=A_{m-1}(t,\omega)-B_{m-1}(t,\omega), \tag{12}$$

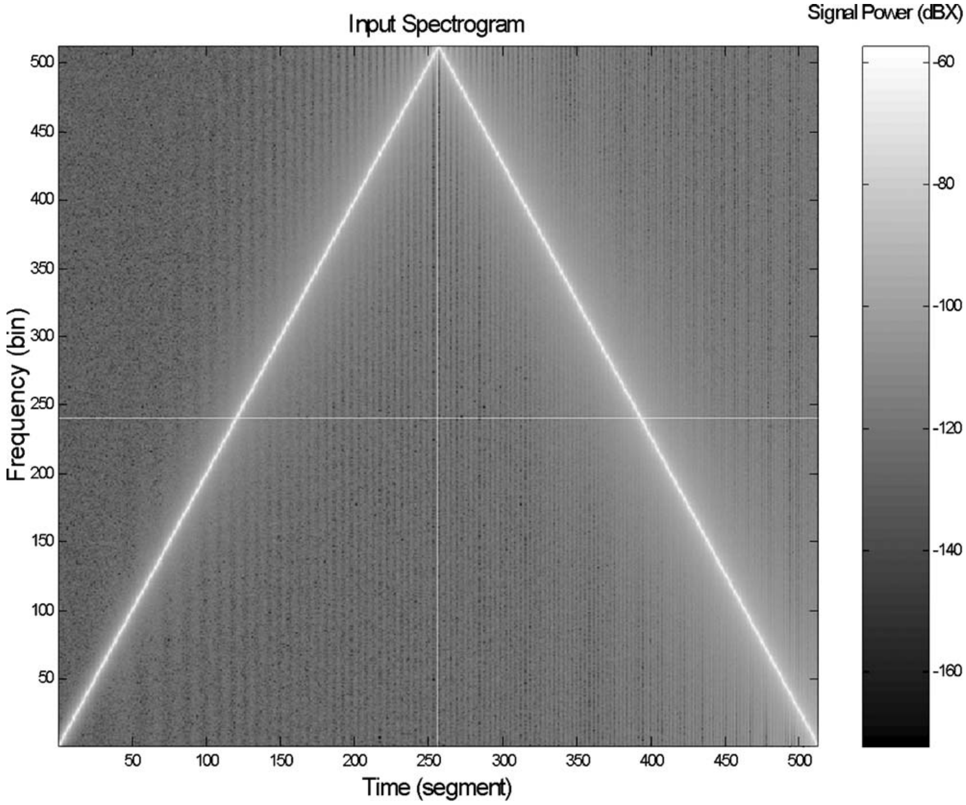

Fig. 1. Input distribution $C_S(t, w)$ when SNR = 70 dB.

$$B_m(t,\omega) = \text{is calculated from } A_m(t,\omega) \text{ through a frequency average,} \tag{13}$$

$$C_m(t,\omega) = \text{is calculated from } B_m(t,\omega) \text{ through a time average.} \tag{14}$$

In addition, we will need the characteristic functions for each distribution and we use the following notation $a_m(\theta,\tau)$, $b_m(\theta,\tau)$ and $c_m(\theta,\tau)$. That is

$$a_m(\theta,\tau) = \iint A_m(t,\omega) e^{j\theta t + j\tau\omega}\, dt\, d\omega\tau \tag{15}$$

and similarly for $b_m(\theta,\tau)$ and $c_m(\theta,\tau)$. We now describe the two steps indicated above. For both of them we will use the characteristic function formulation, because it makes the derivation much easier.

3.2. First sub step: Calculation of $B_m(t,\omega)$ from $A_m(t,\omega)$ through a frequency average

The distribution $B_m(t,\omega)$ is obtained from $A_m(t,\omega)$ through a lowpass filtering, with the aim of smoothing out noise along the frequency axis of the input distribution of the stage. The amount of filtering is in general a function of the stage. In the characteristic

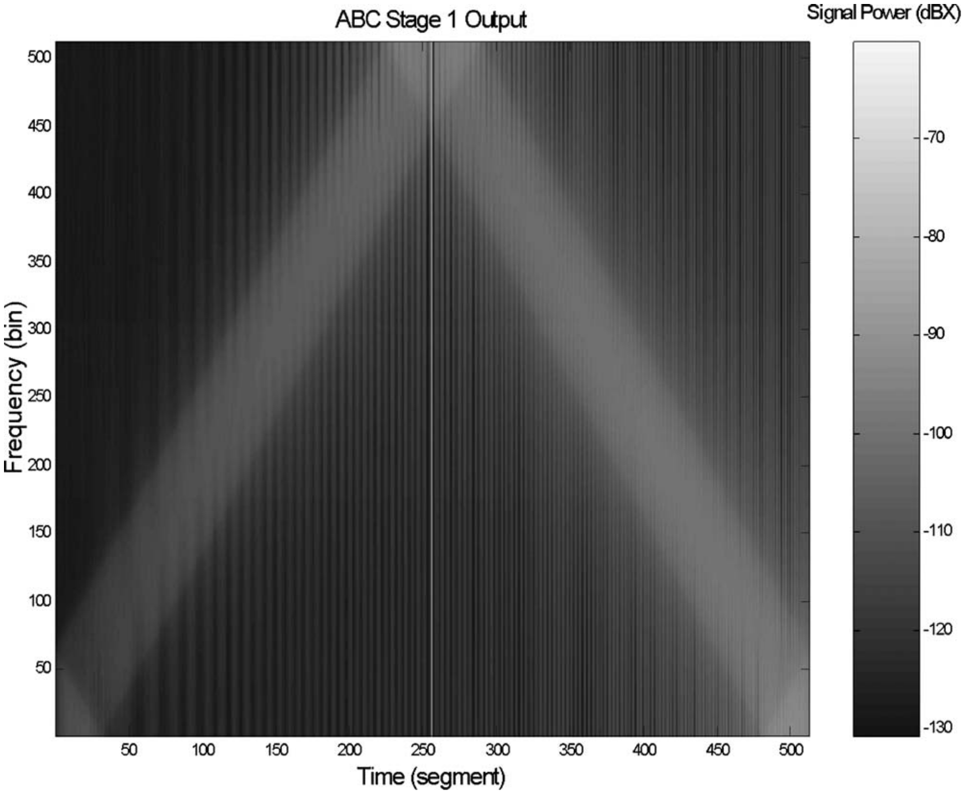

Fig. 2. Output distribution $C_1(t, w)$ at stage 1 (SNR = 70 dB).

function domain we have that, at stage $m = 1, 2, \dots, N$,

$$b_m(\theta, \tau) = \sqrt{2\pi} H_m(\tau) a_m(\theta, \tau), \tag{16}$$

where $H_m(\tau)$ is the transfer function of the lowpass filter at the mth stage. We have defined

$$H_N(\tau) \equiv 1. \tag{17}$$

Also, because of Eq. (12) we see that for $m = 2, 3, \dots, N$

$$a_m(\theta, \tau) = \left[1 - \sqrt{2\pi} H_{m-1}(\tau)\right] a_{m-1}(\theta, \tau) \tag{18}$$

$$= \prod_{l=1}^{m-1} \left[1 - \sqrt{2\pi} H_{m-l}(\tau)\right] M_S(\theta, \tau). \tag{19}$$

Putting together Eqs. (16) and (18) we obtain

$$b_m(\theta, \tau) = \phi_{\omega_m}(\tau) M_S(\theta, \tau) \tag{20}$$

$$= \left[\sqrt{2\pi} H_m(\tau) \prod_{l=1}^{m-1} \left[1 - \sqrt{2\pi} H_{m-l}(\tau)\right]\right] M_S(\theta, \tau) \tag{21}$$

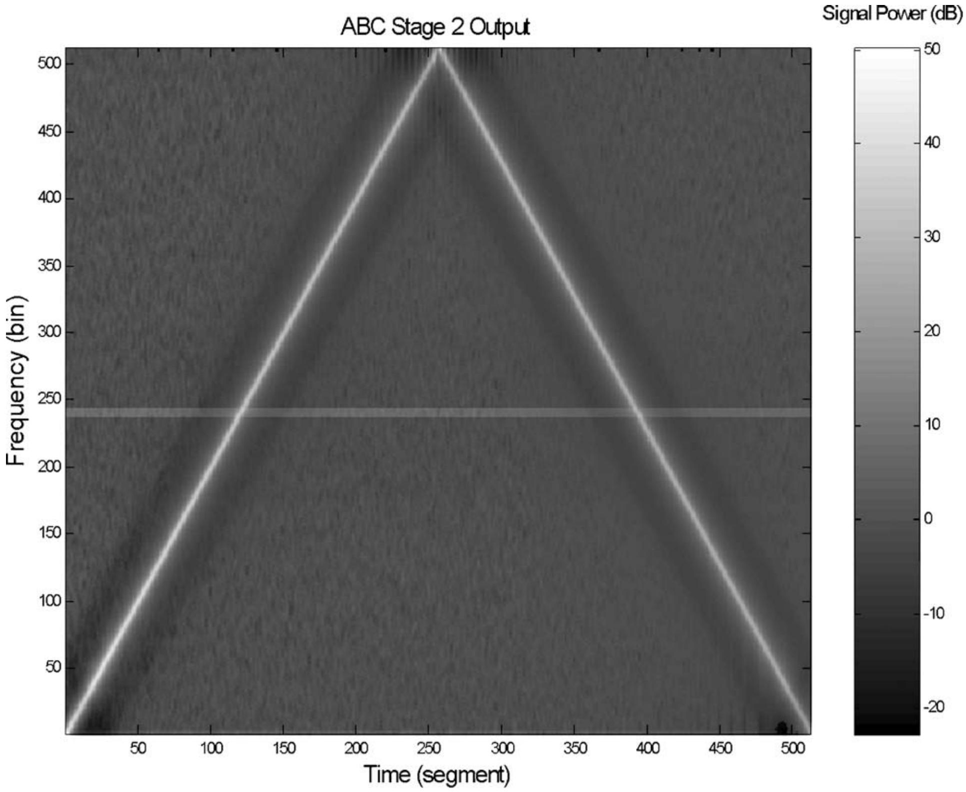

Fig. 3. Output distribution $C_2(t, w)$ at stage 2 (SNR = 70 dB).

where we have defined the frequency averaging kernel as

$$\phi_{\omega_m}(\tau) = \sqrt{2\pi} H_m(\tau) \prod_{l=1}^{m-1} \left[1 - \sqrt{2\pi} H_{m-l}(\tau)\right]. \tag{22}$$

3.3. Second sub step: Calculation of $C_m(t, \omega)$ from $B_m(t, \omega)$ through a time average

The distribution $C_m(t, \omega)$ is obtained from $B_m(t, \omega)$ through a moving average in time, with the aim of reducing noise along the time direction of the input distribution of the stage. If we consider the mth stage of the algorithm, $m = 1, 2, \ldots, N$, the time averaging can be written in the time-frequency domain as

$$C_m(t, \omega) = \frac{1}{T_m} \int_{t-T_m/2}^{t+T_m/2} B_m(t', \omega)\, dt' \tag{23}$$

$$= \frac{1}{T_m} \int P_{T_m}(t - t') B_m(t', \omega)\, dt' \tag{24}$$

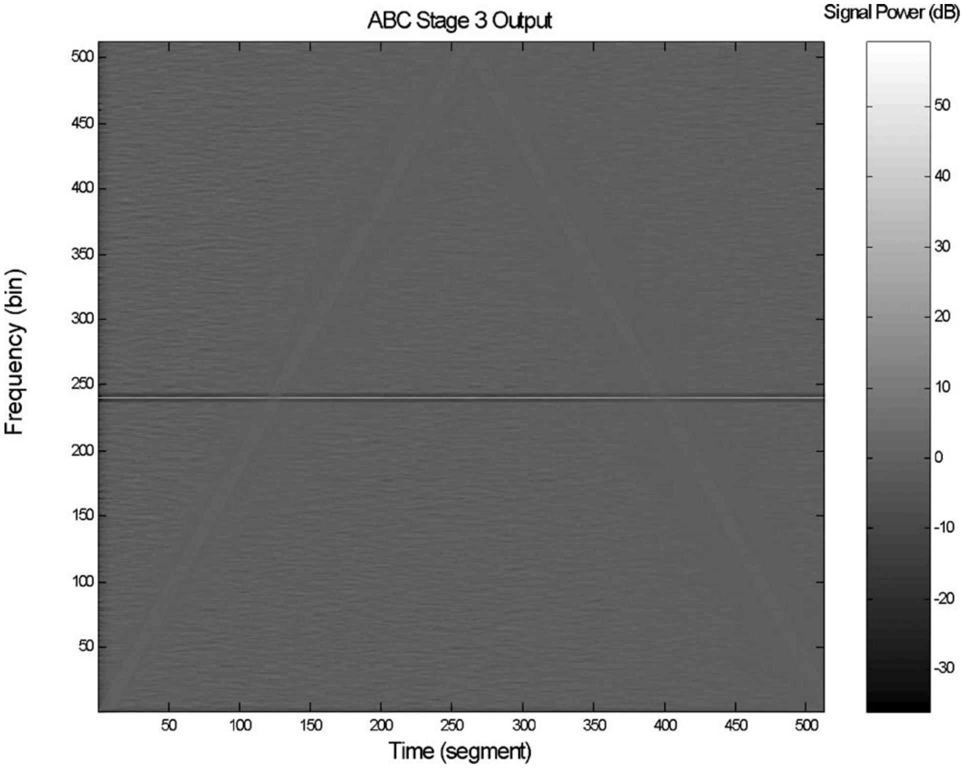

Fig. 4. Output distribution $C_3(t, w)$ at stage 3 (SNR = 70 dB).

$$= \frac{1}{T_m} P_{T_m}(t) B_m(t, \omega), \tag{25}$$

where the star sign indicates convolution and $P_{T_m}(t)$ is the rectangular window defined as

$$P_{T_m}(t) = \begin{cases} 1, & -T_m/2 < t < T_m/2, \\ 0, & \text{elsewhere} \end{cases} \tag{26}$$

and also $b_N(\theta, \tau) \equiv a_N(\theta, \tau)$. In the characteristic function domain we have that

$$c_m(\theta, \tau) = \phi_{t_m}(\theta) b_m(\theta, \tau) \tag{27}$$

$$= \sqrt{2\pi} \frac{1}{T_m} \bar{P}_{T_m}(\theta) b_m(\theta, \tau) \tag{28}$$

where $\bar{P}_{T_m}(\theta)$ is the inverse Fourier transform of $P_{T_m}(t)$ and we have defined the time averaging kernel as

$$\phi_{t_m}(\theta) = \sqrt{2\pi} \frac{1}{T_m} \bar{P}_{T_m}(\theta). \tag{29}$$

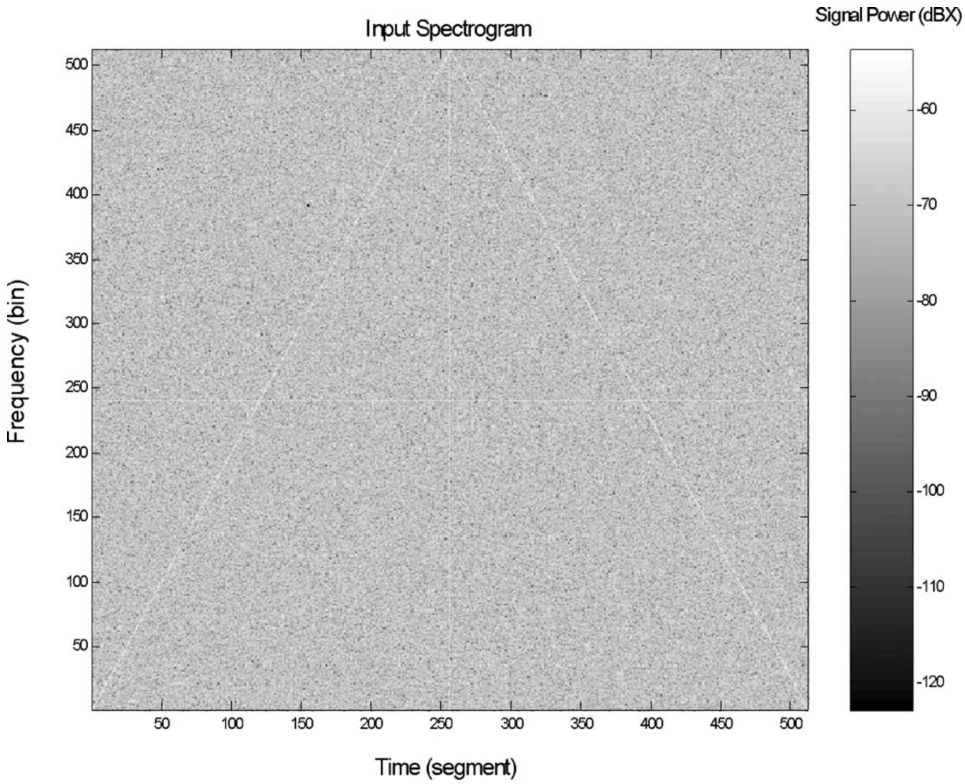

Fig. 5. Input spectrogram $C_S(t, w)$ when SNR = 10 dB.

4. Time-frequency averaging in the ABC algorithm

We will now derive the exact expression for the output distributions generated by the algorithm. We see by considering Eqs. (27) and (20) that the output of stage m is

$$c_m(\theta,\tau) = \phi_{t_m}(\theta) b_m(\theta,\tau) \tag{30}$$

$$= \phi_{t_m}(\theta)\phi_{\omega_m}(\tau) M_S(\theta,\tau) \tag{31}$$

$$= \left[2\pi \frac{1}{T_m} \bar{P}_{T_m}(\theta) H_m(\tau) \prod_{l=1}^{m-1} \left[1 - \sqrt{2\pi} H_{m-l}(\tau)\right]\right] M_S(\theta,\tau) \tag{32}$$

$$= \phi_m(\theta,\tau) M_S(\theta,\tau), \tag{33}$$

where

$$\phi_m(\theta,\tau) = \phi_{t_m}(\theta)\phi_{\omega_m}(\tau) \tag{34}$$

$$= 2\pi \frac{1}{T_m} \bar{P}_{T_m}(\theta) H_m(\tau) \prod_{l=1}^{m-1} \left[1 - \sqrt{2\pi} H_{m-l}(\tau)\right], \tag{35}$$

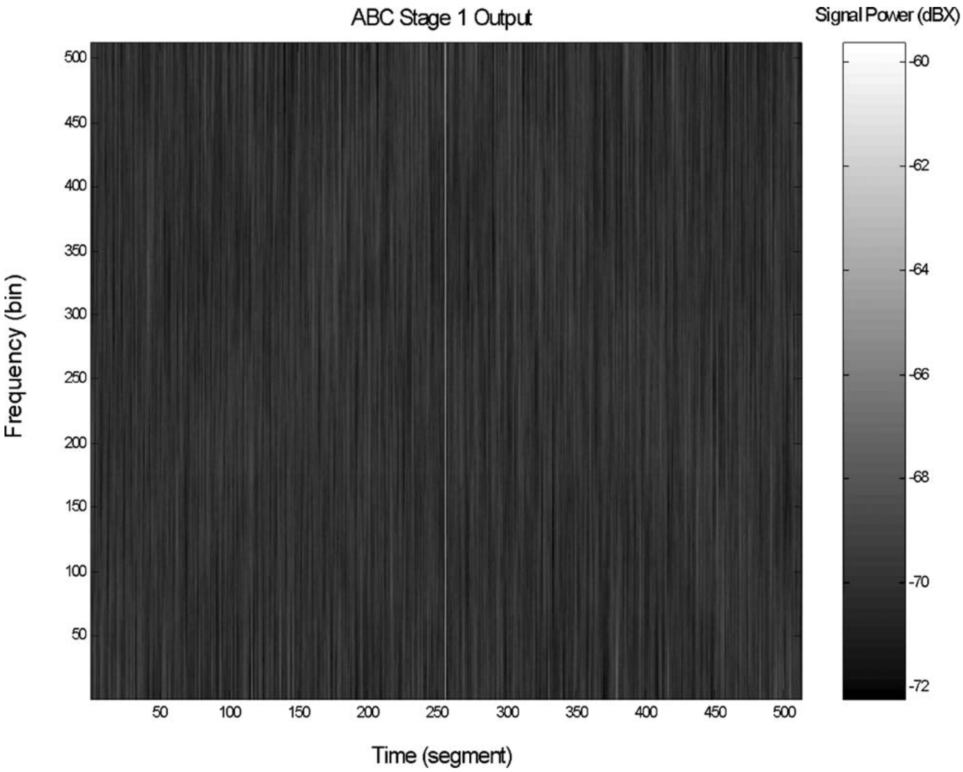

Fig. 6. Output distribution $C_1(t,w)$ at stage 1 (SNR = 10 dB).

is the kernel of the distribution at stage m, that is hence independent from the input distribution. We note that at stage $m = 1$ the multiplication operation $\prod$ has to be set equal to 1.

Convergence and weighted averages.[2] We now address the issue of the convergence of the algorithm. We have found from experience that the algorithm always converges and we believe that some insight into this issue can be gained by the following considerations. In [2] it is shown for the discrete-time case that the ABC frequency averaging of the input is equivalent to a filter-bank decomposition. Therefore, just as the output components of a filter bank can be recombined to "converge" to the input, the outputs identified by Eq. (11) can be recombined to "converge" to the input. Also, in [15] a simple analytic example is presented and at least for that example one can see the that indeed at each step one gets the appropriate convergence. One of the advantages of formulating the algorithm by way of Eqs. (11) and (10) is that it crystallized the procedures and allows for the possibility of a mathematical study of the convergence. This issue is currently being studied.

In the above some parameters are estimated and averaged simply but of course one could use weighted average. Weighted average is always an option and any specific

[2] We thank the referees for bringing some of these points to our attention.

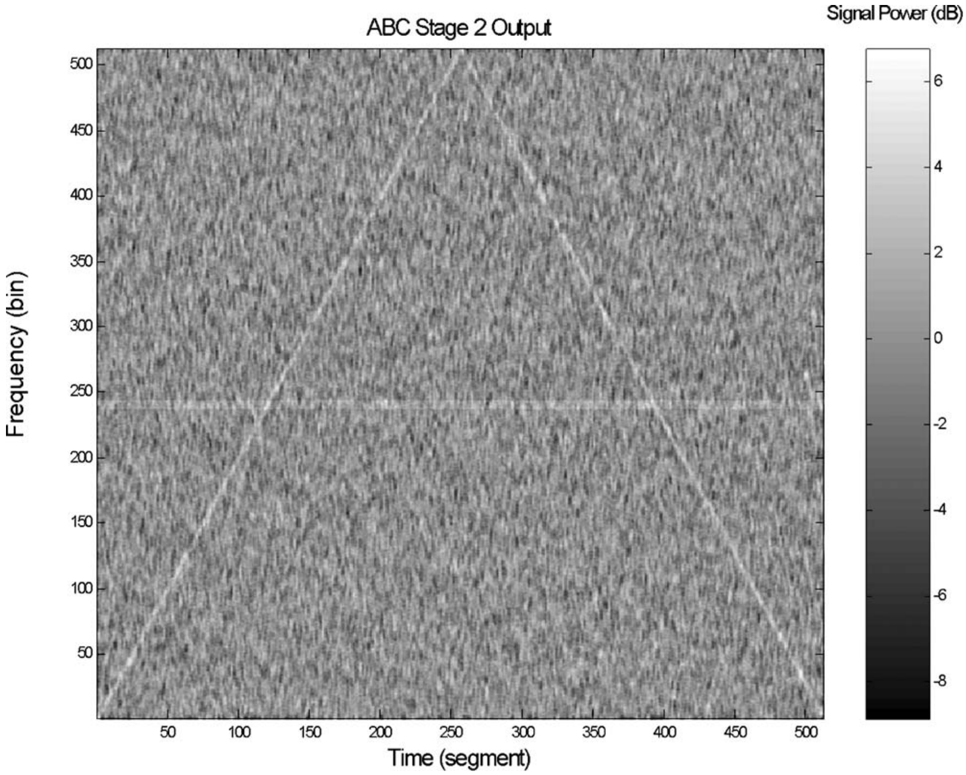

Fig. 7. Output distribution $C_2(t, w)$ at stage 2 (SNR = 10 dB).

choice of filter parameters will always be "optimal" for some signal scenarios and "sub-optimal" for others. This paper focuses on formulating the ABC process in continuous-time and continuous-frequency, from the original discrete-time, discrete-frequency formulation. This new formulation then lends itself to study this issue. Similar issues regarding weighted averages are considered in [16].

5. Examples

To demonstrate the application of the ABC process we present a number of cases. The first is a signal composed of the sum of a sinusoid, a chirp (swept frequency), an impulse, and additive white Gaussian noise. The term "white" refers to the fact that the noise power is uniform across frequency. For this case, the noise power is low, with the signal-to-noise power ratio (SNR) set to 70 dB for the sinusoid as measured in a frequency bin. The spectrogram generated is based on a 1024 sample FFT, with a rectangular data window, no data overlap between time segments and logarithmic scaling. The amplitudes of the chirp and impulse signal components are set to achieve similar power levels per FFT bin

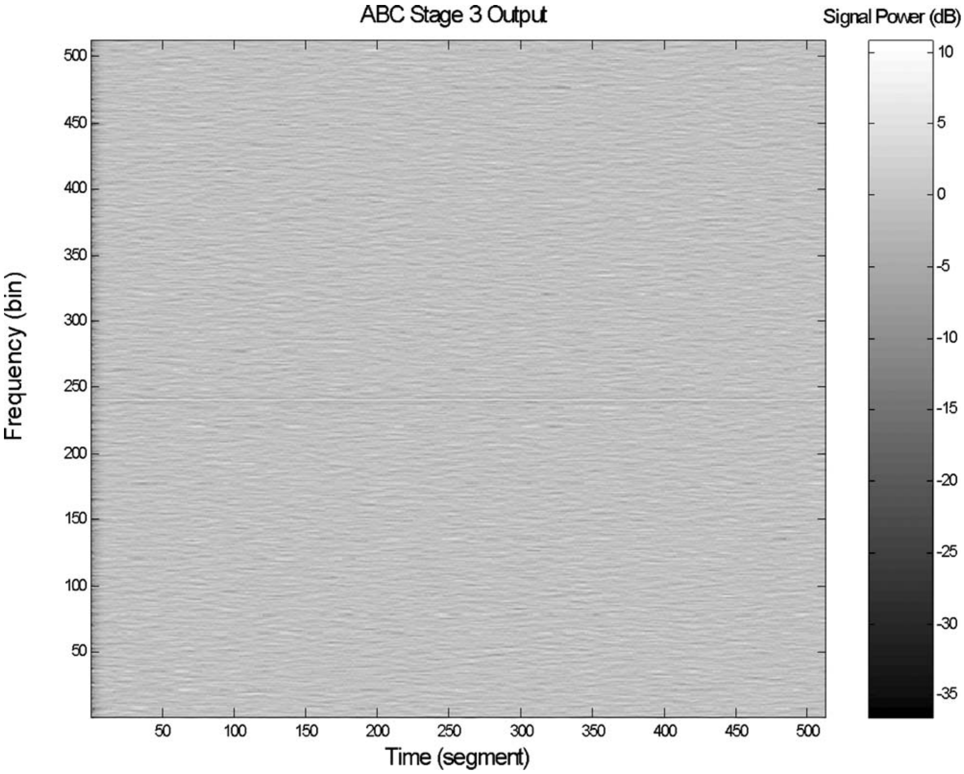

Fig. 8. Output distribution $C_3(t, w)$ at stage 3 (SNR = 10 dB).

as the sinusoid component. The intent is to demonstrate separation of these unique signal components into the various output stages by the ABC process.

The second example is essentially the same as the first, with the exception that the additive noise component is increased substantially such that the sinusoidal SNR is now 10 dB per FFT bin. Thus the sinusoid, chirp and impulse are the same as in the first signal. For each case, the signal is quantized to 16 bits for storage to file prior to the ABC processing.

For both signals, the ABC parameters are set to the same values. In particular, 3 processing stages are used. The first stage lowpass filter is a finite impulse response (FIR) filter of 129 coefficients, each coefficient equal to 1/129. Likewise, the stage 2 lowpass filter is a 7 coefficient FIR filter, each coefficient equal to 1/7. Thus both filters are implemented as simple moving averages. Note that filter design will affect the ABC processing performance. While the parameters chosen are appropriate for the signal scenarios presented, these parameters have not been optimized. (The effect of this choice of parameters will be apparent.) In addition to frequency averaging, time averaging is accomplished in the second and third stages of the implemented ABC process. An average of 2 time segments is accomplished in the second stage, and an average of 10 time segments is accomplished in the third stage.

Results are shown in Figs. 1–4 for the 70 dB SNR case, and Figs. 5–8 for the 10 dB SNR case. As seen in Fig. 1, the sinusoid is at bin 240 for all segments. The chirp component sweeps up in frequency from bin 0 to 511, then back down to 0. The impulse occurs at time segment 256. Note that in progressing from stage to stage, the desired components are much more distinguishable from each other, and from the background additive noise. However, note also that the energy of the chirp signal is present in both stage 1 and stage 3, in addition to the dominant chirp output in stage 2. Likewise, the sinusoidal component is dominant in stage 3, but also noticeable in stage 2. This observation relates to the need for optimization of the filter parameters of the ABC process, when there exists a priori information regarding the input.

In Fig. 5, note the adverse affects of increasing the additive noise component. The sinusoid, chirp and impulse are difficult to discern. Even so, the benefits of the ABC process are easily observed. The desired signal components are separated in preparation for post-processing, such as threshold-based detection.

6. Conclusions

We have shown that the ABC method is effectively formulated in terms of time-frequency distributions and we have explicitly obtained the kernel for each step in transforming one distribution into another. We now discuss why the procedure works well and the further research suggested by the current formulation. We believe that what is happening is an averaging procedure in the time-frequency plane that reduces noise, perhaps dramatically, while preserving the time-frequency resolution.

We also mention two subsidiary issues we are currently exploring. First is the issue of the starting distribution. Noga, in his original work used the log-spectrogram, but other starting distributions are possible, and perhaps may be more effective. How the final distribution depends on the initial distribution can now be studied theoretically because one can explicitly express the steps in the determination of the kernels. This is currently being explored. Secondly, in the original formulation the log-spectrogram was used and this has a number of advantages. We have not done so in the current formulation because we wanted to understand the time and frequency averaging operation done by the algorithm and keep that issue separate from the benefits of using the log-spectrum.

References

[1] A.J. Noga, Adjustable Bandwidth Concept Signal Energy Detector, US patent 5,257,211, October 1993.
[2] A.J. Noga, Adjustable Bandwidth Concept (ABC) Performance Evaluation, Interim Report, AFRL Rome Site, July 2003.
[3] A.J. Noga, Performance Aspects of the Adjustable Bandwidth Concept (ABC) Predetection Processor, in: Proc. of SPIE, vol. 5096, 2003, pp. 607–615.
[4] L. Cohen, Time-Frequency Distributions—A Review, in: Proc. of IEEE, vol. 77, 1989, pp. 941–981.
[5] L. Cohen, Time-Frequency Analysis, Prentice Hall, 1995.
[6] P. Loughlin (Ed.), in: Proceedings of the IEEE, Special Issue on Applications of Time-Frequency Analysis, vol. 84, no. 9, 1996.
[7] L. Cohen, Generalized phase-space distribution functions, J. Math. Phys. 7 (1966) 781–786.

[8] E. Wigner, On the quantum correction for thermodynamic equilibrium, Phys. Rev. 40 (1932) 749–759.
[9] Y. Zhao, L. Atlas, R. Mark II, The use of cone-shaped kernels for generalized time-frequency representations of nonstationary signals, IEEE Trans. ASSP 38 (7) (1990) 1084–1091.
[10] H. Choi, W. Williams, Improved time-frequency representation of multicomponent signals using exponential kernels, IEEE Trans. ASSP 37 (6) (1989) 862–871.
[11] J. Jeong, W. Williams, Kernel design for reduced interference distributions, IEEE Trans. Signal Process. 40 (2) (1992) 402–412.
[12] J. Jeong, W. Williams, Variable-windowed spectrograms: connecting Cohen's class and the wavelet transform, Spectrum Estimat. Model. (1990) 270–274.
[13] L. Cohen, The wavelet transform and time-frequency analysis, in: L. Debnath (Ed.), Wavelet Transforms and Signal Processing, Birkhäuser, 2002, pp. 3–22.
[14] P. Loughlin, J. Pitton, L. Atlas, Bilinear time-frequency representations: new insights and properties, IEEE Trans. Signal Process. 41 (2) (1993) 750–767.
[15] L. Galleani, L. Cohen, A. Noga, Iterative Basis of the Adjustable Bandwidth Concept, in: Proceedings of Defense Applications of Signal Processing, 2004, in press.
[16] E. Fournie', J. Lasry, J. Lebuchoux, P. Lions, Applications of Malliavin calculus to Monte Carlo methods in finance II, Finance Stochast. 5 (2001) 201–236.

Leon Cohen received the B.S. degree from City College in 1962 and the Ph.D. degree from Yale University in 1966. He is currently Professor of Physics at the City University of New York. He has done research in physics, astronomy, quantum mechanics, and signal analysis.

Lorenzo Galleani received the B.S. and Ph.D. degrees in electrical engineering from Politecnico di Torino in 1997 and 2001, respectively. He is an assistant professor at the Dipartimento di Elettronica, Politecnico di Torino, Italy. His main research interests are in modern spectral analysis and dynamical systems, and nonstationary signal analysis applied to time scales and atomic clocks.

Andrew Noga received the A.S. degree in engineering science from Mohawk Valley Community College, Utica, NY, in 1981, the B.S. degree in electrical engineering from Clarkson College of Technology, Potsdam, NY, in 1983, and the M.S. and Ph.D. degrees in electrical engineering from Syracuse University, Syracuse, NY, in 1988 and 1995, respectively. His research interests include communications signal processing and signal detection and parameter estimation for software radios.