High-Resolution Time-Frequency Methods' Performance Analysis

The MIT Faculty has made this article openly available. Please share how this access benefits you. Your story matters.


As Published: http://dx.doi.org/10.1155/2010/806043

Publisher: European Association for Signal Processing / Hindawi

Persistent URL: http://hdl.handle.net/1721.1/61007

Version: Final published version: final published article, as it appeared in a journal, conference proceedings, or other formally published context

Terms of use: Creative Commons Attribution
Research Article
High-Resolution Time-Frequency Methods’ Performance Analysis

Imran Shafi,1 Jamil Ahmad,1 Syed Ismail Shah,1 Ataul Aziz Ikram,1 Adnan Ahmad Khan,2 Sajid Bashir,3 and Faisal Mahmood Kashif4

1 Information and Computing Department, Iqra University Islamabad Campus, Sector H-9, Islamabad 44000, Pakistan
2 College of Telecommunication Engineering, NUST, Islamabad 44000, Pakistan
3 Computer Engineering Department, Centre for Advanced Studies in Engineering, Islamabad 44000, Pakistan
4 Laboratory for Electromagnetic and Electronic Systems (LEES), MIT Cambridge, Cambridge, MA 02139-4307, USA

Correspondence should be addressed to Imran Shafi, imran.shafi@gmail.com

Received 31 December 2009; Accepted 6 July 2010

Academic Editor: L. F. Chaparro

Copyright © 2010 Imran Shafi et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This work evaluates the performance of high-resolution quadratic time-frequency distributions (TFDs) including the ones obtained by the reassignment method, the optimal radially Gaussian kernel method, the t-f autoregressive moving-average spectral estimation method and the neural network-based method. The approaches are rigorously compared to each other using several objective measures. Experimental results show that the neural network-based TFDs are better in concentration and resolution performance based on various examples.

1. Introduction

The nonstationary signals are very common in nature or are generated synthetically for practical applications like analysis, filtering, modeling, suppression, cancellation, equalization, modulation, detection, estimation, coding, and synchronization. The study of the varying spectral content of such signals is possible through two-dimensional functions of TFDs that depict the temporal and spectral contents simultaneously [1]. Different types of TFDs are limited in scope due to multiple reasons, for example, low concentration along the individual components, blurring of autocomponents, cross terms (CTs) appearance in between autocomponents, and poor resolution. These shortcomings result into inaccurate analysis of nonstationary signals.

Half way in this decade, there is an enormous amount of work towards achieving high concentration along the individual components and to enhance the ease of identifying the closely spaced components in the TFDs. The aim is to correctly interpret the fundamental nature of the nonstationary signals under analysis in the time-frequency (TF) domain [2]. There are three open trends that make this task inherently more complex, that is, (i) concentration and resolution tradeoff, (ii) application-specific environment, and (iii) objective assessment of TFDs [1–3]. Tradeoff between concentration and CTs’ removal is a classical problem. The concepts of concentration and resolution are used synonymously in literature whereas for multicomponent signals this is not necessarily the case, and a difference is required to be established. High signal concentration is desired but in the analysis of multicomponent signals resolution is more important. Moreover, different applications have different preferences and requirements to the TFDs. In general, the choice of a TFD in a particular situation depends on many factors such as the relevance of properties satisfied by TFDs, the computational cost and speed of the TFD, and the tradeoff in using the TFD. Also selection of the most suited TFD to analyze the given signal is not straightforward. Generally the common practice have been the visual comparison of all plots with the choice of most appealing one. However, this selection is generally difficult and subjective.

The estimation of signal information and complexity in the TF plane is quite challenging. The themes which inspire new measures for estimation of signal information and complexity in the TF plane, include the CTs’ suppression, concentration and resolution of autocomponents, and the ability to correctly distinguish closely spaced components.
2. Experimental Results and Discussion

Various objective criteria are used for objective evaluation that include the ratio of norms-based measures [10], Shannon & Rényi entropy measures [11, 12], normalized Rényi entropy measure [13], Stankovi measure [14], and Boashash and Suic performance measures [15]. Both real life and synthetic signals are considered to validate the experimental results.

2.1. Bat Echolocation Chirp Signal. The spectrogram of bat echolocation chirp sound is shown in Figure 1(a), that is blurred and difficult to interpret. The results are obtained using the TSE, RAM, OKM, and NTFD, shown in Figure 1.

The TF autoregressive moving-average estimation models for nonstationary random processes are shown to be a TF symmetric reformulation of time-varying autoregressive moving-average models using a Fourier basis [6]. This reformulation is physically intuitive because it uses time delays and frequency shifts to model the nonstationary dynamics of a process. The TSE models are parsimonious for the practically relevant class of processes with a limited TF correlation structure. The simulation result depicted in Figure 1(c) demonstrates that the TSE is able to improve on TF correlation structure. The spectrogram of the signal is shown in Figure 2(a), given as

\[
x_1(n) = e^{-j\pi((5/2)−0.1\sin(2\pi n/N))n} + e^{j\pi((5/2)−0.1\sin(2\pi n/N))n}.
\]

The spectrogram of the signal is shown in Figure 2(a), referred to as test image 1 (TI 1).

The second synthetic signal contains two sets of nonparallel, nonintersecting chirps, expressed as

\[
x_2(n) = e^{j\pi((n/6N))n} + e^{j\pi((1+(n/6N))n) + e^{-j\pi(n/6N)n}} + e^{-j\pi((1+(n/6N))n)}.
\]

The spectrogram of the signal is shown in Figure 3(a), referred to as test image 2 (TI 2).

The third one is a three-component signal containing a sinusoidal FM component intersecting two crossing chirps, given as

\[
x_3(n) = e^{j\pi((5/2)−0.1\sin(2\pi n/N))n} + e^{j\pi(n/6N)n} + e^{j\pi((1/3)−(n/6N))n}.
\]

The spectrogram of the signal is shown in Figure 4(a), referred to as test image 3 (TI 3). The frequency separation is low enough and just avoids intersection between the two components (sinusoidal FM and chirp components) in between 150–200 Hz near 0.5 sec. This is an ideal signal to confirm the TFs' effectiveness in deburring closely spaced components and check its performance at the intersections.

Yet another test case is adopted from Boashash [15] to compare the TFs' performance at the middle of the signal duration interval by the Boashash's performance measures. The authors in [15] have found the modified B distribution (β = 0.01) as the best performing TFD for this particular signal at the middle. The signal is defined as

\[
x_4(n) = \cos(2\pi(0.15t + 0.0004t^2)) + \cos(2\pi(0.2t + 0.0004t^2)).
\]

The spectrogram of the signal is shown in Figure 5(a), referred to as test image 4 (TI 4).

The synthetic test TFs are processed by the neural network-based method and the results are shown in Figures 2(b)–5(b), which demonstrate high resolution and good concentration along the IFs of individual components. However, instead of relying solely on the visual inspection of the TF plots, it is mandatory to quantify the quality of TFs by the objective methods. The quantitative comparison can be drawn from Figure 6 (in Figure 6, the abbreviations not mentioned earlier are the spectrogram (spec), Zhao-Atlas-Marks distribution (ZAMD), Margenau-Hill distribution
Figure 1: TFDs of the multicomponent bat echolocation chirp signal by various high resolution t-f methods.
(MHD), and Choi-Williams distribution (CWD)), where these measures are plotted individually for all the test images. On scrutinizing these comparative graphs, the NTFD qualifies the best quality TFD for different measures.

Boashash’s performance measures for concentration and resolution are computationally expensive because they require calculations at various time instants. We take a slice at \( t = 64 \) of the signal and compute the normalized instantaneous resolution and concentration performance measures \( R_i(64) \) and \( C_n(64) \). A TFD that, at a given time instant, has the largest positive value (close to 1) of the measure \( R_i \) is the TFD with the best resolution performance at that time instant for the signal under consideration. The NTFD gives the largest value of \( R_i \) at time \( t = 64 \) in Figure 7 and hence is selected as the best performing TFD of this signal at \( t = 64 \).

On similar lines, we have compared the TFDs’ concentration performance at the middle of signal duration interval.

**Figure 2:** TFDs of a synthetic signal consisting of two sinusoidal FM components intersecting each other. (a) Spectrogram (TI 2) [Hamm, \( L = 90 \)], and (b) NTFD.

**Figure 3:** TFDs of a synthetic signal consisting of two-sets of non-parallel, non-intersecting chirps. (a) Spectrogram (TI 3) [Hamm, \( L = 90 \)], and (b) NTFD.
A TFD is considered to have the best energy concentration for a given multicomponent signal if for each signal component, it yields the smallest instantaneous bandwidth relative to component IF \( \left( \frac{V_i(t)}{f_i(t)} \right) \) and the smallest side lobe magnitude relative to main lobe magnitude \( \left( \frac{A_S(t)}{A_M(t)} \right) \).

The results plotted in Figure 7 comparative graphs for Boashash concentration resolution measure indicate that the NTFD gives the smallest values of \( C_{1,2}(t) \) at \( t = 64 \) and hence is selected as the best concentrated TFD at time \( t = 64 \).

3. Conclusion

The objective criteria provide a quantitative framework for TFDs' goodness instead of relying solely on the visual measure of goodness of their plots. Experimental results
Figure 6: Comparison plots, numerical values of criterion versus method employed, for the test images 1–4, (a) The Shannon entropy measure, (b) Rényi entropy measure, (c) Volume normalized Rényi entropy measure, (d) Ratio of norm based measure, and (e) Ljubisa measure.
Numerical value of the measure

<table>
<thead>
<tr>
<th>Spec</th>
<th>WVD</th>
<th>ZAMD</th>
<th>CWD</th>
<th>BJD</th>
<th>Modified B</th>
<th>NTFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.55</td>
<td>0.65</td>
<td>0.75</td>
<td>0.85</td>
<td>0.95</td>
<td>0.5</td>
<td>0.7</td>
</tr>
</tbody>
</table>

**Figure 7:** Comparison plots for the Boashash’s TFD performance measures versus different types of TFDs, (a) The proposed modified Boashash’s concentration measure \(C_n\), and (b) The Boashash’s normalized instantaneous resolution measure \(R_i\).

References


demonstrate the effectiveness of the neural network-based approach against well-known and established high resolution TF methods including some popular distributions known for their high CTs suppression and energy concentration in the TF domain.
Preliminary call for papers

The 2011 European Signal Processing Conference (EUSIPCO-2011) is the nineteenth in a series of conferences promoted by the European Association for Signal Processing (EURASIP, www.eurasip.org). This year edition will take place in Barcelona, capital city of Catalonia (Spain), and will be jointly organized by the Centre Tecnològic de Telecomunicacions de Catalunya (CTTC) and the Universitat Politècnica de Catalunya (UPC).

EUSIPCO-2011 will focus on key aspects of signal processing theory and applications as listed below. Acceptance of submissions will be based on quality, relevance and originality. Accepted papers will be published in the EUSIPCO proceedings and presented during the conference. Paper submissions, proposals for tutorials and proposals for special sessions are invited in, but not limited to, the following areas of interest.

Areas of Interest

• Audio and electro-acoustics.
• Design, implementation, and applications of signal processing systems.
• Multimedia signal processing and coding.
• Image and multidimensional signal processing.
• Signal detection and estimation.
• Sensor array and multi-channel signal processing.
• Sensor fusion in networked systems.
• Signal processing for communications.
• Medical imaging and image analysis.
• Non-stationary, non-linear and non-Gaussian signal processing.

Submissions

Procedures to submit a paper and proposals for special sessions and tutorials will be detailed at www.eusipco2011.org. Submitted papers must be camera-ready, no more than 5 pages long, and conforming to the standard specified on the EUSIPCO 2011 web site. First authors who are registered students can participate in the best student paper competition.

Important Deadlines:

<table>
<thead>
<tr>
<th>Type of Submission</th>
<th>Deadline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposals for special sessions</td>
<td>15 Dec 2010</td>
</tr>
<tr>
<td>Proposals for tutorials</td>
<td>18 Feb 2011</td>
</tr>
<tr>
<td>Electronic submission of full papers</td>
<td>21 Feb 2011</td>
</tr>
<tr>
<td>Notification of acceptance</td>
<td>23 May 2011</td>
</tr>
<tr>
<td>Submission of camera-ready papers</td>
<td>6 Jun 2011</td>
</tr>
</tbody>
</table>

Webpage: www.eusipco2011.org