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An Innovative Digital Signal Processing Method for Spectrum Monitoring and Management

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***Abstract*-**The frequency spectrum is a limited shared resource, nowadays interested by an ever growing number of different applications. Generally, the companies providing such services pay to the governments the right of using a limited portion of the spectrum, consequently they would be assured that the licensed radio spectrum resource is not interested by significant external interferences. At the same time, they have to guarantee that their devices make an efficient use of the spectrum and meet the electromagnetic compatibility regulations.
In this framework, the competent authorities are called to control the access to the spectrum adopting suitable management and monitoring policies, as well as the manufacturers have to periodically verify the correct working of their apparatuses. To these aims an innovative measurement method for spectrum monitoring and management is proposed in this paper. It performs an efficient sequential analysis based on a sample by sample digital processing. Three main issues are in particular pursued: (i) measurement performance comparable to that exhibited by other methods proposed in literature; (ii) fast measurement time, (iii) easy implementation on cost-effective digital signal processing hardware.

I. Introduction

Frequency spectrum is a limited resource and the demand for its use is nowadays increasing. Many governments in the world, recognizing its market value, began auctioning the right to use their airwaves. Companies that purchase spectrum license, offer a wide range of for-fee services such as voice calls, text messaging, wireless Internet, High-Definition Television (HDTV) and so on. For service providers and equipment manufacturers, sums of money are at stake in the production and delivery of wireless products and services. Extensive regulatory requirements have been designed to avoid unwanted interference between users that share the radio spectrum resource. Special groups routinely monitor emissions to ensure that transmission equipments comply with regulations. Compliance monitoring of signal spectrum is continuously increasing.
The growth of commercial signal monitoring applications has increased significantly with the diffusion of wireless devices [1]. In fact inadvertent interfering emissions can be very costly to cellular network operators. Likewise, commercial broadcasters can lose substantial market audiences due to a poorly controlled adjacent channel station. Furthermore the RF spectrum is continually getting more crowded. More consumer devices are starting to communicate with one another, and computer networking is expanding at a phenomenal rate [1]. All of these competing spectrum users must coexist without serious interference. In such RF environment, all equipment must meet spurious emission requirements to allow a clean path to neighboring signals.
Determining fault in interference cases begins with monitoring of transmitted spectral emissions [2]. Spectrum regulators need to monitor many different signal types to determine if enforcement actions are warranted [3].
As a result, the need of spectrum measurement and monitoring is becoming more and more mandatory. Several measurement solutions have been proposed. They are based on two main classes of instruments: (a) real-time spectrum analyzers (RSAs) and (b) measurement receivers.
The former can be considered as an advanced version of the standard Vector Signal Analyzers (VSAs), specifically addressed to the analysis of complex digitally modulated signals. They are mainly used for general-purpose wireless spectrum monitoring applications. In addition, thanks to their special hardware architecture, they can perform a high number of Discrete Fourier Transforms (DFTs) in a very short time as to guarantee both a seamless acquisition and the estimation of the spectrogram [5], which correlates time and frequency information. However, the cost dimensions and weight of such instruments may limit their use, especially for on-field applications. Differently from RSAs, measurement receivers are specifically addressed to a target application, for example a particular communication standard. This turns out into proper features, such as built-

in "personalities", mandated to warrant standards-compliant measurements of wireless formats [4]. Moreover, newer solutions complemented with additional DSP-based hardware are now appearing on the market, capable of providing a spectrogram analysis as RSAs do. They exhibit attractive weight, size and dimensions, even though showing worse accuracy than that peculiar to RSAs [6],[7].
Stemming from their past experience in the field of power and spectrum measurements of digital communication signals [8], [9], the authors propose a new method for spectrum monitoring and management entitled to be a valid, cost-effective alternative to the abovementioned solutions. Three main issues are in particular pursued: (i) easy implementation on cost-effective DSP (Digital Signal Processing) or FPGA (Field Programmable Gate Array) hardware, (ii) measurement performance, in terms of accuracy, resolution and sensitivity, comparable to that exhibited by RSAs; and (iii) measurement time lower than those characterizing RSAs.
The proposed method relies on a sequential approach based on a sample-by-sample processing. It could overcome typical limits that ordinary solutions, performing a batch processing on fixed-length overlapped segments of data, like those based on FFTs or Short-Time Fourier Transforms (STFTs), suffer from.
In the following, after a brief description of the proposed measurement method, some numerical results are given. In the full paper more details will be given about the theoretical background and the suitability of its hardware implementation on cost-effective hardware.

II. Theoretical Background

Traditional power spectrum density (PSD) estimation methods can be classified in two categories: nonparametric and parametric. Parametric methods can exhibit a reduced convergence time and are entitled to provide more significant results than those achievable from nonparametric approaches when the acquired record covers a relatively short time interval. Furthermore they can be implemented in an optimized manner (sequential estimation), thus allowing measurement results to be updated whenever a new sample is available and removing the need to locally store a large number of acquired samples [8]. Thanks to these characteristics they can be a good candidate to be implemented in cost-effective hardware platforms.
Among the several parametric PSD estimation methods the widespread used are the autoregressive (AR) estimation methods [9]-[11]. They suppose that the analyzing signal is the output of a linear system as specified in the following:

$$x(n) = -\sum_{m=1}^{p} a_{p,m} x(n-m) + \varepsilon(n) \tag{1}$$

where $x(n)$ is the analyzed signal sample at the time interval n, $a_{p,1},a_{p,2},\ldots,a_{p,p}$ are the model coefficients, $\{\varepsilon(n)\}$ is a white noise process with variance σ^2_p, and p is the model order. The PSD of a signal modeled in this way is totally described by the model parameters and the variance of the white noise process

$$S(f) = \frac{\sigma_p^2 T_S}{\left|1 + \sum_{m=1}^{p} a_{p,m} e^{-j2\pi m f T_s}\right|^2} \qquad |f| \leq f_N \tag{2}$$

where T_S=1/f_S is the sampling interval and f_N=1/(2T_S) is the Nyquist frequency.
Consequently, with known p, it is necessary to properly estimate the p+1 parameters $a_{p,1},a_{p,2},\ldots,a_{p,p}$ and σ^2_p.
This is the most popular approach for AR parameter estimation with N-1 data samples and was introduced by *Burg* in 1967 [12]. It estimates the model parameters for order i starting from those previously estimated for order i-1 by calculating the *reflection coefficients* $a_{i,i}$ [13] which minimize a sum of forward and backward linear prediction error energies:

$$SS_i(N-1) = \sum_{n=i}^{N-1}\left[\left|e_i(n)\right|^2 + \left|b_i(n)\right|^2\right] \qquad \text{for } 1 \leq i \leq p \tag{3}$$

where N-1 is index corresponding to the actual discrete sample time, $e_i(n)$ is the forward linear prediction error at order i, $b_i(n)$ is the backward linear prediction error at order i, whose expressions are:

$$e_i(n) = \sum_{k=0}^{i} a_{i,k} x(n-k) \quad \text{and} \quad b_i(n) = \sum_{k=0}^{i} a_{i,k} x(n-i+k) \quad \text{for } 1 \leq i \leq p \text{ and } i \leq n \leq N\text{-}1 \tag{4}$$

Note that $a_{p,0}$ is defined as unity.
The AR parameters are computed using the so called *Levinson-Durbin* recursions [13]. Consequently substituting (4) into (3) and using the *Levinson-Durbin* recursions, it is possible to demonstrate that SS_i depends only by $a_{i,i}$, and it can be minimized by imposing:

$$a_{i,i} = K_i(N-1) = -\frac{2\sum_{n=i}^{N-1} e_{i-1}(n) b_{i-1}(n-1)}{\sum_{n=i}^{N-1}\left[\left|e_{i-1}(n)\right|^2 + \left|b_{i-1}(n-1)\right|^2\right]} \quad \text{for } 1 \le i \le p. \tag{5}$$

Equation (5) in combination with the *Levinson-Durbin* recursions, for i =1,…,p forms a recursive algorithm for the PSD estimation. Even thought this method is characterized by good metrological performance, it is not suitable to be implemented on cost-effective platforms, because, operating on batch data, it asks a huge memory requirement and a computational burden not compatible with cost-effective hardware platforms [11].
Fortunately a time-update recursive formulation for (5) is given by [14]

$$K_i(N) = K_i(N-1) - \frac{\left[K_i(N-1)\left(\left|e_{i-1}(N)\right|^2 + \left|b_{i-1}(N-1)\right|^2\right) + 2e_{i-1}(N) b_{i-1}(N-1)\right]}{\sum_{n=i}^{N}\left[\left|e_{i-1}(n)\right|^2 + \left|b_{i-1}(n-1)\right|^2\right]}. \quad \text{for } 1 \le i \le p. \tag{6}$$

Equation (6) in combination with the *Levinson-Durbin* recursions, for i =1,…,p and with initial conditions $e_0(N)$ = $b_0(N)$ = $x(N)$, forms a sequential time-update algorithm for the reflection coefficients.
This is the sequential Burg algorithm and it can update the PSD estimate whenever a new sample is available and it is characterized by a good trade-off between metrological performance and hardware requirements [11]. Unfortunately it is affected by an infinite memory, and doesn't track the PSD time evolution. In this way the output of its analysis is a snap-shot of what it is happened during the total observation period. This effect is clearly shown in the section IV in which some experimental results are given. A possible solution to reduce this effect might be to reset the algorithm output in prearranged time intervals. This solution shows some limits related to the length of the observation period, which it should be short enough to warrant an adequate spectrum tracking, and at the same time long enough to warrant the convergence of the sequential estimation. Inaccuracies and loss of repeatability may be otherwise observed. Therefore alternative solutions have to be considered.

III. The Proposed Method

To reduce the influence of previous acquired samples respect to the recent ones two hypotheses have been done: the former adopts a fixed-length sliding window, the latter an exponentially growing window [15].
The fixed-length sliding window permits considering only a finite number of past data values. Even though it seems to be effective, its implementation requires to store in the memory as many past input values as are included in the window length. The exponentially growing window weighs the input samples giving more importance to the recent samples and attenuating the effects of the past ones. This window does not need to store samples in memory, thus resulting more proper for development on cost-effective hardware. In the following this second approach is adopted, by modifying the traditional Burg cost function (3) in this way:

$$SS_i(N-1) = \sum_{n=i}^{N-1} \lambda^{N-1-n}\left[\left|e_i(n)\right|^2 + \left|b_i(n)\right|^2\right] \quad \text{for } 1 \le i \le p \tag{7}$$

where λ, termed *forgetting factor*, is in the following range $0 < \lambda < 1$. Note that $\lambda = 1$ results in the traditional Burg case. Typical values of λ are included in the range from 0.9 to 1 [15].
It is possible to demonstrate that, analogously to the sequential Burg algorithm, (8) can be minimized by imposing:

$$K_i(N-1) = -\frac{2\sum_{n=i}^{N-1}\lambda^{N-1-n} e_{i-1}(n) b_{i-1}(n-1)}{DEN_i(N-1)} \quad \text{where } DEN_i(N-1) = \sum_{n=i}^{N-1}\lambda^{N-1-n}\left[\left|e_{i-1}(n)\right|^2 + \left|b_{i-1}(n-1)\right|^2\right] \quad \text{for } 1 \le i \le p \tag{8}$$

A time-update recursive formulation for (8) is given by:

$$K_i(N) = K_i(N-1) - \frac{\left[K_i(N-1)\left(\left|e_{i-1}(N)\right|^2 + \left|b_{i-1}(N-1)\right|^2\right) + 2e_{i-1}(N) b_{i-1}(N-1)\right]}{\lambda DEN_i(N-1) + \left|e_{i-1}(N)\right|^2 + \left|b_{i-1}(N-1)\right|^2} \quad \text{for } 1 \le i \le p. \tag{9}$$

where N is the actual time index.
Equation (9) in combination with the Levinson-Durbin recursions, for i =1,…,p and with initial conditions $e_0(N)$ = $b_0(N)$ = $x(N)$, forms the modified sequential Burg time-update algorithm for the reflection coefficients. The proposed method operates as follows: after a preliminary initialization stage, every time a new sample is acquired a new loop starts. In every iterations of the loop it updates the model parameters, the reflection coefficients K_i and the prediction errors e_i and b_i respectively. The loop is composed by a number of iterations equal to the model order p. When the loop is ended a new PSD of the analyzing signal is suitably estimated.

IV. Preliminary Experimental Results

To choose the optimal value of the forgetting factor λ a preliminary experimental test campaign performed in Matlab 7TM simulation environment has been conceived. In particular, the proposed measurement method has been adopted to track a disturbing signal that changes its frequency characteristics during the observation period.
To this aim, a special test signal characterized by the frequency behavior reported in Figure 1 has been designed, in order to emulate typical test cases that it are possible to find in real applications. It is composed by a single frequency tone that for the first 20 μs is equal to 20 MHz, successively it hops at 21.7 MHz and starts a linear frequency sweep reaching 41.6 MHz in 120 μs. At the end it makes a large hop to 30 MHz, stabilizing on this value for the last 20 μs.
As for the measurement method, a sampling rate equal to 100 MS/s has been considered. Preliminary analyses provided a suitable model order *p* equal to 40. The following figures of merit have been analyzed:

(i) the settling time (t_{set}). It represents a convergence time and is evaluated as the mean time required to coerce the percentage frequency error (difference between the imposed and the estimated frequency divided by the imposed frequency, expressed in percentage) inside an area bounded by a threshold equal to ±1.5%;
(ii) the mean convergence frequency error (μ_{ef}) defined as the mean frequency error evaluated after the settling time;
(iii) the standard deviation of the convergence frequency error (σ_{ef}) defined as the standard deviation of the frequency error evaluated after the settling time.

All the figures of merit are evaluated for different values of λ ranging in its typical interval, from 0.9 to 1, (see [15]).
As regard the figure of merit (i), it has been evaluated at three different interesting points:
1) at the start time ($t_{set,in}$), in order to estimate the initial transient of the algorithm;
2) when the first frequency hop happens and the signal starts its frequency sweep ($t_{set,A}$). This information is useful because it allows estimating how the proposed method reacts to a sharp frequency variation followed by a smooth one;
3) when the second hop happens and the signal frequency is settled at 30 MHz ($t_{set,B}$). With this analysis it is possible to estimate the method behavior after a very sharp frequency variation.
The measurement results related to the settling time analysis are reported in Table I. This figure of merit was not evaluated when $\lambda = 1$ was involved because it is not able to track the signal frequency.
From the analysis of the obtained measurement results it is possible to highlight that:
a) $t_{set,in}$ is almost constant and it does not seem to be influenced by the forgetting factor, λ, in the interval 0.990-0.999. Outside this interval $t_{set,in}$ starts noticeably to increase, reaching values near to 15 μs at λ=0.900;
b) $t_{set,A}$ and $t_{set,B}$ are influenced by the forgetting factor value, in particular the proposed method seems to reduce its convergence time when λ value decreases from 0.990 to 0.900. Outside this interval it possible to note a reversal;
c) $t_{set,B}$ values are ever lower than $t_{set,A}$ ones, demonstrating that the even though this situation is characterized by a long frequency hop, the final frequency remains constant, making easier its tracking by the proposed method;
d) values of λ lower than 0.940 show a $t_{set,B}$ equal to 20 μs, i.e. equal to duration of the 30 MHz-tone, demonstrating an insufficient ability to track the signal.
Thanks to these consideration only the values of λ included in the interval 0.990-0.999 was considered in the subsequent stages of the work.
As regard the figure of merits (ii) and (iii), it has been evaluated in the following time intervals:
1) $t_{set,in}$<t<20 μs, in order to estimate the frequency tracking performance of the proposed method after the starting transient and in presence of a single tone;
2) $t_{set,A}$<t<140 μs. this analysis allows evaluating the measurement performance in presence of a

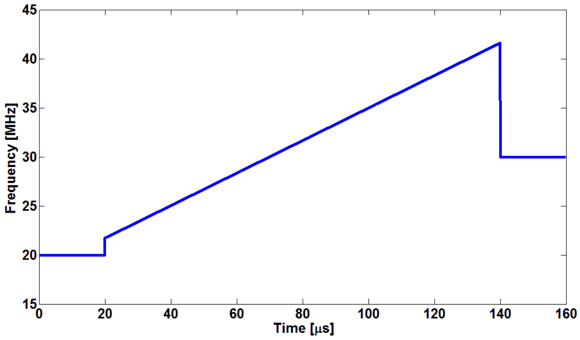


Figure 1. Frequency-time behaviour of the test signal.

Table I. Settling Time Versus Forgetting Factor.

Forgetting factors λ	**Settling time**		
	$t_{set,in}$ [ns]	$t_{set,A}$ [μs]	$t_{set,B}$ [μs]
λ = 0.999	280	19.38	1.05
λ = 0.998	280	9.23	0.80
λ = 0.996	280	3.47	1.14
λ = 0.994	280	1.59	0.83
λ = 0.992	280	1.00	0.65
λ = 0.990	280	0.83	0.55
λ = 0.980	330	51.29	0.28
λ = 0.960	380	98.89	14.65
λ = 0.940	11890	99.87	19.99
λ = 0.920	14980	100	20.00
λ = 0.900	14990	100	19.99

swept-frequency tone, after a short transient caused by a little frequency hop;
3) $t>t_{set,B}$, analyzing the method performance in presence of a single tone after a deep frequency hop.
From the analysis of the measurement results, reported in Table II, the following considerations can be drawn:
a) the mean frequency error obtained when the analyzing signal is a single tone at a fixed frequency is ever lower than 66 kHz, that corresponds to 0.33%;
b) the mean frequency error experienced during the linear frequency sweep is ever higher than one evaluated when a simple tone is applied;
c) the experimental standard deviation (σ_{ef}) seems to be influenced in inverse proportion by λ consider that the frequency resolution of the analysis is 24 kHz;
d) a value of λ = 0.996 seems to grant a good trade-off between measurement accuracy and convergence time.

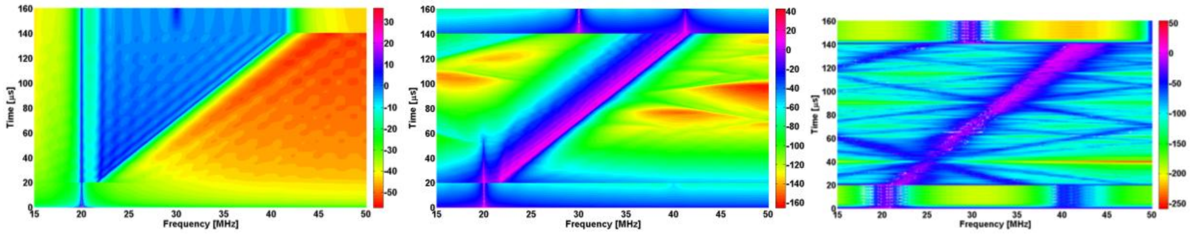
In Figure 2, as an example, the obtained spectrograms for three values λ are reported. In particular the values considered in Figure 2 are λ = 1.000 (absence of forgetting) λ = 0.996 and λ = 0.900. The information related to the amplitude of the PSD is coded by the color and the measurement unit is dBm. From the analysis of these results the following consideration can be drawn:
a) all the measures are characterized by a good signal to noise ratio (SNR);
b) measurement results, obtained when λ = 1 is involved, are affected by the memory effect that does not allow a good frequency tracking;
c) a value of λ equal 0.9 seems to be not adequate for this analysis, showing an instability in frequency tracking performance;
d) an intermediate value of λ equal to 0.996 seems to present negligible memory effects and a good frequency tracking performance.

IV. Conclusions

An innovative digital processing method for spectrum management and monitoring has been designed. It is based on a modified version of the sequential Burg algorithm in the order to mitigate its memory effects and giving the ability to track the frequency variation of the analyzing signal during the observation period.
In particular the Burg cost function has been modified by using an exponentially growing window with the aim of weighing the input samples giving more importance to the recent samples and attenuating the effects of the past ones. This solution avoids the need to store samples in the memory. This feature makes it a suitable

Table II. Measurement Performance at Steady-State. Mean Convergence Frequency Error and Standard Deviation of the Convergence Frequency Error Versus Forgetting Factor.

Forgetting factors λ	$t_{set,in}<t<20$ μs		$t_{set,A}<t<140$ μs		$t>t_{set,B}$	
	μ_{ef} [kHz]	σ_{ef} [kHz]	μ_{ef} [kHz]	σ_{ef} [kHz]	μ_{ef} [kHz]	σ_{ef} [kHz]
λ = 0.999	26	46	-95	40	22	12
λ = 0.998	27	47	-74	81	18	13
λ = 0.996	21	51	-73	96	23	23
λ = 0.994	20	57	-77	93	27	34
λ = 0.992	25	68	-61	92	21	44
λ = 0.990	66	77	-72	84	36	58



$\lambda = 1.000$ $\lambda = 0.996$ $\lambda = 0.900$

Figure 2. The obtained spectrograms, evaluated considering three values of λ.

candidate to be implemented on a cost-effective digital signal processing platform (DSP-based or FPGA-based). A preliminary measurement campaign has been designed to analyze the tracking capabilities and the measurement accuracies of the method. To this aim a test signal, characterized by a single tone that makes a little frequency hop and after that starts a linear sweep and then it carries out a deep frequency hop stopping at a fixed frequency, has been considered. This choice allows simulating some conditions that are common in practice, especially in spectrum monitoring.

Experimental results have highlighted that the proposed method shows a good trade-off between the measurement accuracy and the convergence time when a value of λ equal to 0.994 has been involved. In particular, a good settling time, not influenced by λ, has been experienced when a single frequency tone is tracked. Excellent convergence time has been evaluated when the method tracks a signal that after a little hop start a linear frequency sweep or when the signal makes a deep frequency hop and then stop its frequency variations. Small mean frequency error, ever lower than 0.33% when the test signal is characterized by a single frequency tone, has been evaluated. Future studies will be devoted to a deep characterization of the method and to comparison with the traditional methods such as short time Fourier transform, to implement it on a cost effective hardware platform and make a comparison with other measurement instruments available in the market.

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