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POWER OPTIMIZED LOW COMPLEXITY WIGNER VILLE DISTRIBUTION USING CLOCK GATING TECHNIQUE

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ABSTRACT: This project proposes a low complexity VLSI architecture design Methodology for Wigner Ville Distribution (WVD) computation. The proposed methodology performs both auto and cross WVD computations using only the half number of Fast Fourier transform (FFT) computations as opposed to the state of the art methodologies. A novel clock gating is applied to memory design to further reduce the activity along the clock distribution network. Moreover, it is also employed in the input and output ports of the memory block to decrease their loading, thus saving even more power.

Keywords: Wigner Ville Distribution, Fast Fourier transform, Complex tuple, Clock gating, Power optimization.

INTRODUCTION: High-rate dynamic systems are defined as engineering systems experiencing high-amplitude disruptions (acceleration >100 gn) within a very short duration (<100 ms) [1]. Examples of high-rate systems include blast mitigation mechanisms, hypersonic aircraft, and advanced weaponry. Generally, these systems experience rapid changes in their dynamics that can cause malfunctions and sudden failures. The capability to conduct real-time identification of such changes combined with real-time adaptation is critical in ensuring their continuous operation and safety [2]. In terms of system identification, the high-rate problem consists of being able to identify and quantify changes in dynamics over a very short period of time for dynamics containing (1) large uncertainties in the external loads; 2) high levels of non-stationarities and heavy disturbance, and (3) un modeled dynamics from changes in system configuration. Work directly addressing the problem of high-rate state estimation, or system identification is limited. In previous work, the authors have proposed an adaptive sequential neural network with a self-adapting input space enabling fast learning of nonstationary signals from high-rate systems [3].Although the data-based technique showed great promise at high rate state estimation, it did not provide insight into the system's physical characteristics, as it is generally the case with data-based techniques. Physics-driven methods, such as those borrowing on model reference adaptive system(MRAS) theory, showed great promise in handling nonlinearities, uncertainties, and perturbations [4,5].MRAS was applied to the problem of high-rate state estimation in [6], where the position of a moving cart was accurately identified under 172 ms through a time-based adaptive algorithm used in reachingthe reference model with an average computing time of 93 μs per step, obtained through numerical simulations conducted in MATLAB. A frequency-based approach was proposed in [7] to identify the position of that same cart. Their algorithm consisted of extracting the dominating frequency througha Fourier transform over a finite set of data and matching that frequency to a set of pre-analyzed finiteelement models. The authors applied their algorithm experimentally using a field programmable gatearray (FPGA), and were able to accurately identify the position of the cart within 202 ms with a 4.04 msprocessing time per step.A net advantage of frequency-based methods over time-based methods is thatthey do nottypically rely on the tuning of parameters such as adaptive gains. However, they are harder to apply inreal time because they are inherently batch processing techniques. It follows that, to enable applicationsto high-rate systems, one must integrate a temporal approach to the frequency technique in order toextract the required real-time information, a method known as time-frequency representation (TFR).For example, this was done in [7] through the use of a non-overlapping sliding window of 198 mslength. The objective of this paper is to explore the applicability of TFRs to the high-rate problem.TFRs are widely used for the detection and quantification of faults through vibration-baseddata [8]. Frequency domain characteristics, such as frequencies, damping ratios, energy in differentfrequency ranges, and time-frequency domain characteristics, such as time frequency spread [9],can be used as key features to conduct structural health monitoring [9]. A number of TFRs forinstant frequency recognition have been proposed. Popular approaches include linear non-parametricmethods, such as short-time Fourier transform (STFT), wavelet transform (WT), and Wigner–Villedistribution (WVD) [9,10]. The application of these methods results in a trade-off between time andfrequency resolutions [1]. An adaptive non-parametric method have also been proposed, includingthe Hilbert–Huang transform (HHT) [2–4], the Cauchy continuous wavelet transform (CCWT) [15],the instantaneous frequencies (IF) re-assignment methods, synchrosqueezing transform (SST) [6], andthe multi-SST (MSST) [7].

LITERATURE SURVEY: A wealth of information could be found in the time-frequency (TF) analysis literature [1]–[4], such as linear andquadratic TFRs [5], polynomial TFRs [6], [7], etc. Most ofrecent studies developed so far are low-order TFRs, mainlyincluding linear short-time Fourier transform (STFT), linearfractional Fourier transform (FRFT) [8], [9], quadratic pseudoWigner-Ville distribution (PWVD) and classical Cohen's classTFRs [10]. Despite high TF resolution of nonlinear TFRs, theygenerally suffer from cross-term (CT) interference and irreversible TF transform, which cause a serious barrier to modereconstruction. Prior studies that have noted the importance ofmode deconstruction emphasize on linear TFRs due to theirlow computation cost and invertibility [11].The theory of linear TFRs has been investigated quiteintensively during the past decades. Wavelet transform (WT)[12], which is regarded as a classical linear TFR, employsadaptive window sizes to improve TF resolution compared tolinear STFT. Signal representation was afterwards improvedby implementing post-processing based on WT or STFT.The reassignment (RS) methods [13], [14] assign the averageenergy in certain domains to the gravity center of energydistributions to gain IF trajectories. However, a major problemassociated with RS related methods is the infeasibility ofmode reconstruction. Further, the synchrosqueezing transform(SST) [15] derived on WT [16] or on STFT [17] squeezes TFcoefficients into the IF trajectory only in frequency direction instead of in both time and frequency directions for RS,with the aim of reconstructing signal modes. In recent years, advantages to mode representation and reconstruction have resulted in an increasing interest in the development of SST-based methods [18]–[21]. Inspired by the SST, Yu et al. proposed the synchroextracting transform (SET) [22], whichemploys a newly developed synchroextracting technique to generate a more energy concentrated TFR, and meanwhile the invertible SET allows for mode reconstruction. Thanks to the simplicity and immunity to CTs of linear TFRs, Abdoush etal. [23] developed two linear TF transforms, based on which an adaptive IF estimation method for noisy multi-mode signalswas implemented.

TIME-FREQUENCY ANALYSIS: Theoretical aspects of time-frequency analysis have been intensively studied over the last two decades . In parallel, their various applications have been exploited as well. Namely, for an efficient analysis of nonstationary signals, such are radar, sonar, biomedical, seismic, and multimedia signals, time-frequency representations are required. Time-frequency distributions are most commonly used for this purpose. Many of the researchers have made significant efforts in defining a distribution that is optimal for a wide class of frequency-modulated signals As a result, a number of time-frequency distributions have been proposed. However, the efficiency of each of them is more or less limited to a specific class of signals and, consequently, to a specific application. One of the goals of this paper is to highlight the most important features of some popular time-frequency distributions and to give an idea of how to choose the most appropriate distribution depending on the signal form. The linear, quadratic, higher-order, and multiwindow time-frequency distributions are considered. The short-time Fourier transform, as the most commonly used linear transform, is firstly discussed. Next, the Wigner distribution, as the best known quadratic distribution, is presented. Also, the Cohen class and some specific distributions belonging to this class are considered . It is shown that the quadratic distributions are optimal for a linear frequency-modulated signal.

EXISTING METHOD:

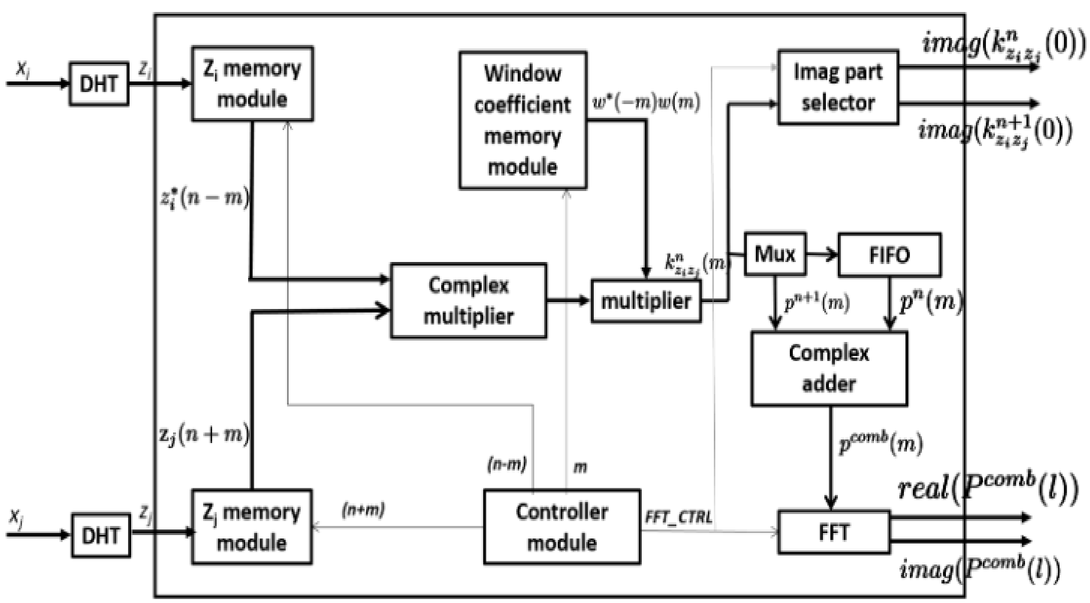

Figure1: existing WVD architecture

WIGNER-VILLE DISTRIBUTION: The Wigner-Ville distribution Ws of a time series signal s(t) is defined as

$$W_s(t,\omega) = \int_{-\infty}^{\infty} s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-i\omega\tau} d\tau. \quad (1)$$

[7] This distribution was first introduced by Eugene Wigner in his calculation of the quantum corrections of classical statistical mechanics . It was independently derived again by J. Ville in 1948 as a quadratic representation of the local time-frequency energy of a signal. The time series function s(t) in equation (1) can be either real or complex. The only type of complex signal considered in this paper is the analytic signal, which is defined as (s(t) + iH[s(t)]) where H denotes the Hilbert transform [e.g., Cohen, 1994]. The analytic signal has the same spectrum (or, to be precise, the spectrum multiplied by two) as that of the original real signal at positive frequencies but keeps the spectrum at negative frequencies zero. [8] A significant characteristic of WVD, which essentially correlates the signal with a time- and frequency- ranslated version of itself, is that it does not contain a windowing function as those in the Fourier and wavelet frameworks. This unique feature frees WVD from the smearing effect due to the windowing function, and, as a result, the WVD provides the representation that has the highest possible resolution in the time-frequency plane. For example, if a wave packet is nonzero only for t∈ (t1, t2), it can be shown that the corresponding Ws has to be 0 for t outside this exact time interval.

[9] There is, however, a well-known disadvantage of using WVD. When there are multiple components in a signal, the WVD can become difficult to interpret. Suppose that the signal s(t) is composed by the sum of two signals, s1(t) and s2(t), the WVD becomes

$$W_s(t,\omega) = W_{s_1}(t,\omega) + W_{s_2}(t,\omega) + 2\Re W_{s_1,s_2}(t,\omega), \quad (2)$$

in which $W_{s_1,s_2}(t,\omega) \equiv \int_{-\infty}^{\infty} s_1\left(t+\frac{\tau}{2}\right) s^*_2\left(t-\frac{\tau}{2}\right) e^{-i\omega\tau} d\tau$

is called the “cross” Wigner-Ville function. Representing the “interference” between the two signals, the term $2\Re W_{s_1,s_2}(t,\omega)$ has significant nonzero values located between the auto terms in the time-frequency plane. This cross-term interference makes it difficult at times to interpret signal properties from WVD.

[10] One of the special properties of the interference term is that it is highly oscillatory in the time-frequency plane compared to the auto terms that represent the true signals [e.g., Cohen, 1994]. This property inspired the idea that a smoothing function, or a “kernel,” can be used to suppress the interference pattern without much of an effect on the desired signal. In this approach, the kernel is placed in the Wigner-Ville function as

$$\widetilde{W}_s(t,\omega) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \phi(t',\omega')\, W_s(t-t',\omega-\omega')\, dt'd\omega', \quad (3)$$

PROPOSED METHOD:

CLOCK GATING MEMORY:

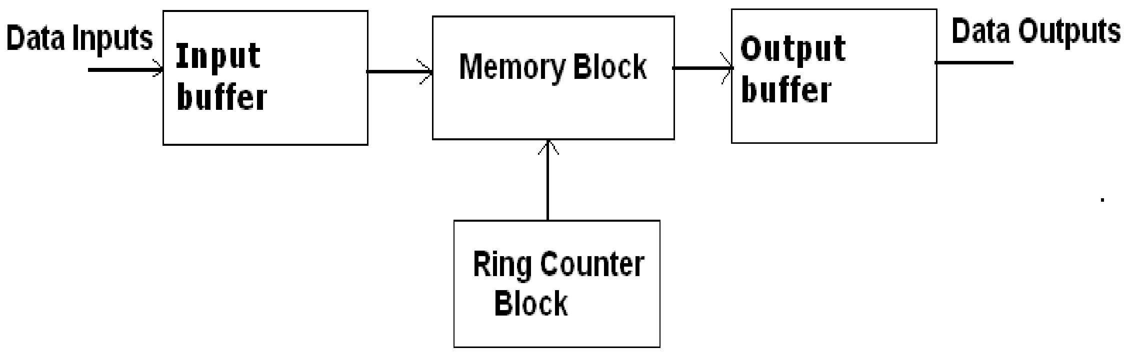

Figure2 : Block Of Memory Organization

INPUT BUFFER:

The Input buffer is also commonly known as the input area or input block. When referring to computer memory, the input buffer is a location that holds all incoming information before it continues to the CPU for processing. Input buffer can be also used to describe various other hardware or software buffers used to store information before it is processed. Some scanners (such as those which support “include” files) require reading from several input streams. As flex scanners do a large amount of buffering, one cannot control where the next input will be read from by simply writing a YY_INPUT() which is sensitive to the scanning context. YY_() is only called when the scanner reaches the end of its buffer, which may be a long time after scanning a statement such as an include statement which requires switching the input source.

MEMORY BLOCK:

(RAM) Random-access memory (RAM) is a form of computer data storage. Today, it takes the form of integrated circuits that allow stored data to be accessed in any order (that is, at random). "Random" refers to the idea that any piece of data can be returned in a constant time, regardless of its physical location and whether it is related to the previous piece of data. The word "RAM" is often associated with volatile types of memory (such as DRAM memory modules), where the information is lost after the power is switched off. Many other types of memory are RAM as well, including most types of ROM and a type of flash memory called NOR-Flash.

Scan design has been the backbone of design for testability (DFT) in industry for about three decades because scan-based design can successfully obtain controllability and observability for flip-flops. Serial Scan design has dominated the test architecture because it is convenient to build. However, the serial scan design causes unnecessary switching activity during testing which induce unnecessarily enormous power dissipation. The test time also increases dramatically with the continuously increasing number of flip-flops in large sequential circuits even using multiple scan chain architecture. An alternate to serial scan architecture is Random Access Scan (RAS). In RAS, flip-flops work as addressable memory elements in the test mode which is a similar fashion as random access memory (RAM). This approach reduces the time of setting and observing the flip-flop states but requires a large overhead both in gates and test pins. Despite of these drawbacks, the RAS was paid attention by many researchers in these years. This paper takes a view of recently published papers on RAS and rejuvenates the random access scan as a DFT method that simultaneously address three limitations of the traditional serial scan namely, test data volume, test application time, and test power.

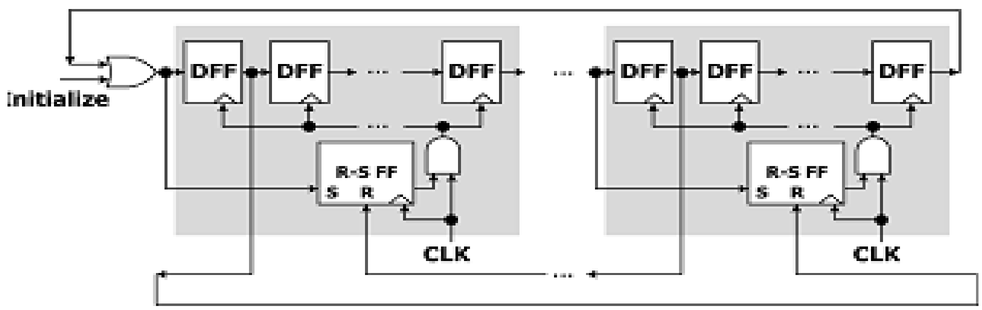

Figure3 : Ring Counter With SR Flip-Flops

The above block diagram shows the power controlled Ring counter. First, total block is divided into two blocks. Each block is having one SR FLIPFLOP controller

RESULTS:

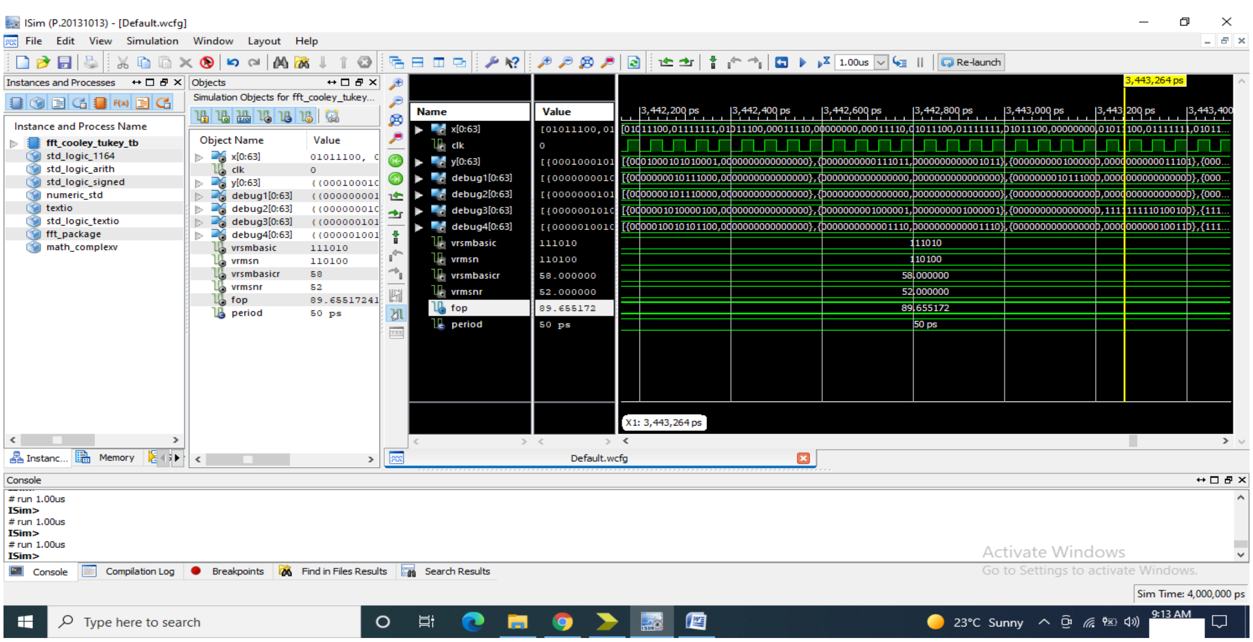

Fig4: Proposed simulation output

CONCLUSION: Finally, this project proposed an architecture design methodology for low complex Wigner Ville Distribution (WVD) computation which performs both AWVD and XWVD and saves 50% FFT computations when compared with the state of the art methodologies. It also significantly reduces the energy consumption. Extension in this concept produces low latency accessing with atmost efficient reading and writing.

FUTURE SCOPE: The implementation of any algorithm can be realized either with software programs or hardware logic circuits . Software realization has limitations since the defined instruction set has to be used. As a future scope 16 point, 32 point, etc. processor can be implemented with the help of the enhanced multiplierto get high speed and power efficient devices.

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